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A SYSTEMATIC REVIEW OF BUSINESS INTELLIGENCE THE SENTIMENTAL ANALYSIS ON THE ONLINE MARKET

ZAHRA DAHISH [1]

[1] Faculty of Management Information System, Jazan University, Jazan-Saudi Arabia
E-mail: [1]zdahsh@jazanu.edu.sa

ABSTRACT

Obviously, social networking voices (VoC) for analysts able to perform customer-driven business intelligence (BI) analysis have emerged as quality evidence. However, to the best of the understanding of scholars, there is still a shortage of study that deals with such impressive content sources and deals with different accessible data from the BI science viewpoint (e.g., social media, intellectual property). This analysis has therefore been aimed at evaluating the applicability of social network data in BI research and systematically reviewing the primary research papers in this area. This research contrasts social network data in terms of data quality, processing, updating capability and framework, with other accessible data (e.g. grey literature, public service data), which is decided through a cautious discussion with experts. Then, the research collected 57 papers from the Web of Science (WoS) website centered on social networking, and three questions on details, methodology, and findings have been examined with a view to unraveling the field of analysis. The results are to educate current researchers regarding potential research recommendations, encourage entrants to gain insight into the overall analysis process of social media data, and offer practitioners environmentally friendly approaches to social media analysis.

Keywords: *Customer Behaviour, Business Intelligence, Online Reviews, Social Networking and VoC*

1. INTRODUCTION

Easy access and versatility have enabled customers to share opinions on social media in the most powerful and effective way for almost a decade (Alkhodair, Ding, et al. 2019; Chang, Ku, et al. 2017). Similarly, most consumers share their viewpoints without any restriction on a product or service (Wolf- gang, Misuraca, and others, 2018), simply by sharing or interacting on different WWT platforms like Twitter, Flipkart, Facebook, and Amazon. In specific, most consumers only blog about their enjoyment or thoughts of a social media product or service, while some influencers provide a thorough overview of the key features of the product or service and/or truthful assessment of its drawbacks. Such consumer subjective views may decide whether other potential customers buy a product or not because most customers' purchasing choices are likely to depend on the judgment of individuals with prior usage (Rose, Hair, etc., 2011). In addition, commercial companies or businesses can use online consumer feedback to determine overall consumer desire, loyalty, or product specifications. Important advice on new product development, functionality enhancement, or quality control may also be given in detailed posting items with comprehensive information (Bashir, Papamichail et al. 2017). In this sense, it is apparent that contemporary clients are not passive commodity consumers but active users who, by their powerful voices rooted in social media, control explicitly or implicitly the potential growth direction and survival of the commodity.

Most commercial businesses, which have multifunctional goods such as mobile phones, have introduced their own networks to connect to their consumers on social networking sites including Facebook, Instagram, and Twitter (Shirdastian, 2017). The fundamental technology of these high-tech goods is already established, so product creation is very challenging by way of a technical solution such as in-house R&D. In order for the potential production of the product to focus on buyers, the technology-intensive businesses should follow a market-oriented strategy. For e.g. innovative products such as the Samsung Galaxy Note are still faced with consumer requests for additional or improved functionality such as Samsung payroll, touch pen, and software (Jeong, Yoon et al, 2018), which can be used to create a technologically advanced product from now on. In addition, the opinions of consumers affect business economies tremendously. In fact, in 2008 Starbucks, one of the leading firms in the coffee chain market launched a website called ’My Starbucks Idea’ for people’s suggestions and for consumer experiences in order to gather input or ideas for their consumers about their prior goods or services.

A research named "Social Media Analytics," in which different social media data are collected and analyzed, and useful hidden information is extracted, has created some scholarly interest in social media data. Many analysts have collected a large amount of consumer data from social media and received statistical findings, quantified satisfaction ratings, or text topics that allow companies to determine strategically in their business environment. More precisely, Jeong, Yoon, et al. (2018) collected online feedback from Reddit, which is a social networking platform, and recorded questions of clients about the battery’s life, the touch, the video, and so forth. In addition, by using the feeling analysis and opportunity algorithm, they have calculated the effects of content and significance and defined the opportunities for each subject. This information which they derive can support the decision-making of the associated company in the creation of a product or service by supplying product features with high but low satisfaction rates. Furthermore, Amazon’s evaluation results on three rival smartphones were obtained by Trappey, Trappey et al. (2018), measure the interest of consumers utilizing the core elements they identified. Their findings tend to enhance the customer-oriented product by the preferences of consumers and the relative location of each product in the com-demand sector. In addition, various experiments are being performed to quantitatively measure consumer loyalty using an emotion study for online user results. These researches seek to include consistency and decision-making knowledge modern business intelligence (BI) was described in a market setting and certain methods or analytical processes (Chang, Ku, et al. 2017, Ku, Jeong, et al. 2018, Wang, Feng et al. 2018) scholars.

This thesis analyses social network data in terms of the details, compilation, processing, and composition of the data, and discusses the benefits and features of this data in relation to the other accessible data used in BI science. This analysis also provides a special handbook for the compilation and implementation of BI studies in social media. In this study, we concentrate on the evidence used in social networking in previous studies and the findings obtained from their analysis into BIs with three related research concerns. (1) What are actually in use in these study fields the popular social networking platforms? (2) How can researchers adopt prevailing social network data methodologies or algorithms for the BI? (3) Whose smart knowledge emerges from BI analysis in social media? Three submissions are planned for this article.

