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Review

# Applications of text mining in services management: A systematic literature review

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A B S T R A C T

The importance of text mining is increasing in services management as the access to big data is increasing across digital platforms enabling such services. This study adopts a systematic literature review on the application of text mining in services management. First, we analyzed the literature on which has used text mining methods like Sentiment Analysis, Topic Modeling, and Natural language Processing (NLP) in reputed business management journals. Further, we applied visualization tools for text mining and the topic association to understand the dominant themes and relationships. The analysis highlighted that social media analysis, market analysis, competitive intelligence are the most dominant themes while other themes like risk management and fake content detection are also explored. Further, based on the analysis, future research agenda in the field of text mining in services management has been indicated.

## 1. Introduction

An immense amount of digitized texts is available on the online platform in newspaper content, social media posts, customers' reviews on products and their experiences, scientific articles, and press releases. From some time back, scholars from management have started utilizing the power of text mining in various fields for theory building (Kar and Dwivedi, 2020). In fact, inclination towards digital transformation of industries has increased the quality and volume of unstructured data. This ample amount of unstructured data is now available for the researchers for analysis using big data analytics methodology, of which text mining is an integral part. Methods for theory building is gaining traction which uses text analytics on these large unstructured data (Kar and Dwivedi, 2020).

Further, the Internet's immense growth allows users to share and search for ideas, opinions, and recommendations. Social media platforms like Twitter and Facebook play an important role in direct and indirect communication among users (Chandler et al., 2018). Besides, this massive amount of data available on social media platforms opens a new opportunity for the researchers and market professionals to analyze the status of the product in the market and help to make strategic plans for the growth of products and services as well (Shirdastian et al., 2017). The number of Internet users, as well as social media users, is growing day by day. Therefore, users create vast amounts of data in texts, videos, images, and audios on social media platforms. In addition, data on social media is freely available to users. Therefore, users can extract huge amounts of data from social media platforms in a concise duration. Here, the text mining technique is applied to social media data for many purposes like marketing (AlAlwan et al., 2017), product planning (Jeong et al., 2017), and digital marketing (Aswani et al., 2018). Online platforms like Yelp and TripAdvisor provide a platform for the customers or consumers to contribute fair feedback and explicit opinions to service providers. Therefore, online reviews are a reliable and free source of consumers' or customer's feedback in this digital environment (Dellarocas, 2003). In addition, online reviews or recommendations inspire customers or consumers to purchase or re-purchase the services because they strongly believe that feedbacks or recommendations given by their social networks are more reliable than that from unknown people (Filieri et al., 2015). Thus, online reviews on these platforms play an essential role in the decision-making process of customers or consumers and leave an effect on online or offline sales of the product (Cui et al., 2020; Chevalier and Mayzlin, 2006). Nowadays, industries, suppliers (Pani and Kar, 2011), buyers, and service providers continuously analyze the market to know the product's status among the consumers or customers to maintain the position in this competitive environment (Takata, 2016).

In earlier times, scholars have used qualitative approaches (Mayring, 2015) to analyze the text data with grounded theory (Duriau et al., 2007) or manual coding. However, these manual processes not only very time consuming, labor-intensive and faces challenges of segregating biases of interpretation of coders and uniformity of objectivity in coding. Further, these manual techniques do not have

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the capability to handle a massive amount of text data (Kobayashi et al., 2018; Jamiy et al., 2015). From the last decade, researchers have started to use the functionality of automatic text analysis (Wiedemann, 2013; Janasik et al., 2009). Text mining and natural language processing (NLP) becomes essential where the size of text corpus is vast, and manual content analysis not possible. On digital platforms, user-generated content is growing rapidly day by day in the form of video, audio, image, and text. Therefore, this unstructured data needs tools and methods that can easily extract useful information from the textual information (Fan et al., 2006). Text mining, also called text analytics, is an artificial intelligence technique that converts unstructured data into structured data by using NLP to enhance the analysis using machine learning algorithms. Text mining is a popular technique among computer science, information science, mathematics, and management fields for mining intelligence out of big data (Humphreys and Wang, 2018; Grover and Kar, 2017).

This current study provides a systematic literature review on text mining applications in the service and management fields. In this study, we reviewed 125 research papers from 35 top journals on text mining applications in service and management. Of 125 research papers, 26 papers are generic and the rest of 99 papers demonstrate the application of text mining in various domains. We have attempted to address the following research questions through this review of literature:

1) What are the trends in literature in terms of dissemination that is published on text mining applications in services management?
2) What are the main themes emerging in these literatures and how are these themes associated with each other?

This study is arranged as follows; Section 2 demonstrates search criteria on the Scopus database of research articles on the application of text mining in service management and inclusion/exclusion criteria. Section 3 demonstrates the articles in journals and year-wise, theme-wise, and shows the association among the concepts. Section 4 illustrates the discussions on the various applications of text mining. Section 5 demonstrates the practical implications of the study. Section 6 shows the conclusions and future works of the study.

## 2. Methodology

A systematic literature review methodology has been adopted by this article (Gupta et al., 2018; Chakraborty and Kar, 2017). We selected the Scopus database to analyze text mining literature which has been published in service management because Scopus indexes a very wide coverage of engineering and management literature in terms of journals, conferences and book chapters (Grover et al., 2018; Singh et al., 2020; Agarwal et al., 2017). Further, Scopus provides various options in which users can search for the relevant literature through advanced search. Therefore, for this study, we extracted the research papers from the Scopus database. Initially, we downloaded the research papers from the Scopus database in September 2020.

For downloading the research papers, we decided on the search terms "Text Mining", "NLP", "Semantic Analysis", "Topic Modeling", "Service", and "Management". We used the Boolean "AND" and "OR" operator in the search field to combine the search term. Therefore, the structure of the search query was ""Text Mining" OR "NLP" OR "Semantic Analysis" OR "Topic Modeling" AND "Service" OR "Management"'. It ensures that search terms will come in extracted research papers. We applied a search on "Article Title" and "Article Keywords" for the initial downloading of published research literature. In the first phase, we fetched 6273 research papers from the query result. In the second phase, we restricted our analysis only to journals published literature, then the number of research papers reduced to 3893. In the third phase, we focused only on the business and management area, then the number of research papers reduced to 327. In the fourth phase, we restricted our search only to FT publications; A*, A, and B ranked journals in the Australian Business Dean's Council journal ranking schema and 4*, 3 and 2 in the Chartered Association of Business School's journal ranking schema, to restrict to relatively higher quality articles, then the paper count reduced to 155. These three journal ranking schema were used as collectively they are more inclusive and yet fairly popular globally as a standard for assessing quality of publications. In the fifth phase, we screened titles, keywords, and abstracts of the selected papers so that we can exclude inappropriate papers. We excluded those papers that were not relevant to the objective of the systematic review process of text mining applications in service and management. Finally, we got 125 research papers that were entirely appropriate for studying text mining applications in the service and management field (see Appendix A).

