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What Should Businesses Know About Social Media Analytics?

Gohar Khan
University of Waikato, gohar.khan@waikato.ac.nz

Stuart Dillon
University of Waikato, stuart.dillon@waikato.ac.nz

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Full Paper

Gohar Khan
School of Management and Marketing
University of Waikato
New Zealand
Email: gohar.khan@waikato.ac.nz

Stuart Dillon
School of Management and Marketing
University of Waikato
New Zealand
Email: stuart.dillon@waikato.ac.nz

Abstract

Big social media data generated by customers can be employed start to identify which customer behaviour and actions creates more value. A study by conducted by MIT Sloan Management Review found that 67% of the total 2,500 survey respondents reported that by employing analytics their companies gained a competitive advantage as well it helped them to innovate. Still, many businesses struggle to plan and create value from social data analytics. Hence, using a thematic analysis of current social media analytics (SMA) literature and focus group interview with SMA experts, the aim of this article is to provide an executive overview of SMA concepts, theories, and tools that are vital for understanding and strategically using social media analytics for business intelligence purposes.

Keywords: social media analytics, value creations, SMA opportunities, SMA challenges.

1 INTRODUCTION

Social media data is the new gold and analytics is its digging tool. Social media analytics (SMA) is the art and science of extracting valuable hidden insights from vast amounts of semi-structured and unstructured social media data to enable informed and insightful decision-making (Karim et al. 2016; Khan 2015). It is a science, as it involves systematically identifying, extracting, and analyzing social media data (such as tweets, shares, likes, nodes, and hyperlinks) using sophisticated tools and techniques. It is also an art, interpreting and aligning the insights gained with business goals and objectives. To get value from analytics, one should master both its art and science. There is no doubt that social media activity, and the subsequent application of analytics to that activity has value. One study found that the average value of a Facebook fan in the major consumer areas was $US174.17 (Syncapse 2013). There is also considerable volume associated with social media data. KINAXIS, a supply chain management company, for example, used eighteen employee bloggers and generated over forty-two million leads (Petersen 2012).

The science part of social media analytics requires skilled data analysts, sophisticated tools and technologies, and reliable data. Getting the science right, however, is not enough. To effectively consume the results and put them into the action, the business must master the other half of analytics, that is, the art of interpreting and aligning analytics with business objectives and goals. Interpreting Analytics results, for example, requires representing the data in meaningful ways, having domain-specific knowledge, and training. Analytics should be strategically aligned to support existing business goals. Without a well-crafted and aligned social media strategy, the business will struggle to get the desired outcomes from analytics.

Using a thematic analysis of current SMA literature and focus group interview with SMA experts, the aim of this article is to provide an executive overview of SMA concepts, theories, and tools that are vital for understanding and strategically using social media analytics for business intelligence purposes. Particularly, the following questions are answered:

1. What is the purpose of social media analytics?
2. What are different types of social media analytics and how are they used?
3. What are different social media data types and how they related to analytics?
4. What are the key social media metrics and how to harness them?
5. What are the challenges of social media analytics?

2 THE EMERGENCE OF SOCIAL MEDIA ANALYTICS

Social media analytics is a relatively new but rapidly growing field. As a sub-field within the broader analytics discipline, businesses have begun exploiting social media for competitive advantage (Holsapple et al. 2018). It offers opportunities for organisations and individual to garner significant data insights that aould otherwise be hidden when undertaking traditional descriptive analytics. The value of social media analytics for marketing purposes is of particular value (Tafesse and Wien 2018). Based on Google's trends data (Figure 1), the term social media analytics seems to have appeared over the Internet horizon in July 2006, and interest in it (regarding people searching for it) has steadily increased since then.