Therefore, the database utilized by contemporary researchers may often be improved by illustrating the benefits, unlike conventional knowledge, such as patents or test objects. In fact, this research offers a detailed manual on the collection, pre-processing, and analysis process data from social media that can help prospective analysts or professionals address business issues. Finally, this analysis would be able to address current research ideas and recommendations in the research flow, define popular shortcomings of current research, and suggest future guidance for research utilizing the new algorithms.

There are few previous studies had discussed the applicability of social network data in BI research and systematically reviewing the primary research papers in this area. In Middle East particular, therefore, this research is unique in that it opens the way for researchers to address such topics in the Arab Gulf countries. This article justifies BI offers capabilities for near real-time sales tracking, allows users to discover insights into customer behavioral and forecasting profits.

The rest of this article is distributed into five main sections. The second section proposes a background; the third section provides an evaluation of usability data while the fourth section provides a systematic assessment and performance preceded by the fifth section which is limitation and demerits. Finally, the last section is discussions and remarks.

2. BACKGROUND

This section discusses the definition and classifications of accessible data in order to clarify the historical context of analysis covering BI science in social media.

2.1 Business Intelligence

BI, or "drawing information or awareness of consistency in different market contexts," includes the whole method of discovery, perception, compilation, examination, and derivation (Davenport, 2006). Chaudhuri, Dayal et al. (2011) observed that a BI framework provides information workers/entrepreneurs with a deeper view of their businesses or industries and a prompt decision-making mechanism. Indeed, after the late 1990s, BI was developed as a single word by several excellent physicists, evaluating the vital market data accessible (Chen, Chiang, et al. 2012). The earliest BI types included a data-centric approach to standard evidence, such as trademarks, scientific papers, and commercial records, in the best sense of the writers' understanding. Park and Yoon (2017) suggested a systemic method, in which realistic technological prospects may be recommended to a technology-intensive business by protecting the technical resources of its patents and defining the technology portfolio of related businesses through collective screening. Their research is particularly realistic for small and medium-sized businesses with limited human resources and initial capital and proposes potential directions in the growth of leading corporations' validated technologies. In order for Wang et al. (2018) to recognize evolving trends in the area of target technologies.

It is worth noting that the key data still remain standard data like patents, although several analysts have found out that the more recent developments in BI research remain increasingly being centered on analyzing data produced by the client. Moreover, Chung and Tseng (2012) have indicated another factor in the BI preceding definition by stressing that online product assessments are an essential source of data for consumer and business awareness. Indeed, different approaches to social networking have generated ample and interesting business prospects for company entities or partners through tracking consumer preferences and recognizing competitive position on their platform (Pang & Lee 2008). There is also an agreement that BI researchers will recognize the consumers and the business by presenting the social network data, even as the discussion has been continued about what are the right accessible data for BI analysis. This thesis thus examines several current data outlets and contrasts their methodological adequacy in the next paragraph prior to carrying out a comprehensive analysis of BI studies on welfare coverage.

2.2 Open data classification

Only, mainstream media, newspapers, radio, or TV are found in traditional media (Best Jr & Cumming, 2007). The effective portrayal of market churn or public opinion is used by conventional media evidence in BI analysis (Chan-Olmsted 2002; Rust, Moorman et al. 2010). In addition, the firm is strongly linked to its consumer prospects, geospatial information, such as industry images or financial and industrial evaluation reports. Nevertheless, it is a relatively rare data source (Gibson, 2004; Steele, 2007). Grey Literature journals have accessible documentation or research papers, although not commonly distributed.

There have been several types of research (such as experimental papers, scientifically verified tests, memoranda, etc.) and academic and cultural careers, and literature on exchange and bibliography. The literature of intellectual property representations, such as trademarks and trademarks, is extremely common and is therefore often used in the BI review (Lee and Lee, 2017; Yoon & Kim, 2012). In BI science, however, professional/academic publishing evidence is used reasonably commonly (Porter, Garner, et al. 2018; Shiau, Dwivedi, et al. 2018). In comparison, web-based data involves social networks (e.g. Facebook, Twitter, and Instagram), internet chat forums, and popular media like YouTube, which can be readily accessed and therefore ignore other forms of data. Social networking in particular has been a representative BI Research database, as it provides voluminous data of potential value in real-time and customers created to business businesses, partners, or scholars (Gonzalez-Carrasco, Jimenez-Marquez, et al., 2019). Similarly, online social networking community forums share knowledge about particular subjects, goods, or services formally or informally through a number of users, while Reedit, the Community about Facebook, and the Number on Google are symbolic.

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3. EVALUATION OF USABLE DATA

3.1 Area of assessment of the analysis

In this analysis, the methodological suitability of social network data was analyzed and correlated in four dimensions with other sources of data. Feature of the data collection and review was chosen to represent the general characteristics of accessible data and to indicate the continuous operation of the BI framework. 10 specialists presently active in BI science have chosen the four dimensions. BI study has been carried out by academics utilizing different transparent data, such as social media, project ideas, and patents, to find out around 10 years of market prospects of commodity or technology. Furthermore, students have been active for nearly four years in related fields of study such as social network analysis, consumer awareness, and data-driven market planning.