Fig 1 demonstrates the papers' selection process for the review and the number (N) of papers present in each phase.

## 3. Findings

This section contains three subsections: year wise and journal wise stats, theme wise reporting and interrelation / association among concepts. In the first sub-section, the study shows the year wise distributions of the papers, list of journals and application of text mining. In the second sub-section, the study demonstrates the high-frequency words in the title and author keywords of the papers, which are indicative of thematic focus across these studies. In the third sub-section, the study demonstrates the various domains across various text mining applications. Besides, the study also demonstrates the association rule mining and network diagram on keywords of the papers to demonstrate the association among the knowledge graphs.

### 3.1. Year wise and journal wise stats

Fig 2 demonstrates the year-wise distribution of the publications for the systematic review. Among 125 research papers, only 23 papers are published before 2018; the remaining papers are published between 2018 and 2020. Fig 2 shows incremental growth in publishing literature on text mining in high ranked reputed journals.

Further, we analyzed the selected papers to know the main themes based on the papers' keywords and titles. For that purpose, we set the word cloud approach, which displays the most occurrence words with some appropriate size. We applied the word cloud technique on keywords and titles of the research papers to know the popular keywords or phrases, around which text mining development is twirling (Scanfeld et al., 2010).

Fig 3 demonstrates the distribution of 125 research papers across 35 journals with 07 text mining applications. It was observed that International Journal of Information Management is the most preferred journal among the researchers who are publishing their articles related to text mining applications for services management. Fig 3 also shows that Social Media Analysis and Market Analysis are the most popular text mining application among the researchers for getting insights from social media and online reviews. However, we are considering 125 research papers for the systematic literature review in which 26 research papers are generic in nature because these research papers do not analyze any specific domain but using text mining techniques.

### 3.2. Theme wise reporting

Fig 4 (A) demonstrates the high-frequency words in the titles of the research papers. The most popular words in the titles of the selected research papers are "analysis", "reviews", "sentiment", "social", "service", "Twitter", and "consumer". In Fig 4 (B), the most popular keywords of the selected papers are "text mining", "social media", "online review", "user-generated content", "machine learning", "big data", "customer satisfaction" and "Twitter". It concludes that "machine learning", "customer satisfaction", "social media analytics", "user-generated content", "online review", and "sentiment analysis" are the most dominant themes in the selected research paper for this systematic review of text mining applications.