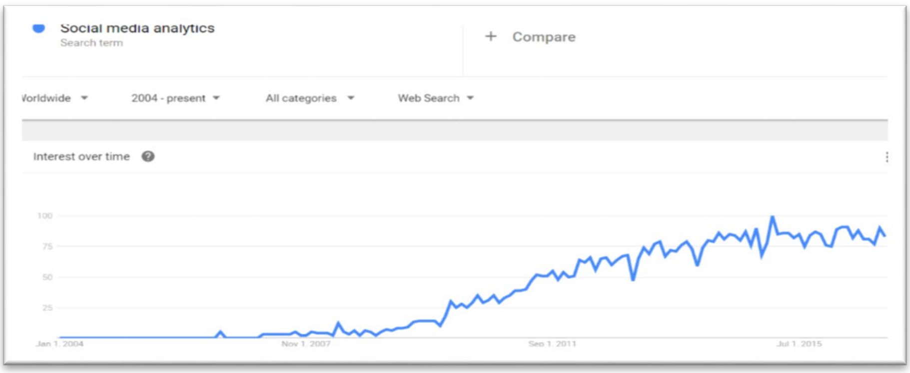

Figure 1 Interest in social media analytics over time

Google trends also show that the majority of the interest in social media analytics is coming from India, Canada, United States and United Kingdom and users interested in social media analytics also searched for a variety of topics including Google Analytics, social media marketing, social media tools, marketing analytics, Facebook analytics, Twitter analytics, and social media management. A full list of social media-related terms, derived from Google Trends, is shown in Table 1. The scoring shown in Table 1 is on a relative scale where a value of 100 is the most commonly searched query, 50 is a query searched half as often, and a value of 0 is a query searched for less than 1% as often as the most popular query.

Terms Searched	Score	Terms Searched	Score
Google analytics	100	Social media management	10
Social media marketing	40	Hootsuite analytics	10
Social media tools	40	SEO	10
Social analytics tools	35	Hootsuite	10
Marketing analytics	35	Instagram analytics	10
Facebook analytics	30	Big data analytics	10
Twitter analytics	30	Social media metrics	10
Data analytics	25	LinkedIn	5
Web analytics	20	Big data	5
Social media analysis	15	LinkedIn analytics	5
Social media tracking	10	WordPress analytics	5
Social media monitoring	10	Social media strategy	5
Social media management	10	Social media dashboard	5

Table 1 Social Media Analytics Related Terms

3 METHODOLOGY USED IN THE STUDY

The concepts, theories, and models, discussed in the article were acquired from thematic analysis of SMA literature. Mainly, three sources were used: 1) academic literature, 2) web resources, and 3) interviews.

3.1 Academic literature

Academic literature on social media analytics was retrieved from the Web of Science (WoS) database using the following research query:

> *Search Query: TOPIC: ("Social Media Analytics" OR "Mining Social Media" OR "Facebook analytics" OR "Twitter analytics" OR "Blog analytics" OR "LinkedIn analytics" OR "Social media analysis" OR "Social media tracking" OR "Social media metrics" OR "Social media strategy" OR "Social media dashboard" OR "social media analytics theories" OR "Social Media analytics models" OR "Social Media Analytics Concept" OR "Managing social media" OR "Social Media Capabilities" OR "social media key performance indicators" OR "social media analytics types" OR "Social media privacy" Or "Social analytics tools"), Timespan: 2004-2017. Indexes: SSCI, A&HCI, CPCI-SSH.*

Since social media analytics is a relatively new area, we restricted our search to the 2004-2017 time window. The research retrieved 186 articles which included 126 journal articles, 42 proceeding papers, 8 editorial materials, 9 book reviews, 1 each news item, meeting abstract, and a book chapter. All these articles were thoroughly scanned to extract themes, concepts, and theories related to SMA.

3.2 Web Resources

In addition to this, we also looked at the jobs description of what employees look for in the SMA related candidates in job-seeking platforms (such as, www.seeks.com.au, indeed.com, and monster.com).

3.3 Interviews

We then undertook interviews with 5 academics and 4 business professionals to confirm and validate the themes, concepts, and theories identified in previous two stages. Based on these interviews the concepts and models were revised as required. Not all the themes identified in the first two stages were discussed in the interviews, but the most widely reported ones, such as SMA analytics cycle, KPIs, use of SMA, and privacy and security issues, were.