The data content, first, demonstrates the intrinsic properties and the willingness to use the access data in the process of making business decisions, such as products, integrity, and the in-house standard of consumers (Jiménez-Marquez, Gonzaléz-Carrasco et al., 2019). Second, the data collection describes the presence of service to gather an overwhelming volume of data via the transparent application programming (API) GUI. This dimension explicitly notes which accessible data are obtained, processed, and used as a reference for analysis in the field of BI in continuous measurements (Stieglitz et al., 2018). Thirdly, the updatability of the data reflects the ongoing updates to the accessible data and the constant upgrading to the software (Cvijich & Michahelles, 2011); this and the processing of data are directly linked to BI analysis systemization. Finally, the data framework tests whether transparent data in the analysis or method of BI can be stored in a hierarchical manner (Huang and Nguyen 2015).

3.2 Assessment outcomes of the analysis

Furthermore, much of the grey literature is routinely written and continuously compiled by the official A-thirties, allowing the creation of comprehensive databases. The grey literature has also been respected in terms of data quality, compilation, upgradability, and composition by the majority of our experts. Public agency results have, though, been tested with the same metrics fewer than the grey literature. In different regions, such as climate, culture, economy, and schooling, it can for example be found that more than 300,000 datasets can be accessed from government agencies from a general public-sector database (Krischnamurthy & Awazu 2016). The data sets (html, bin, xml, pdf, zip, web archive, and CSV) may be supplied as research formats; but they are circulated non-periodically in multiple formats such that data sets cannot be collected or collected continuously. Finally, unusually web-based data and grey literature were examined. Web-based data are mostly categorized by social networking, internet community groups, and citizen-media in real-time to guarantee strong updating capability for general users or consumers. Furthermore, most Web-based data provide an explicitly accessible API method, which can also be used to collect web-based data systemically. More consumers voice their views on individual items, programs, or subjects on social media or private conversation community groups in no form censorship.

4. SYSTEMATIC ASSESSMENT AND PERFORMANCE

4.1 Involved systemic process

For several factors (Webster & Watson, 2002). We chose a structural review approach (Kitchenham, 2004) rather than a concept-centered approach. Initially, a social network-centered analysis on BI originated not from a scientific perspective, but from policy concerns in the market climate. A structural analysis methodology is then used to pick BI study papers focused on social media and to evaluate alternatives to market strategies. Second, rather than pursuing the evolutionary path of theoretical background in mapping citation relation in the field of research, we have attempted to analyze recent developments in BI social media research in terms of the methodology, algorithms, and data used. This research will also include an in-depth tutorial on the entire social network data collection, pre-processing and interpretation process. In addition, the research hope that this comprehensive analysis will inspire prospective investigators to create new study products in this area by proposing different methodologies, data, or challenges. We have specified the following research questions in order to achieve these goals:
Q1. In this field of research, what are the essential forms of networking?

Q2. For beginners. What informative information does the social network extract analysis by BI have?
Certain prominent terms are often used in BI research based on the social media, for example 'social media' or 'commerce.' In addition, terms such as 'product review' or 'service assessment' have also been applied as they contain similar concepts such as key terms and represent one social media category. Researchers refer also to the specific methodology, algorithm, or structure used in the analysis of social media data, such as sentiment analysis, network analysis, or thematic model, in their titles or abstracts, while some use common terminology, including "social media mining" or "social media research."

Therefore, all the papers in the area of social network BI analysis are challenging to cover in this examination and we have produced a search inquiry of full content purity. We have used the "or" operator, as well as the "and" operator, to locate as many academic papers as possible in finding queries for big keywords. In the following search inquiry (SQ), the main keywords described above are identified line. SQ. 'TITLE ('('social' and 'media') and ('mining,' 'analytics'*') NOT Word: "(Systematic' and "review") NOT TITLE. The below diagram will explain the framework of social media in terms of BI research.

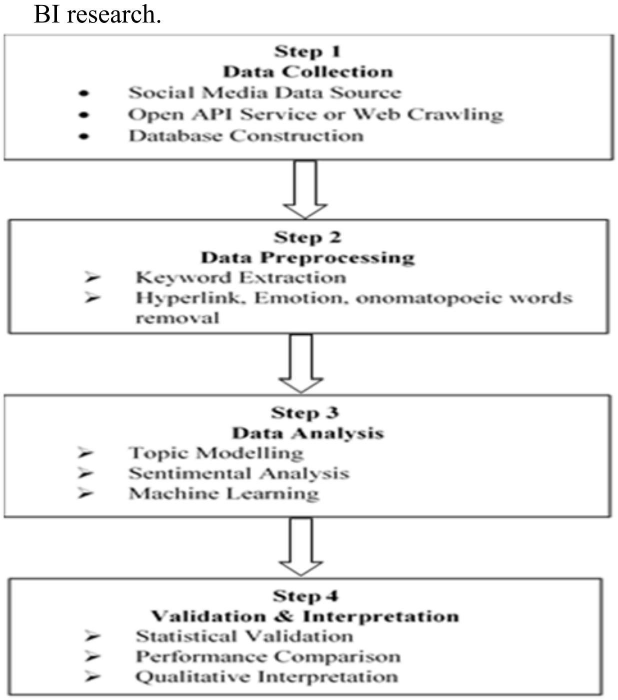

Figure 1. Framework of Social Media in terms to the BI Research

The researcher thus omitted articles in literature reviews including a "systematic study" in their names. This examination sought to discuss the examination of BI studies focused on social media. The issue of the search involves the word "sentence," as sentimental analytics is one of the effective tools used in the field of research that looks at the emotional content embedded into the social network information. The WoS, one of the most common research engines, on 4 July 2018 used this search question. In so doing, we have collected a variety of prospective study papers evaluating social networking to perform BI analysis. Here, we have restricted the duration for the quest to the last five years, limiting the form of paper to journal papers analyzed by peer reviews, given that social mediums have recently evolved as a database for BI analysis. 633 records were returned during WoS's quest for papers using the above search term. These publications contained not only research papers on social network-based BI but research papers to boost algorithm efficiency and/or social media literature studies. In exclusion criteria and pattern analysis, this initial article list (Group 1) has been used as a topic.