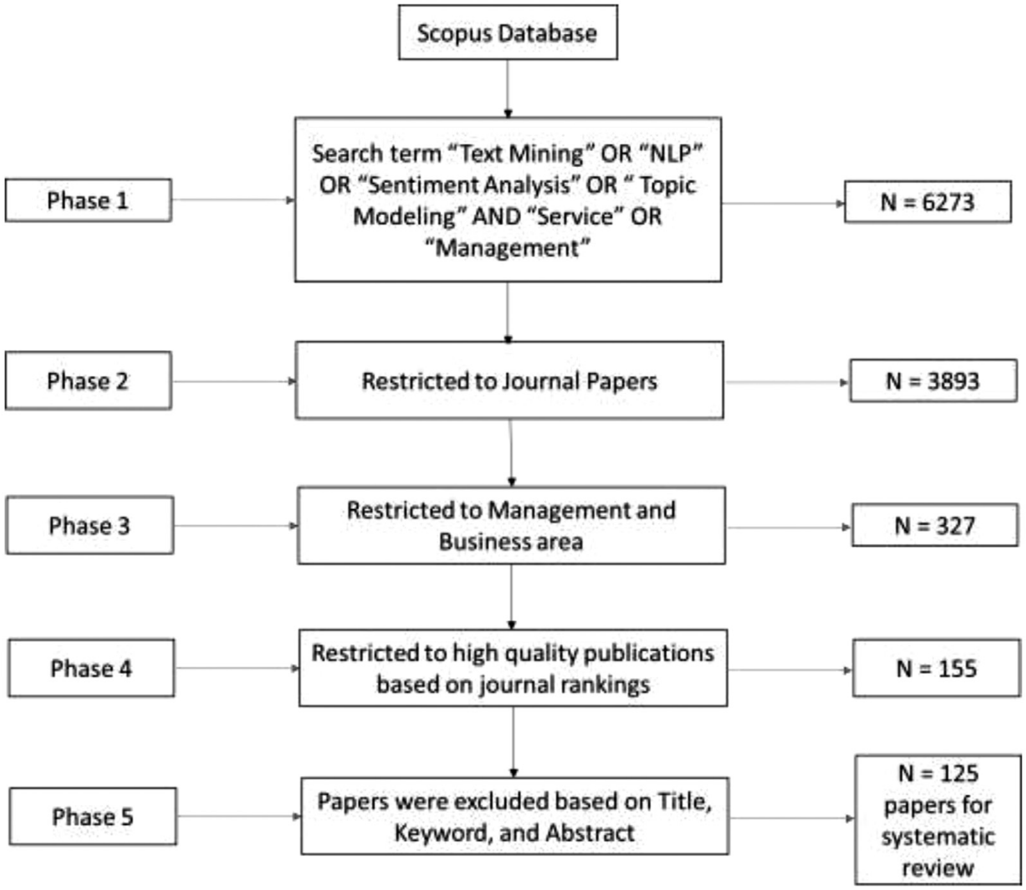


**Fig. 1.** Stages of the study selection process for the literature review.

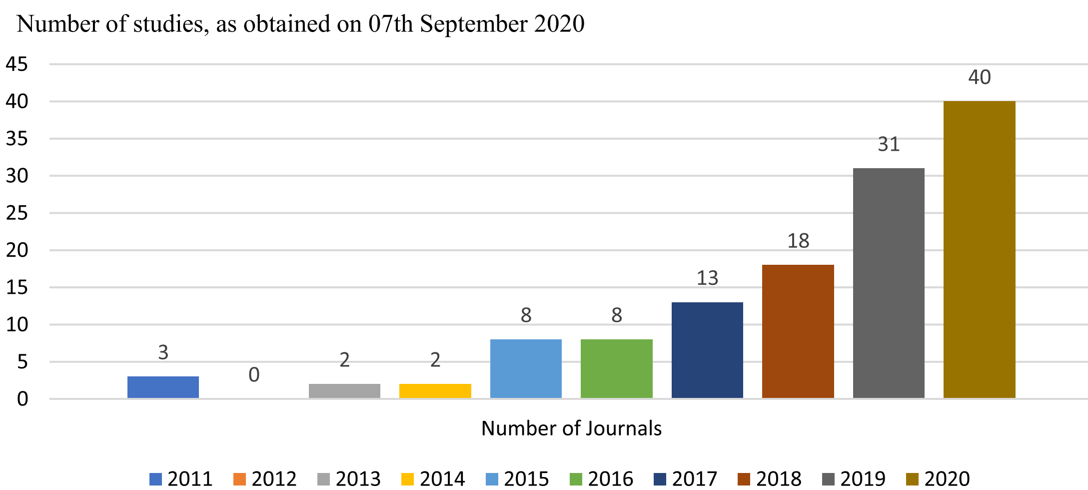


**Fig. 2.** Year wise distribution of research articles as obtained September 07, 2020.

### 3.3. *Association among domains with text mining*

Further, we keen to know those approved areas where text mining can be utilized. Association rule mining is a procedure to find out the relationship and association among a large set of transactions or data items (Kotsiantis and Kanellopoulos, 2006). Apriori (Agrawal et al., 1996), FP-Growth (Kumar and Rukmani, 2010), and Eclat (Zaki, 2000) are few algorithms for association rule mining. In this study, we used the Apriori algorithm for association rule mining on keywords of the selected papers. Association rule mining allows the analysis about the combination of methods within text mining which is more widely adopted for the analysis of big data in published literature. Fig 5 demonstrates the association rule mining on keywords of the selected papers for the systematic literature review process, and the size of the circle shows the frequency of the keywords among the selected papers.

Fig 6 demonstrates the distributions of the domains across various text mining applications. From 125 research papers, only 99 research papers are distributed across these domains. Fig 6 also shows that Sales, Hotel, Restaurant, Business, Tourism, and Airline industry are the most

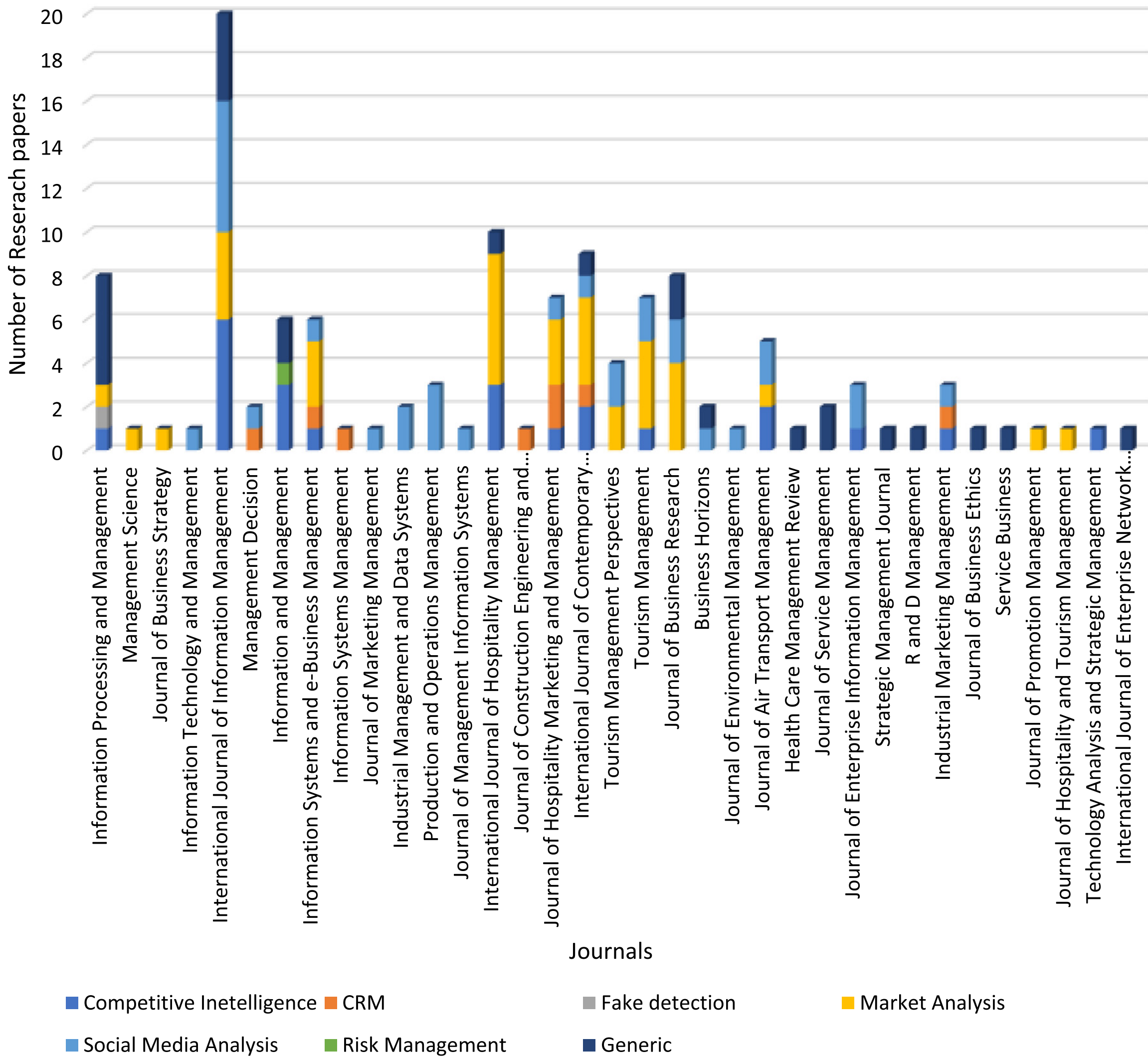


**Fig. 3.** Distribution of research papers across journals and Text mining applications.

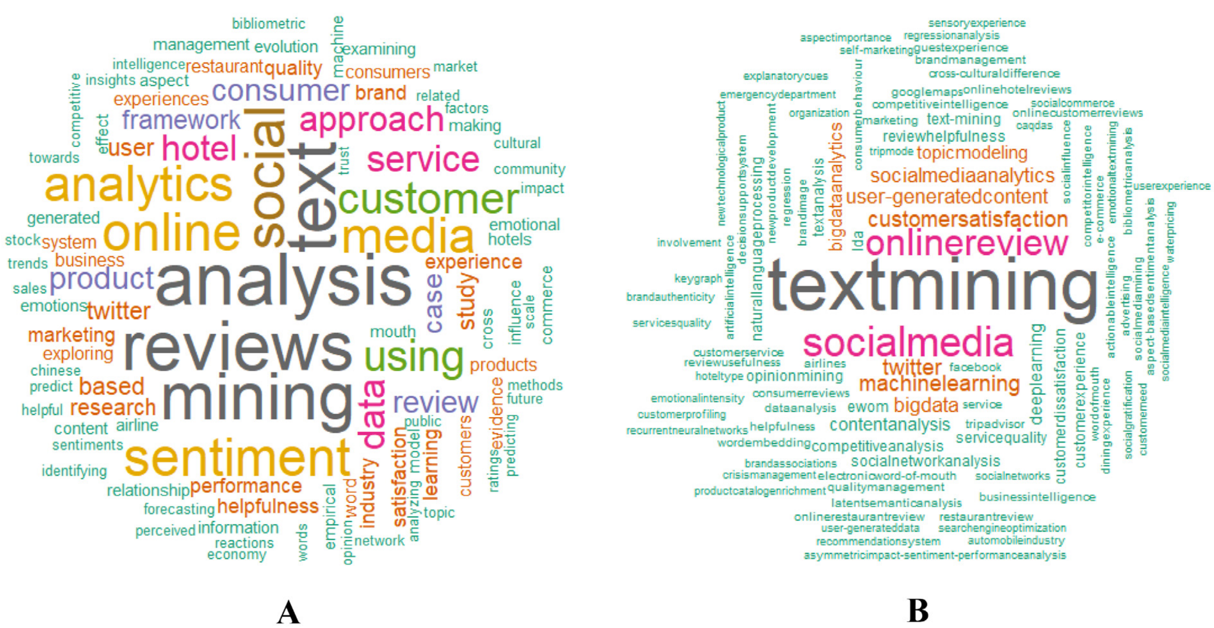


**Fig. 4.** (A) Word cloud of the titles (B) Word cloud of the keywords of the selected papers.

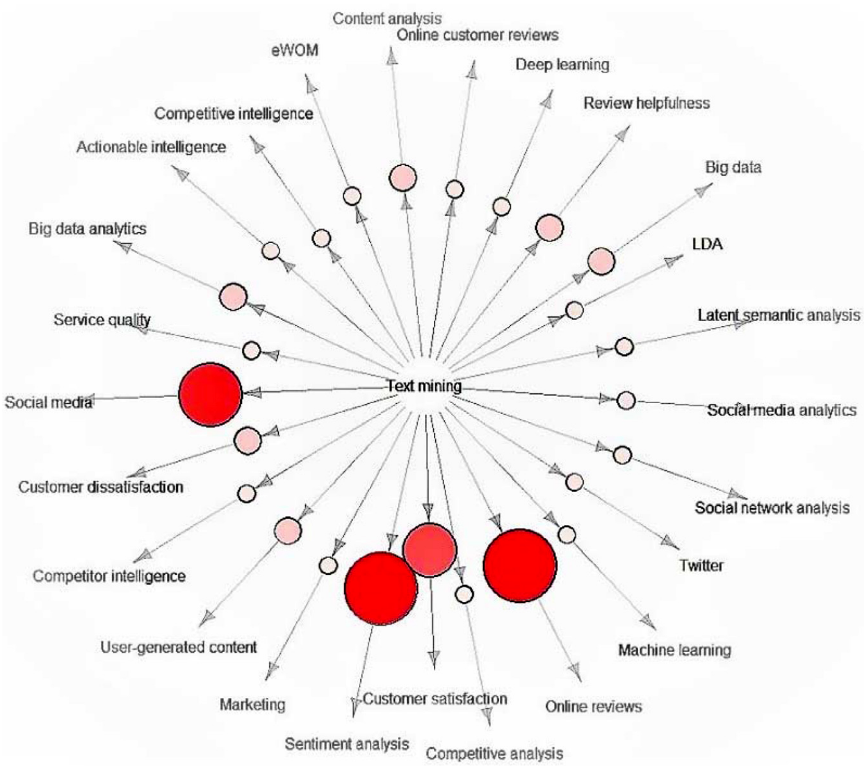


**Fig. 5.** Association rule network of keywords of the selected papers for the systematic review.

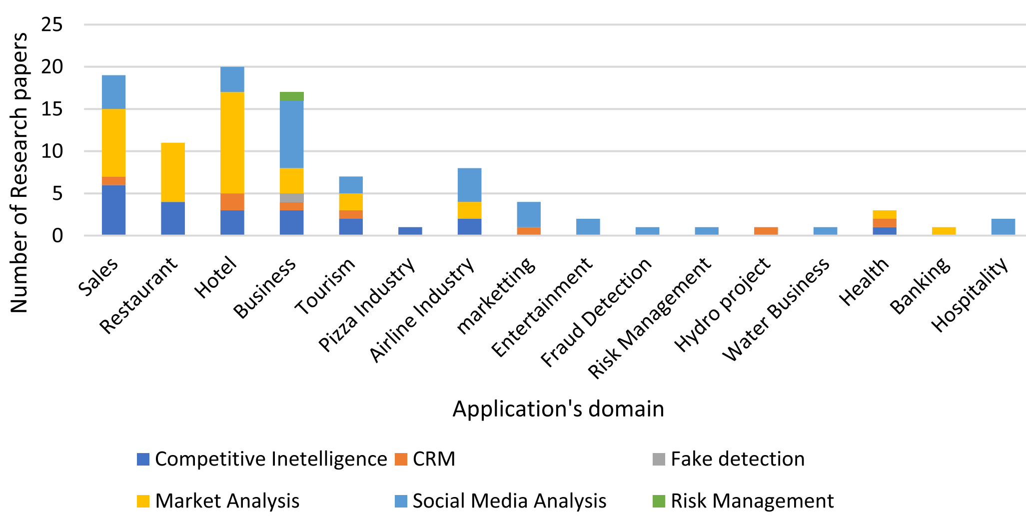


**Fig. 6.** Distribution of domains across the text mining applications.

targeted domains where researchers use Text Mining techniques to get insights from the social media and online reviews of customers.

Further, we created a network diagram by using co-occurrence words in the author's keywords. Fig 7 illustrates the eight significantly unique and thirty one non-significant clusters of closely associated keywords where each cluster has a unique color and demonstrates the themes which contain by the co-occurrence words in the author's keywords.

## 4. Dominant themes in literature

In this section, we present an overview of the major thematic areas which are identified based on the articles selected based on the systematic literature review methodology. The discussions are structured surrounding six thematic areas identified through the reviews.

### 4.1. Social media analysis

Nowadays, social media (SM) platforms have become popular among users as a source of valuable information regarding sales (Lau et al., 2018; Jeong et al., 2019; Rathore and Ilavarasan, 2020), marketing (Guerreiro and Moro, 2017; Moro et al., 2018; Aswani et al., 2018), hotel industry (Calheiros et al., 2017; Geetha et al., 2017; Xu et al., 2017), hospitality (Kim and Im, 2018), airline industry (Guercini et al., 2014; Tian et al., 2019; Punel and Ermagun, 2018; Martin-Domingo et al., 2019), entertainment (Wang et al., 2015; Lee et al., 2018), business (Canhoto and Padmanabhan, 2015; Abrahams et al., 2015; Fan et al., 2013; Lee, 2018; He et al., 2019; Mingione et al., 2020; Greco and Polli, 2020; Liu, 2020), tourism (Park et al., 2020; Ainin et al., 2020), fraud detection (Li et al., 2016), water business (Pawsey et al., 2018), and risk management (Tse et al., 2016; Ragini et al., 2018).