Subsequently, the researcher checked group 1 Papers' title and abstract and chose the key papers to enhance the quality of the research, taking into consideration multiple exclusion requirements. The above is addressed to the following basic exclusion requirements (EC):

1. EC1. And the critical evaluations of a publication are taken into consideration.
2. EC2. It is omitted title or abstract that does not define the analysis in a clear and satisfactory manner.
3. EC3. It only considers papers written in English.
4. EC4. Articles not covering social networking or product review in BI analysis are excluded; for example, articles using social media. Posts that do not extract content knowledge to help organizational social media decision-making are removed.

57 papers have been chosen for systematic analysis, after the selection of Category 1 publications (633 papers) by introducing the criterion for exclusion. In fact, after reviewing the abstracts, 10 papers were duplicated and 566 were deemed meaningless. We also omitted above all research articles that do not meet this assessment

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objective; e.g. studies, sample reports, bibliometric, and conceptualization theoretical. Conference articles or analyses were therefore omitted since their referred study in the journal must be of good quality, high-impact performance. Moreover, we have omitted academic papers dependent on their abstracts, which are tingly linked to BI science in science. In conclusion, the main articles (Group 2) which aim at deriving analytical results or proposing a new approach in the context of BI research to address social media data are summarized.

4.2 Review Results

This section summarizes the findings of the general pattern study of Group 1 journals and discusses the effects of the systematic examination of Group 2 papers.

4.2.1 General Trends

Next, the number of objects in Category 1 by year of publishing was modified by a graph (Table. 1). The statistic indicates that since 2014 there has been a rise in the number of academic papers written (83, 118, 150, and 180). Notably, by the month of July 2018 already nearly 100 research articles were written. The surge in BI study papers focused on social media then appeared to continue. Similarly, for Category 2 publications there was a similar upward pattern. Group 2 publications were four times more frequent in 2012 and 2015 and in 2018, considering the limited duration, it was still strong. Thus, we can conclude that the social network is an acceptable source of knowledge for BI research and that the area of science can be a fruitful one. In this case, we hypothesized that the prevalence of individual writers or publications contributed to this increasing pattern in social networking BI science.

Table 1. Group 2 posts focused on the sort of social network and the particular site

Type	Number of Articles	Specific Platform	Number of Articles
Commercial Reviews (Qualitative Research)	29	iPhone Apps Plus Jindong 2 Booking.com TripAdvisor Yelp Amazon etc	2 2 2 4 5 6 8
SNS (Quantitative Research)	24	Twitter Facebook Yahoo Finance Flickr Weibo	11 2 3 4 2
Discussion group by Online Multi-Data (Qualitative)	2 2	Qzone, Reddit, StockTwits Twitter-Patent Amazon-Patent	2 2 1 1

The papers were written mostly in peer reviews of evidence-driven methods to evidence management and policies, smart structures, and specialist decision support systems. It was not unexpected. The related publications have published social media-driven BI study papers regularly over the observational era. In order to show the social network study applied at various endpoints in diverse industry contexts, many Category publications have already reported papers in separate fields of research, such as advertisement, retail sector, electronic trading and tobacco regulation, and industrial protection.

4.2.2 What are today's promising social media platforms in this field of research?

In order to resolve the RQ1, this comprehensive examination of Group 2 papers analyzed the numerous social network sites used for study in BI. Finally, we defined various sites, grouping their data into four categories, to evaluate the papers effectively: 1) market analysis, 2) SNS, 3) online chat forum, and 4) multi-media. Table 4 demonstrates the dissemination through the social networking sites of Group 2 papers. This suggests that the bulk of the usage of apps is a market analysis or SNS data sort. In specific, Twitter, Amazon, Flipkart, Yelp, and TripAdvisor have often been viewed from the viewpoint of user users and can be deemed a popular social networking site.

Furthermore, our results show numerous features of websites, such as key contents, the process of data transfer, degree of personalization, communication, and culture. In group-centered forums such as Reedit, for example, the popular users are first creating a collective on a particular subject and then posting the article and chatting about the subject; social media contain also many individual sites such as Facebook, Instagram, or Twitter. Individual users normally set up a private network and exchange messages in a restricted area in the above networks. We were also able to analyze the successful mechanisms used in the papers of Group 2.

4.2.2.1 Online reviews on internet products and service market ratings

Online feedback applies to analytical evidence provided by clients who bought or witnessed the goods and services. In comparison, online review sites provide a broad range of details, just like most social networking channels, and most provide free API services to promote the collection of knowledge. In their united subjects, the key strength is the online review results. In these situations, users report about the goods or services they have received, thereby collecting online review data dependent on the product/service, reducing the mechanism of retrieval of data after compilation. We may split it down into two categories of commodity reviews for an e-commerce website (e.g. Amazon and Jindong) and service reviews for multitasked social networking sites (e.g. Yelp and TripAdvisor) owing to the informative nature of trade reviews. To summarizing, out of a total of 29 publications using web product reviewer reports and consumer feedback, 14 of these papers were used web.