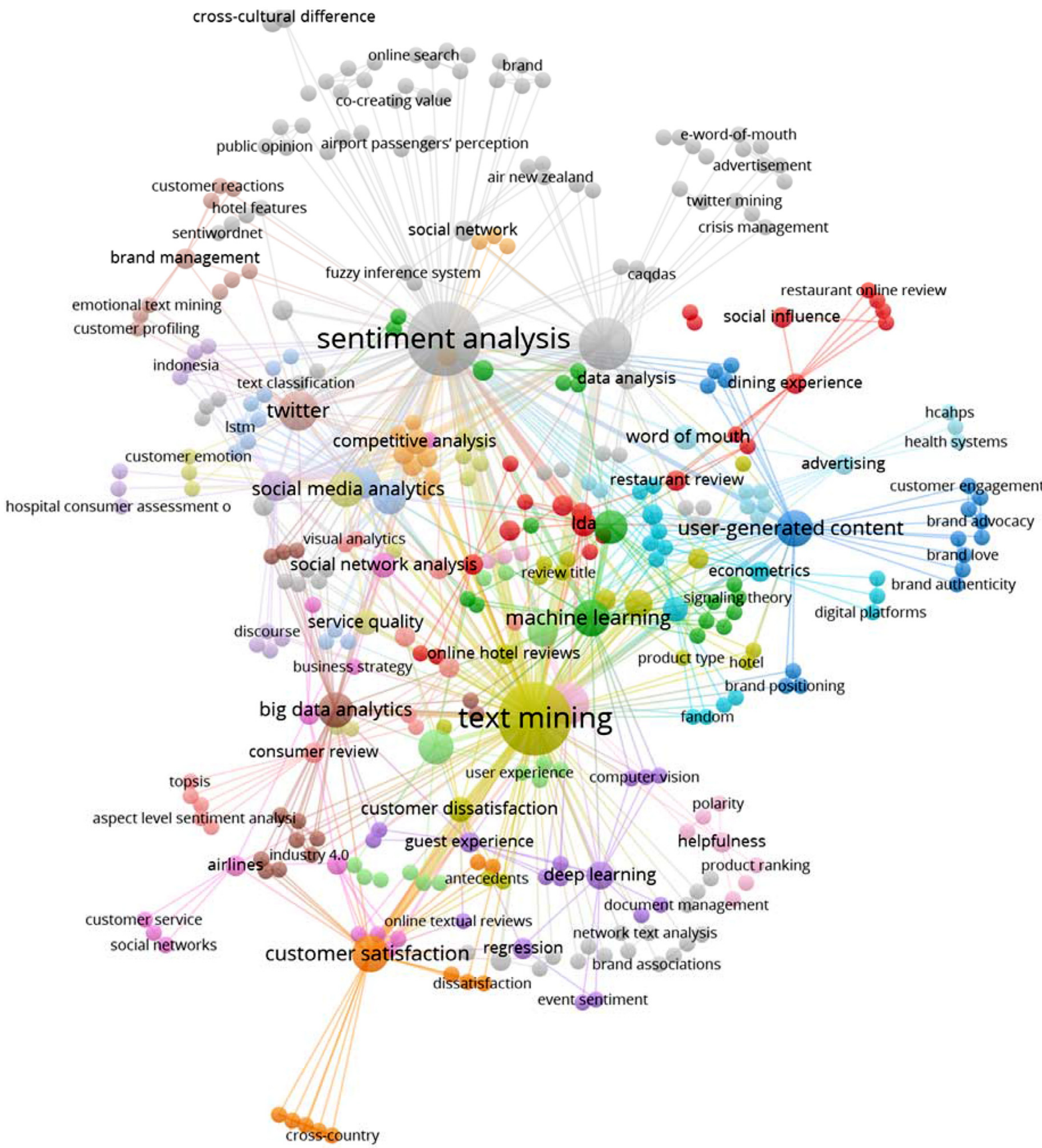


**Fig. 7.** Network association diagram of author's keywords.

Before going to the actual purchase of products or services, customers or consumers utilize the information present on the social media platforms (e.g. Twitter and Facebook) to make purchase decisions (Li et al., 2018). Social media analysis is one of the important text mining applications in the era of service and management whereby the connect with customers can be strengthened easily by the firms (Chatterjee and Kar, 2020). Therefore, industries utilize social media data about the product to know the perception of the quality and opinion of the customers or consumers before or after product launch (Rathore and Ilavarasan, 2020). In addition, social media analysis also has been used to analyze the social media data for demand forecasting using Parallel Aspect-oriented Sentiment Analysis for Demand forecasting (PASAD) framework (Lau et al., 2018). Social media data is full of the views of customers on services or products and provides many methods for the extraction and analysis of this user generated data. Besides, the opportunity algorithm makes strong social media analysis in the sales domain because it analyzes latent features of the product with the help of topic modeling and sentiment analysis (Jeong et al., 2019).

Customers continuously update their service experiences on social media platforms after the service encounters. This user-generated content (UGC) on social media platforms helps service providers to understand the shortcomings and make policies for the betterment of the services and the product (Abrahams et al., 2015; Fan et al., 2013). Generally, customers share their positive and negative service experiences and directly address those industries or companies in which they get bad service experiences. Airline industry utilizes UGC for the evaluation of the service quality by applying sentiment analysis (Guerreiro and Moro, 2017; Punel and Ermagun, 2018; Martin-Domingo et al., 2019) and SERVQUAL model (Tian et al., 2019). In addition, marketers and professionals also utilize big data UGC to get insights to make business decisions and plan to assist the business to business firms. In stock performance, negative sentiments are more impactful as compared to positive sentiments of customers or consumers (Liu, 2020). Emotional text mining (Canhoto and Padmanabhan, 2015) also applies to big data UGC to identify valuable customers who share similar brands on social media (Mingione et al., 2020; Greco and Polli, 2020). In the business prospectus, customers' knowledge plays an essential role in the enhancement of the products and services of the organizations (He et al., 2019).

The tourism industry uses social media to analyze the overall tourism service experience and needs of tourists. Nowadays, the tourism industry has become an essential part of the income of the tourist location and its government. Entertainment is also an industry that is using social media data to analyze the performance of the movie and the manipulation of the sentiments. Sentiment analysis and topic modeling are the methods that have used in the analysis of movie-related tweets to check the performance (Wang et al., 2015) and fake reviews of movies (Lee et al., 2018). In addition, tourists of halal tourism and theme park share their views on social media platforms (e.g. Twitter and Facebook). Sentiment analysis tells about the emotions of the tourists towards halal tourism and theme parks (Park et al., 2020; Ainin et al., 2020). Hotel industry's growth depends on the ratings and emotions that is given by the customers (Geetha et al., 2017). Incomplete reviews and ratings along with differences in the articulation of the words create a problem to understand the overall sentiments (Calheiros et al., 2017) of the tourists or customers about the Hotels. Imputation method solve the problem of incompleteness of the reviews or ratings because it completes the missing values by filling alternate values (Kim and Im, 2018). Latent Semantic Analysis (LSA) and Latent Dirichlet Allocation (LDA) are two very important algorithms which are used to get latent theme among the customer's discussions from the user-generated content on social media (Xu et al., 2017).

In digital marketing, service providers use social media data to analyze the effect of the products or services in the local as well as the global environment. In addition, cultural aspect play an important role in perception of customers on products which helps in decision making process on purchase and sales (Moro et al., 2018). Search Engine Marketing (SEM) is a service that enhances the visibility of products to customers over the Internet. It gives adverse effects on the success of the products in the digital environment if it is not done properly (Aswani et al., 2018). Nowadays, when customers think to purchase any products or services, first they visit online reviews about the products on social media to make purchase decisions. Therefore, the recommendations and tips about the products present on social media platforms play an important role in the decision-making process (Guerreiro and Moro, 2017). Due to the sensitivity and importance of online reviews or conversations on social media platforms, the security and management of the information becomes mandatory (Li et al., 2016; Tse et al., 2016; Ragini et al., 2018).

### 4.2. Competitive intelligence

Nowadays, organizations check their performance or competitiveness in the market on regular basis in terms of services or product offers. This exercise provides an opportunity for the organizations to make better products or services to the customers (Chatterjee, 2019; He et al., 2018). In addition, customers also share their experiences about the products or services on online platforms or an e-commerce website with full emotions and give star ratings according to the performance of the products or services. Some literature reveals that sometimes star ratings and online review's sentiments are biased (Zhang et al., 2011) and do not match with each other (Al-Natour and Turetken, 2020). Hence, automatic sentiment analysis is applied to the available online review to check the overall attitude of the customers, which works as an alternative to star ratings. Contextual attributes like product type and review length play an important role to understand the actual sentiment of the reviews (Kim and Kang, 2018). Generally, it is very difficult to analyze product competitiveness in big data. Therefore, the discriminative attribute of the product helps to analyze the competitiveness in the market (Chen et al., 2017). Comparison of word-of-mouth of products gives meaningful insights which provide help to the organization to make product useful (Tang et al., 2016; Lipizzi et al., 2015; He et al., 2015). VOZIQ is an analysis tool that analysis tweets of business organizations to extract meaningful information (Jeong and Jang, 2011).

The customer experience (CX) plays an important role in the success of the restaurant industry. CX is basically a perception of the restaurant's quality by customers (Mathayomchan and Taecharungroj, 2020). Food, atmosphere, service, and value are the restaurant's attributes that give a competitive advantage to the restaurants (Bilro et al., 2019; He et al., 2013). Customer's online reviews related to the restaurant industry has been used to analyze to understand the status of the restaurant in the market. VADER is a sentiment analysis algorithm that analysis the online reviews around a restaurant's attributes (Bilro et al., 2019). Positive customer experience influences customers for customer engagement and advocacy for the products (Francesco and Roberta, 2019; Nakayama and Wan, 2019). In addition, the local culture and geolocation of the restaurants play a significant role in customer experience and positive word-of-mouth. Hence, online reviews and ratings of the restaurants and hotels differ between local and foreign customers on social media and online platforms (Lee et al., 2017; Lee and Yu, 2018). Yelp is the most famous website for online reviews about restaurants. In addition, explanatory, temporal and sensory element of the restaurants also influence customer for positive word-of-mouth and recommendations to other customers (Siering et al., 2018). In the context of hotel industry, negative emotions more influences customer on selection of hotel for future stay as compared to positive emotions while reading the online reviews of hotels from TripAdvisor (Sezgen et al., 2019).

The airline industry comes under the service category. The airline industry utilizes the online and offline feedbacks of valuable customers to retain the customer's satisfaction and maintain the airport service quality (ASQ) (Klostermann et al., 2018). Customer feedback helps policies maker for the enhancement of customer satisfaction and services to retain in the competitive markets. Generally, Customer satisfaction may vary according to the class of air travel. When customers are traveling in economic class then staff behavior is the key factor for customer's satisfaction. Product value and low price are the key factors for the customer's satisfaction when the traveler is traveling in premium class and low-cost class respectively (Mitra and Jenamani, 2020; Singh et al., 2017).

### 4.3. Market analysis

Market analysis is one of the best text mining applications in business management. It analyzes the online reviews about the product or services to identify potential competitors, valuable customers and evaluate the brand image. Perception regarding the products or services in the mind of consumers is called brand image. Nowadays, brand image plays a crucial role in managerial decision making (Ren and Hong, 2019). Sentiment Concept Mapper (SCM) and Association Based SWOT analysis are the two techniques of Online Brand Image (OBIM) which are used to get latent themes from the associated online reviews (Dowling and Weeks, 2011). Whenever consumers consume the service then they update their experience with emotions on the online platforms or e-commerce websites. Then, these online reviews help other customers to make decisions on purchase or sell of the product (Fan et al., 2017; Archak et al., 2011; Kar and Rakshit, 2015). A combination of online reviews and historical sales data of the products can play a significant role in product sales forecasting. Sentiment analysis and the Bass/Norton model collectively utilize the combination of online reviews and historical sales data to make a sales forecasting (Chern et al., 2015). In addition, review ratings, product type, price (Sharma et al., 2019; Tussyadiah and Park, 2018), geographic location, discount rates, word of mouth, and review's sentiment are very important factors in sales forecasting in all type of predictive models (González-Rodríguez et al., 2016; Wen et al., 2020).

In the tourism industry, accommodation is an essential part of attracting tourists for visiting the tourism destination. For that, the hotel industry publishes its potential services regularly online or offline to attract tourists. Trust is the main influence factor that gives confidence in booking hotels online (Jia, 2020). Service providers use online reviews in marketing of tourism destinations. Positive and negative reviews or word of mouth gives a clear picture about the tourism destination to the consumers or tourists and provide a support to service providers to understand the tourists needs (Guerreiro and Rita, 2020). When tourists plan to trip to the tourism destination, then they want to enjoy the culture and food of the destination. Accordingly, they share experience on online platform and give ratings to the restaurants and their foods. Service providers used these online reviews and ratings to understand the customer's need. Positive and negative reviews and recommendation about the restaurants help to marketers to better marketing of restaurants in digital space. Topic modeling, sentiment analysis and regression techniques help to understand the customer's view about the restaurants (Pezenka and Weismayer, 2020; Li et al., 2020; Rosado-Pinto et al., 2020; Lucini et al., 2020; Gitto and Mancuso, 2017; Mittal et al., 2015). The airline industry also utilizes online customer reviews to enhance the competitive market. Customer satisfaction is the main objective of the airline industry. Sentiment analysis and topic modeling are widely used techniques to evaluate the overall customer satisfaction in the airline industry (Kim and Lee, 2019; Yang et al., 2019). Medical tourism also applies text mining technique on online news articles to identify the views of the public and medical industry. It uses CONCOR analysis, network analysis and clustering technique (Yang et al., 2015) to extract the main keywords and theme related to the medical tourism (Bigorra et al., 2019).