First of all, online product reviews typically offer feedback and trade impressions with consumers ordering the goods on e-commerce platforms. For example, online product review data include experience and input from consumers on the features, look, and requirements of a device. In reality, the analysis data were used in 14 papers to understand consumer preferences and to evaluate commodity competitiveness in the market (Wang, Feng et al., 2018). Qi, Zhang, et al. (2016) also increased online product analysis to provide techniques for the development of client-oriented goods. In specific, collaborative research and emotion research are used for approx. 700,000 Jindong Online Reviews, defining consumer needs and presenting fresh and creative concepts for online product reviews. The fresh or related product creation to other experiments (Chong, Li et al. 2016). Provided for on-line analysis of goods has a significant effect on the purchase pronouncements of consumers, multiple research was not unexpectedly carried out (Govindaraj & Gopalakrishnan, 2016). It is noteworthy that most of them follow nostalgic research to evaluate the advantages of online feedback and to rate successful goods (Salehan & Kim, 2016) (Liu, Bi, etc., 2017).

Service analysis is often a kind of marketing evaluation, through which clients who have used online reservation or offline facilities (e.g., a restaurant and lodging business) report their impressions. These mutual interactions of providers may also impact buying decisions by other clients (Xu, Wang, et al., 2017) and can impact the image of products either positively or negatively (Filieri, McLeay et al., 2018).). Moreover, details from the service review may relay fruitful information, including feedback, opinions, and experiences, which can be used to recognize past issues, customer needs and measure the quality of services. In reality, the advantages of data revision and its ripple impact on customers in Group 2 were considered in 15 papers, by expanding data to BI analysis. Particularly Chang, Ku, et al. (2017) have empirically noted the nuanced relationships between customers, emotions, and type of customer utilizing TripAdvisor data and Google Trends data, suggesting an integrated framework involving data collection, pre-packaging, and data analysis. In addition, a variety of in-depth research has been performed based on the dynamic association between consumers and their rating results (Gui, Zhou et al., 2017; The findings will allow businesses to identify individual characteristics of their consumers through extensive review figures and provide customized services to the crowd. Consequently, it can be verified here that a substantial number of service review data not only represent the preferences of the consumer then also display the quality of the service they have received.

In summary, customer understanding will summarize the key questions of the research in market feedback.
Brand/product/service loyalty, and client and evaluation interaction study. Finally, many commercial analyses demonstrate that owing to the consistency of content, pre-processing is a critical phase. However, abbreviations, emoticons, or patterns often appear in online analysis, similar to other social network posts. In addition, several automatic texts are used in online product reviews and therefore the data purification phase is needed before the study.

4.2.2.2 Service Platforms and Social networking

In reality, sometimes seen as a limited social networking term, SNS is focused on a private network of individual users (e.g. Facebook or LinkedIn) or a micro-blog (e.g. Twitter, Weibo, and Flickr). Whatever the unique capabilities of the SNS systems, a large number of popular users make up the key usage layer, and content is created in real-time in many places and a large number of SNS data are therefore created. Moreover, several SNS platforms provide their single free API tool. SNS details, however, have a reasonably great number and involve pre-processing forms. Emoticons and so on. Tweeting, for example, produces more than 500 million messages a day on average in more than 22% of posts in Category 2. This website restricts to 140 characters and prompts the consumer in abbreviated terms and sentiments to share their concepts, thoughts, feelings, etc. Thus, while the Twitter data include explicit opinions about different subjects, like new goods, facilities, or brands, a comprehensive pre-processing mechanism is needed to delete and optimize the keywords accessible from short texts and draw their conceptual significance.

These stressful characteristics are also seen in the research papers obtained by the BI. In specific, the immensity of SNS data is used by social network BI analysis of this kind. In reality, most research utilizing SNS data gathered hundreds of thousands of textual data and filtered the dataset according to language and keywords. Moreover, a study into Flickr's visual data accumulated more than 100,000 datasets (Miah, Vu et Al., 2017; Sun & Lee, 2017). These SNS research studies reasonably quickly capture goal data utilizing free API resources (e.g., Cardiff Social Network Observatory) (Burnap, Rana, et al. 2015). Such a form of hierarchical compilation is an integral pillar in the implementation of the methodology or research indicated in each report. In other terms, a holistic approach to compilation, such as accessible API, can be used in order to build a BI framework instead of doing a single analysis.

Information collected from the SNS files, including text, images, places, and user details such as Twitter, Flickr, and Facebook. The textual data provides details regarding the users' interests, browsing and emotions, and so on, comparable to most social networking, and therefore many studies have attempted, utilizing text mining, emotion analysis, or often machine learner (ML) algorithms which will use to trail the topics the users are mostly involved in and their reactions (Xu, Qi, et al. 2018; Yoo, Music, et al. 2018). In addition, a variety of delicate studies rely on textual details by defining the words or problems that have a strong analytical significance or are correlated with the duration of a statement (Lo, Chiong et al, 2017; Wong and Lacka, 2017). On the other side, multiple research based on users that produce SNS data (Fang, Sang and others, 2014; Xie, Li, and others, 2014). In the SNS forum, SNS users build and communicate with each other in their own private network through exchanges of views on messages, activities, topics, etc. Thus, user groups or influencers (leaders of opinion) are naturally created inside the social network. Various analysts have discussed user identity details in order to further interpret consumer desires or preferences by defining possible user groups and evaluating influencer views.