In the early stage of product design and development, Customer Experience (CX) [019) (Song et al., 2019) plays a crucial role to know the product features and customers' preferences. Customers share the experience of the products on social media and e-commerce websites. This customer-generated content often analyzed by Sentiment Analysis to know the opinions about the products and their features and checked its impact on customer's satisfaction (Zhang et al., 2019). Kano model gives clear classification to the products based on their kano category (Berezina et al., 2016). After consumption of the products or services, generally, customers create valuable electronic word-of-mouth (eWOM) on online platforms or e-commerce websites and gives star ratings to the products. In addition, e-WOM and star ratings help in predicting the future profitability of the organizations also (Lipizzi et al., 2015).

### 4.4. Customer relationship management (CRM)

Customer Relationship Management (CRM) refers to the relationship between the customers and industries (organizations) in which both can communicate with each other. In traditional CRM, the Hotel manager is the only person who interacts with customers personally or by phone. In this case, only a single customer affected by the response of the hotel manager. Nowadays, customers are using online platforms to book a hotel and share their experiences with the organizations. In this case, several customers can view feedback and change their perception of the hotels (Nave et al., 2018). Management positive responses to negative comments improve the chance to choose the hotels by 84 percent. In addition, negative responses reduce the chance of choosing a hotel by 64 percent (Sezgen et al., 2019). Number of management responses and the response similarity on customers' online feedback play a significant role in hotel bookings. High similarity in management response significantly reduce the booking of hotels on Expedia (Kar, 2015). Satisfaction and unsatisfaction of the customers depend on tangible and intangible services of the hotels. In addition, Satisfied customers more often share intangible experience (e.g. Staff behavior and hospitality) when he (she) goes to recommend hotel with others. At the other end, unsatisfied customers share their tangible experience (e.g. room quality, finance problem) (Guercini et al., 2014).

Decision Support System (DSS) is an automated system that gives support to the managers to understand the needs of the customers in specific domains with the help of analytical decision models. The adaption of proactive nature is required to gain a competitive advantage and understand the available opportunity for the investment. Decision Support System (DSS) gives support to managers to set strategic plans and offers according to the customer's needs (Li et al., 2016). The behavior of customers shows that how the customers understand the things and relationship with the brand, who are often connected in social media (Malthouse et al., 2013). Besides, qualitative research investigates the relationship between the brand and the consumers (Shen et al., 2020). Nowadays, social media is gaining more attention in the field of marketing because of its reachability, availability, and low cost. Hence, customers can easily avoid marketing advertisements, compare products or services price, and spread wrong information to the rest of the world (Jiang et al., 2016). Therefore, it becomes important for organizations or companies to elaborate on CRM strategies with online platforms (Varanasi and Tanniru, 2015). Information Technology (IT) industries and non-IT companies also utilize user-generated content (UGC) on social media (Twitter or Facebook) to extract the knowledge and needs of the customers and engage customers with the services provided (Chen and Xie, 2008). Sentiment analysis is the most popular technology among IT and non-IT companies to know the sentiments of customers about products and services to make a future decision- making and strategies with CRM (Ha et al., 2015; Dhar and Chang, 2009).

### 4.5. Fake information (misinformation) management

Nowadays, customers plan to purchase a new product based on online product reviews and online recommendations from e-commerce websites (Sotiriadis and Van Zyl, 2013). The Internet has become a new sensation for information because around 24 % of customers use the Internet to search for products before going to actual purchases (Awad and Ragowsky, 2008). Therefore, online review plays a crucial role in the purchase decision of the customers and affects many areas such as entertainment (Jindal and Liu, 2007), accommodations (Aswani et al., 2018), and e-retailers (Barbado et al., 2019). The importance of online reviews is growing at a rapid rate with increasing the popularity of the Internet. Therefore, businesses and organizations want to take the advantage of online reviews to improve their reputation in the online space by means of ethical or unethical. Fake reviews are the most popular among unethical methods which are used by many organizations to make the product valuable to the customers (Yang and Kent, 2014). Further, doctored and planned misinformation is often used to change general perceptions in social discussions (Gallaugher and Ransbotham, 2010). Generally, all fake reviews do not harmful to the organizations and customers as well. Good quality products with fake negative reviews harms the reputation of the organizations but at the other end, poor quality products with fake positive reviews are very harmful to the customers. Barbado et al., 2019 (Dickinger et al., 2017) proposed a feature framework for detecting fake reviews in the electronic domain.

Social media provides a platform for organizations to understand the sentiments of the customers. Social media has enhanced the relationship between customers and organizations (Xu, 2018). Organizations are taking benefit from positive word-of-mouth of the customers which is enhancing the reputation in the market. On the other end, organizations face problems due to negative word-of-mouth especially during crises (e.g. security hacks) (Mittal et al., 2019). A lot of times, such crisis is artificially created by automated bots and fake social media profiles (Gallaugher and Ransbotham, 2010). Justice theory and Sentiment Analysis (SA) help organizations to understand the customer reactions during the crises like security hacks on social media platforms.

**Table 1**
Methods and frameworks used in text mining applications.

| Text Mining Application | Used Methods/Frameworks |
|---|---|
| Social Media Analysis | SVM (Support Vector Machine),Qualitative content analysis (QCA), Principle Component Analysis (PCA) and logistic regression, Clustering, LSA, Descriptive Analysis, Imputation method, PASAD, Clustering, community detection algo, Emotional Co-Creation Score (ECCS), Clustering, SERVQUAL, Opportunity Algo, Circumplex Model, Emotional Text Mining (ETM), Sentiment Analysis, Emotional analysis, Network analysis |
| Market Analysis | Qualitative and Quantitative research, SPSS Text analytics, Project Sentiment Analysis (PSA), multi criteria decision making method, SEM, Recommendation System, Co-relation analysis, Network Analysis, text link analysis, Engagement dictionary, Fake Review Detection Framework, VADER (sentiment analysis algorithm), Clustering, Topic mining, aspect-based sentiment analysis, Aspect level sentiment analysis, House of quality (HoQ),WOMSFA (Word of mouth sales forecasting algorithm), deep learning fine-grained sentiment analysis, Content analysis and repertory grid analysis (RGA), Big data analytics |
| Competitive Intelligence | Qualitative and Quantitative research, SPSS Text analytics, Project sentiment analysis (PSA), Multi criteria decision making method, SEM, Recommendation System, Co-relation analysis, Network Analysis, Text link analysis, Engagement dictionary, Fake Review Detection Framework, VADER (sentiment analysis algorithm), Clustering, Topic mining, aspect-based sentiment analysis, Aspect level sentiment analysis, House of quality (HoQ) |
| Fake detection & Risk management | Fake Feature Framework (F3), Justice theory |

## 5. Discussion

This review of literature provides a summarized view of the existing literature which has used text mining, for exploring the area of services management. A systematic literature review has been adopted as the methodology to identify articles indexed in the Scopus database. Analysis has been done using different methods involving text mining, network mining and qualitative analysis of these published literature. Finally, a synthesis of literature has been developed for summarization of the findings.

### 5.1. Synthesis of literature

There are 90 papers out of 125 in this systematic literature review in which most research papers were using Social Media Analysis, Market Analysis, and Competitive Intelligence to understand the customer's needs and take the advantage of social media and online reviews. This systematic review also reveals the various domains where text mining is playing a very crucial role to understand the user's perception towards the service and management. The various domains are sales, tourism, entertainment, airline industry, marketing, food industry, hotel, and hospitality. Risk management and Fake detection are the two application of text mining which has been less used by the researchers in the field of service and management.

In the sales domain, most of the researchers have used various methods like Social Media Competitive Analysis (Jeong and Jang, 2011), Sales Forecasting Model (González-Rodríguez et al., 2016), Network Analysis (He et al., 2015), LSA, Labelled LDA (Chen et al., 2017), PASAD (Lau et al., 2018), Neural Network (Wen et al., 2020), Opportunity Algorithm (Jeong et al., 2019), and Emotional Analysis (Rathore and Ilavarasan, 2020) to analyzes the social media discussions and online reviews to understand the nature of the market for the products and to check the reputation of the products in the market as well.

Tourism, Entertainment, and Hospitality industries have also used various methods like LDA (Mittal et al., 2018), LSA (Baek et al., 2020), Clustering (Jia, 2020), Text Link Analysis (Lee et al., 2017), Circumplex Model (Park et al., 2020), Big Data Analytics (Hu, 2020; Luo et al., 2020; Kauffmann et al., 2020), Content Analysis (Agarwal et al., 2020), and Deep Learning Fine-grained Sentiment Analysis (Singh et al., 2020), to analyze the market and customer's need to make better policies for the enhancement of the services.

The airline, Business, Marketing, Risk Management and Food industries (Sezgen et al., 2019) (Singh et al., 2017) have also utilized various methods like LDA (Kim and Lee, 2019), Fake Review Detection (Chintalapudi et al., 2020 bib29), Fake News Detection (Sanjeev et al., 2020 bib115), DeepFake Video Detection (Mittal et al., 2020 bib98), Emotional Text-Mining (Greco and Polli, 2020), and Kano Model (Berezina et al., 2016) to gain the benefits of the social media data and online reviews and to make the better policies for the customers. Table 1 describes the methods and frameworks used in text mining applications.

### 5.2. Practical implications

This study analyzes the various text mining application in the field of management and services by using online reviews and social media data. Our study found various text mining applications like Social Media Analysis, Competitive Intelligence, Market Analysis, CRM, Fake Detection, and Risk Management. These applications have been implemented in various domains like Sales, Tourism, Marketing, Entertainment, Hotel, Hospitality, Business, Restaurant, and Airline. Sentiment Analysis (Aggarwal et al., 2021; Sharma et al., 2020 bib119) is the most popular method in all most the applications to evaluate the sentiments about the products or services. Organizations or businesses utilize online reviews and social media conversations to check the reputation, product comparisons, make product development strategies, and in the marketing of the product in digital space.

In practical, online platforms and social media platforms provide a free platform to share their feedback, recommendations, and experiences about the services or products. Customers are free from any restrictions for sharing their views, and experiences about the products or services on the e-commerce websites and social media platforms. Hence, customers can post their negative and positive reviews on these platforms anonymously. In the service and management fields, these online reviews or social media platforms help to text mining applications like market analysis, competitive intelligence, social media analysis, and CRM. Fake reviews detection and risk management are the two important text mining applications in the service and management fields. On behalf of online reviews and social media data, it becomes crucial to understand the fake reviews before making decisions because these reviews can drop down the reputation of organizations and products in the markets. Risk management can handle online reviews and social media conversations because customers can feel dissatisfied during that period and can share negative views on online platforms.

### 5.3. Research agenda

Our findings show that social media analysis (Nasir et al., 2020), market analysis, and competitive intelligence are the main text mining applications in the field of service and management which is utilizing online reviews (e.g. Amazon, Yelp, TripAdvisor, Booking, Expedia) and social media data (e.g. Twitter and Facebook). These text mining applications have been extensively used in sales, restaurant, hotel, small business, tourism, and airline domains to understand the needs of the customers. In addition, Fake detection and Risk Management are some of the unexplored text mining applications and can become a hot topic for future research.

Further, we found that Twitter is the first choice for the data analyst to analyze the consumer's behavior. Still, it allows users to extract approximately 1% of twitter's data. Therefore, a huge amount of valuable user-generated content is not coming into the analysis. However, in the digital world, Facebook, Yelp, online communities, discussions, and blogs have vast user-generated big data, which is equally valuable as Twitter. Therefore, it is an open opportunity for researchers and market analysts to use these platforms for analyzing the status of the consumer's behavior. Further, most of the research has utilized Twitter's text data written in the English language to know the customer's or consumer's behavior to the products or services. It is another an open platform for the researchers to include other languages text data, images, and videos in the analysis.

Further, it is also needed to be identified how a combination of big data research is needed capturing various media types for assessing digital services and service design improvements. The assessment may be done at the point of service consumption and during the service delivery journey as well. Service encounter contact points may provide such big data [145,146] which can be analysed using methods of machine learning for contributing back to service science literature.

## 6. Conclusion

The objective of this study is to explore the text mining application in the area of services and management. Initially, the study found the explored or unexplored potential areas of text mining in the field of service and management. Most of the literature is using descriptive analysis on the online reviews or social media data to gain the benefits in various domains. Our systematic literature review reveals that papers related to the application of text mining have been extensively published in the International Journal of Information Management followed by the International Journal of Hospitality Management, the International Journal of Contemporary Hospitality Management, Journal of Business Research, and Information Processing and Management.

Due to increase in the popularity of the internet and social media, nowadays, customers are searching and comparing information on the Internet about the products or services before making any purchase decisions. Hence, online reviews and social media data are playing an important role in the fields of sales, marketing, business, tourism, and airline industries. Online platforms and social media platforms are freely available to share ideas, feedback, and recommendations about the products or services for the customers or the organizations. Sometimes customers or rival organizations misuse these platforms by posting fake reviews to ruin the image of any organization. These practices may cause an adverse impact on the business of any organization. Misinformation detection [147] and risk analysis using text mining and NLP can be explored in the future to get more understanding of user needs in the field of service and management.

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