4.2.2.3 Group for Online discussions

Internet forums apply to channels for consumer communities to address relevant problems, such as particular goods, technology, or resources, and share viewpoints and knowledge on this subject through the creation of articles and feedback. Of the different channels of social networking, reedit has over 1.2 million websites, including news, research, videos, novels, and songs, which are the nearest to the public community party. Members of the subedit are more likely than other social network users to have a special experience or expertise in the subject and thus provides more detailed and thorough content with their submissions (Park, Conway, and others, 2018). By following an illustration of a certain device, consumers not only communicate their happiness with the app but also identify basic attributes, advantages, and drawbacks and equate them with other similar devices. In addition, many topical problems, including calling, app upgrades, Samsung compensation, camera, and battery life, have been covered according to an analysis that examined the Samsung Galaxy Note 5 text (Jeong, Yon et al., 2018). Several ambitious researchers have recommended the use of Reddit's text data (Ko, Jeong et al., 2018) as a quantitative guide to identifying product/service opportunities, but this data is anticipated to be useful in study BI due to its sufficient textual contents. Like many other sites of social networking, Reddit often contains inscriptions, typos, and emoticons that need pre-processing, however due to the comprehensive textual details it is considered to be appropriate.

4.2.3 What are the Prevailing or Applications methods used for the SOCIAL Network DATA by business intelligence APPLIA?

The approaches followed by Group 2 papers in this section were based on defining effective widespread control of social network info. This method consists of 4 steps: data selection, pre-processing, multi-algorithm study and validation and evaluation of findings.

Second, data processing relates to the compilation and modification of a data base, the backbone for the study, of text, the photographs or the video data by open API or a site crawling. Provided that social network details are most relevant for evaluating the data from social media but are frequently overlooked, as, in the Cambridge Analytical case, the simplest way of utilizing free API resources will be (Cadwalladr & Graham-Harrison 2018). Thereby, all free API platforms and websites where social network details were exchanged were researched in order to include unique guides for study in social networking. The data pre-processing of text data consists in particular of a method of extracting keywords from text, by processing them in natural languages and of optimizing keywords by eliminating stop words. It is necessary, as mentioned earlier, to improve the keyword selection, as social media users generally compose very short texts using emoticons, typos, and abbreviations. Furthermore, some scholars have used the frequency of a keyword (TF; phrase frequency) or the number of publications (DF; paper frequency) where the keyword occurs in order to gain more accurate keywords. The general terms of "product," "assembly," "computer" etc. and non-relevant words ("day," "month," etc.) are sometimes omitted from the supply of an emoticon ("^^.", ":-D" etc.), site links ("www," onomatopoeic phrases, etc.). The unstructured text details were normally translated to a standardized format after this comprehensive elimination phase (e.g., content matrix) by the chosen keywords. Any researchers can use short text data processing word embedding results without any problems.

Different algorithms and methods were used during data processing and validation; nevertheless, the depths of the algorithms described differed. We divided it into five theoretical ones by considering the complexity and purpose behind the usage of algorithms.

The vast use of sentiment analytics reveals especially that the majority of BI research in social networking focuses on the customers' emotional response or subjective views (Burnap, Rana, et al., 2015; Sun, Wang et al. 2015). Since sentiment analysis computes the polarity of feelings of people as part of a score that is integrated into the texts, the majority of Group 2 publications embraced this study to quantitatively evaluate customer responsiveness or satisfaction regarding a brand and the product of the mentioned product and finally the subject (Duan, Yu, et al . , 2016; Kang & Park, 2014). In particular, the calculated feeling sentiment allows researchers to assess subjectively the measure of customer interest for qualitative data, for example, whether the customer's reactions are positive or negative.

The sentimental analysis also can discern the polarity of emotions in the brief, low-quality text (Guzman & Maalej, 2014), which allows the reasonably accurate and effective analysis of social media data, consisting of short sentences of a few keys, which includes stopping words similar to short-range abbreviations and emoticons. Several Group 2 papers have also used emotion analyses to determine client satisfaction, quality of service, and/or brand image for social media with relatively low quality (Chang, Ku, et al., 2017; Xu, Wang, and al., 2017). For instance, feeling analysis findings in real-life business settings allow entrepreneurs or analysts to recognize their customers ' specific preferences or enthusiasm with their products or services. Their products and services. Sensitivity analysis will then serve as an effective basis for better understanding customers that social media mining. Besides sentimental analysis, more analyses are needed to achieve better results, such as ML algorithms, network research, or different theories, for social media-based BI study.

In fact, various subject-modeling algorithms, like Latent Allocation Dirichlet (LDA) and Latent Semantic Analysis (LAS), have been utilized to customize and voice key topics from a wide range of user-generated data. Any text and the keywords are spread probabilistically by each pattern, for example through the use of the LDA in the document keyword matrix (Blei, ng, et al., 2003). -- Subject can then be mostly described by using high likelihood keywords and the central subject addressed by any paper can be defined based on the LDA findings. In particular, the papers in Group 2 used thematic modeling to classify all the subjects or incidents that are frequently referred by general users or to evaluate their concerns or opinion on a particular issue, commodity, service, or brand (Grandt, Bendler, et al., 2017; Trappey, Trappey, et al . , 2018; Xu, Qi et al . , 2018).

ML algorithms have been successfully developed to detect social network performance, simulate or cluster issues. problems. Pioneering studies have sought in particular to forecast asset markets by utilizing several models (such as artificial neural networks, vector machine help, regression analysis, and the Naïve Bayesian model) (Jiang, Liang, et al. 2014), commodity sales (Chong, Li et al. 2016), or sentiment value (Yoo, Song et al . , 2018). Their prediction accuracy correlates with current model predictions in terms of precision, memory, precision, and F-measurement, and these studies have a similar output testing method. Researchers who aim to forecast objective statistics such as market rates or purchases of goods have demonstrated a propensity to use emotional qualities as individual criteria in social network text (Jiang, Liang, et al., 2014; Nguyen, Shirai, et al., 2015; Sul, Dennis et al . , 2017). In order to equate their output with current models, confronting researchers seeking to resolve the polarity of feeling inside the social network text (Gui, Zhou et al. 2017). Although their well-established models are more accurate, warn and F-measured than traditional MLs, researchers can validate and refine their models utilizing various social media databases to enable them to be extensively employed in future studies. The researchers should use the ML model to enhance the consistency and specificity of their models. Moreover, the plurality of experiments utilizing emotional research findings in ML-based models enables a researcher to determine their qualitative values by establishing the criterion for classifying sentiment scores in broad sample datasets.

Customers, names, keywords and subjects may be found in social network mining. Their partnerships are, nevertheless, dynamic and multiple, rendering the data framework challenging to interpret. Some scholars have used social network visualization as a network or as a visual framework for coping with such dynamic and large social networking details (Miah, Vu et al. 2017; Xie, Li et al. 2014). The overall structure can be defined through the modeling of the interactions of nodes that are connected in various directions and through well-known quantitative indicators including centerless, central proximity, and central position visually evaluating important nodes (Kim & Hasstak 2018). The social network analysis offers information about the overall structure. The creation of the network utilized many techniques, including the principle of clustering or assembling maps, and attempted to classify the user population that was latent (Xie, Li, et al. 2014) or active users (Fang, Sang, et al. 2014).

4.2.4 What smart knowledge does BI analysis extract from social media?

Researcher classified social media theoretical field and implementation approaches to extract their intelligent knowledge using the social network details and methods of Group 2 papers description in above sections. Customers who primarily use social media, their friendship, the goods they create, or the features of social media itself are interested in social network-based BI research identified by Group 2 papers. Every investigator tried, by recognizing the views of consumers, latent consumer interactions or issues of high interest, to consider consumers or social networking from their viewpoint.

A range of experiments have been carried out to identify product trends or even business opportunities through semantical review of general users' content. These studies will include reasonably intuitive marketing opportunities, such as a collection of keywords or branded subjects, which will allow business companies directly to reflect their views or experiences with regard to the product creation (Jeong, et al., 2018). Not only by supplying businesses with found resources specifically but also by evaluating business information or defining industry success or market position, some authorities have aimed to obtain further empirical findings (Jin, Ji, et al., 2016). Several analysts who are involved in quantitatively assessing consumer loyalty, service efficiency, and the commodity danger for a good, service or brand that is offered by the commercial firms assessed in quantity, allowing businesses to represent client demand or views on their performance (Kang & Park, 2014; Mummalaneni, Gruss, et al . , 2018; (Shirdastian, 2017); (Song, Leee, 2014); In these cases, many scholars have placed out systemic methodologies, including the advice approach and help framework of experts

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(Jeong, Yoon, et al. 2018; Stavrianou & Brun, 2015). In several of the experiments, consumer retention, engagement, or understanding was evaluated in one-off form. To conclude, the inherent knowledge of consumers from the text they compose has been suggested methodologies or structures consider the causes, which can give business organizations customer-focused perspectives. Furthermore, many leading scholars have sought, by the collaborative study of social networking and patents, to uncover new functionality or emerging inventions of goods specific to their established consumer requirements (Li, Xie et al., 2018; Trappey, Trappey, et al., 2018).

Several studies centered on consumers who use social network engagement and partnerships (Fang, Sang et al., 2014; Miah, Vu, et al., 2017). The goal was to increase consumer awareness by acknowledging a possible market with a user pool or finding active consumers or adopters of goods (Xie, Li, et al., 2014; Zhao, Wang, et al., 2016). Instead, many researchers conducted an overview of each consumer by analyzing its emotional transition and response to emerging technology, issues, goods, and brands (Burnap, Rana et al. 2015; Li, Xie, et al. 2018; Yoo, Music, et al. 2018). Contrary to the research flows above, some challenges show that our customers are not only affected by products but also by the status of business enterprises and the price of inventory included (Chong et al. 2016; Ho, Damien et al.). 2017; Jiang, 2014; The Customer's influences on stock prices, product sales, etc. Likewise, several researchers utilize social network monitoring to evaluate the lifecycle of utilities (Kim & Lee, 2017). However, although the potential in such fields of study is increasing, further progress seems to be necessary. Researchers who want social networks have tried to define or quantify the benefits of each user's comments against social media business review details and commodity price evidence (Filieri, McLeay et al. 2018; Hu and Lee, 2017; Salehan & Kim, 2016). Although these findings can seem bad in terms of the essence of BI, their findings may enhance the perception of social network data in business organizations or other researchers.

4 LIMITATION AND DEMERITS

This study has some limitations that can be taken into account in the results. First, the lack of previous research studies on the topic has allowed for further analysis. Another limitation of this study was that not much research has been done regarding explore the use of social networking in the study of BI. It was difficult to find a starting point to build on as the majority of the studies conducted regarding exploring the use of social networking in the study of BI. Second, the limitations in the technology used to collect data. A third limitation to this study was having a short period of time to conduct the research. A result of this is that the generalization of there being no relationship between the uses of the term BI on the social media analysis the methodological appropriateness of social networking is not 100% accurate.

5 DISCUSSIONS AND REMARKS

The purpose of this research was to explore the use of social networking in the study of BI and current science innovations. This was done by evaluating free social media information as input and examining social media articles in depth. BI study in the mainstream. The assessment findings obtained after adequate expert analysis have shown that social media are highly important for study in BI since the data are gathered, processed, and organized in large numbers. We thus inferred that in BI analysis the methodological appropriateness of social networking is greater than other accessible data. Moreover, the institutional analysis findings have shown some applicability of social networking, as general developments have shown a growing abundance of BI study papers focused on social networks obtained from WoS.

A comprehensive analysis of Category 2 publications deemed closest to our scientific intent allowed the classification of different social networking channels included in this research field as well as defining the most successful social network typology (e.g., web feedback, SNS, web, and multi-data conversation groups) and social media sites (e.g. Twitter, Amazon, Yelp, TripAdvisor). We then identified the prevailing practices or algorithms used for BI analysis by researchers in the social network and examined their frequency with respect to their empirical objectives. This paper is intended to be, by means of the above empirical findings, the first phase in explaining current research patterns in social network analysis in BI, and in recognizing the advantages and shortcomings of earlier studies in this research area.

Our comprehensive review on Group 2 papers with 3 main RQs offered an accurate overview in terms of methods, details, and intelligent findings of BI social media-based study. However, we noticed a range of points of growth. Next, BI research on social networking would possibly focus highly on emotional insight to maximize consumer awareness. Feelings analysis is a well-established approach since it helps researchers to properly understand the language of consumers and their findings are intuitive. However, social media-based BI studies cannot rely entirely on an interpretation of emotions in order to offer insightful knowledge that a commercial organization may turn to in a true market setting. That is to suggest that leading researchers must constantly create and introduce quantitative methods to track whether a product has earned unfavorable feedback from its clients and to find innovative ways to satisfy current clients or to build a new model. Rather than conduct sentimental analysis to social network results, to analyze whether consumers are nice or poor as a great deal of social networking information contains, besides the feeling ranking, a range of details, such as emails, users, places, images or videos, secret feedback regarding product trends, emergent technology or customer-driven functions are provided. Similarly, BI studies of social networking may progress beyond one-off research into a structural or context. Some ground-breaking academics, for example, have introduced complex and surprisingly complicated social network data algorithms in a real-life market setting to replicate identical findings across multiple datasets. These excellent researchers may then build stronger support networks for specialists, Consideration of their methods' reproductively or functional utility.

Next, the BI researcher on social networking should propose merging social network data with other accessible data like patents in order to perform BI analysis from a wider viewpoint. As previously reported, social network data without any filtering represents customer-led knowledge. However, as decision-making in a real business environment should not only be regarded for clients but also for technologies, businesses, or competitive environments, social media-focused BI researchers could also try to analyze other open information, which are patents, research documents, and public data with social media data, in order to represent a variety of perspectives. Our results in Group 2 studies suggest that certain efforts are being made to merge scientific knowledge like patents, specifically or implicitly, with social network details like Twitter and Amazon. Such efforts must, however, be more active and developed. In particular, several inertia researchers analyzed the two data in a comparatively difficult analysis due to their poor re-productivity, by incorporating qualitative methods such as ontology, or by evaluating time-series models in a volatile business environment. When examining all different data in conjunction, trademark data could be used as a mediator, or proven text mining techniques could be implemented. Product name or trademark details can give researchers insight into the connection between technological data and customer requirements. In addition, common terms used by consumers should be matched with technical terms in patent documents by using word embedding results accurately. In addition, word embedding should be extended to text pre-processing to improve existing methods which will not be stable in social media typologies or abbreviations. With these advanced techniques, BI researchers in social media may grasp and communicate more effectively with client languages.

Author has already established a realistic use of social media in BI research and explored future directions with the experts.

The findings of this research will inspire leading researchers to participate in and further grow social media-based BI study. We also explained how the BI study should use social media information and described the method of data collection and analysis to help new researchers not disregard social media usage. Answers to the three research questions will extend the analysis by recommending for existing researchers in this field new methodologies or software systems. This guide will also allow professionals or clinicians in a real business environment to consider the latest trends and investigate new approaches in the field. Experts are able to find and adopt suitable methodologies for the business environment through a comprehensive approach or system analysis. This paper introduces diverse scholarly and functional classes, but there are some limitations.

Very outstanding. However, considering the substantial influence of certain conference papers (Asur & Huberman 2010), numerous quest

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and conference papers may be used to find further study papers in potential practice. Further, a concept-center, by evaluating the papers quoted for further study times, and comparing them for different market ideas may even be used for social media-based BI research posts. In order to examine Group 2 papers from a more complex viewpoint, more relevant analysis matters must also be included. Finally, this paper should not address some facets of BI analysis focused on social networking, such as the vocabulary of social media and associated market domains.

The papers collected examined the terms of the consumers in many fields such as the travel industry, pharmacy, restaurant, video, software, technology, and food services that were not specifically included in the study. Therefore, it will be necessary to evaluate consumer functionality or classify social networking sites by market area. Moreover, the language of social media must be studied as knowledge regarding material can be accessed from a human, regional, or national viewpoint. Most of the papers published in this document use social media written in English and Chinese, and potential research studies in various languages could be obtained and analyzed by social media content. The future work will focus on a deeper understanding of this area that will be gained if those issues are properly handled. Therefore, in future works, the researcher will cover more topics in this area in different Arab countries.

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