4 RESULTS

4.1 Types of Social Media Data

By reviewing the literature, we identified that at a minimum, social media has eight layers of data, namely, text, networks, actions, hyperlinks, and mobile, location, multimedia, and search engine data (Khan 2018) . Each layer carries potentially valuable information and insights that can be harvested for business intelligence purposes. Out of the eight layers, some are visible or easily identifiable (such as text and actions), and others are invisible (such as social media hyperlink and networks).

Layer One: Text—social media text analytics deals with the extraction and analysis of business insights from textual elements of social media content, such as comments, tweets, blog posts, and Facebook status updates. Text analytics is mostly used to understand social media users' sentiments or identify emerging themes and topics. Social media text analytics, also known as text mining, is a technique to extract, analyze, and interpret hidden business insights from textual elements of social media content. Organizations use text analysis techniques to extract hidden valuable meaning, patterns, and structures from the user-generated social media text for business intelligence purposes.

Layer Two: Networks—social media network analytics extract, analyze, and interpret personal and professional social networks, for example, Facebook, Friendship Network, and Twitter. Network analysis can be employed to identify influential nodes (e.g., people and organizations) or their position in the network; it can also be used to understand the overall structure of a network. Businesses can use network analysis to explore their Twitter or Facebook followers and identify influential members on those networks.

Layer Three: Actions—social media actions analytics deals with extracting, analyzing, and interpreting the actions performed by social media users, including likes, dislikes, shares, mentions, and endorsement. Actions analytics are mostly used to measure popularity, influence, and prediction in social media. Social media actions are of great value to social media marketers because of their role in increasing revenue, brand value, and loyalty. Organizations can employ actions analytics to measure the popularity and influence of a product, service, or idea over social media.

Layer Four: Mobile—mobile analytics is the next frontier in the social business landscape. Mobile analytics deals with measuring and optimizing user engagement with mobile applications (or apps for short). The main purpose of apps analytics is to measure and analyze user behavior; improve user experiences; and drive revenue, engagements, and loyalty.

Layer Five: Location—location analytics, also known as spatial analysis or geospatial analytics, is concerned with mining and mapping the locations of social media users, contents, and data. Hyper-local advertising has had fundamentally changed the marketing landscape. It allows marketers to use a smartphone's GPS data to geographically target audiences for the purpose of delivering relevant ads.

Layer Six: Search Engines—search engines Analytics focuses on analyzing historical search data for gaining valuable insight into a range of areas, including trends analysis, keyword monitoring, search result, search engine optimization, and advertisement history, and advertisement spending statistics. Social media marketers strive to develop search engine strategies to make their websites appear at the top of search results. It is important for their websites to appear at the top (e.g., in the first page of the search results) in the SERP (search engine result page), as users pay closer attention to the top results on search engines (Pan et al. 2007).

Layer Seven: Hyperlinks—Hyperlink analytics is about extracting, analyzing, and interpreting social media hyperlinks (e.g., in-links and out-links). Hyperlink analysis can reveal sources of incoming or outgoing web traffic to and from a web page or website.

Layer Eight: Multimedia—Social media multimedia analytics is the art and science of harnessing business value from video, images, audio, and aminations, and interactive contents posted over social media outlets.

5 PURPOSE OF SOCIAL MEDIA ANALYTICS

While the main premise of social media analytics is to enable informed and insightful decision making by leveraging social media data (Bekmamedova and Shanks 2014; Chen et al. 2012); it is employed by various sectors including government, telecommunications, pharmaceutical, retail, healthcare, academia, banking, financial, and insurance services. Uses span from market research, generating business leads, competitive intelligence, connecting and engaging with current customers and counter-terrorism/threat detection to medical research. Here we discuss some of them.

Use by Business—business use SMA for a variety of purposes including market research, survey content analysis, social media analysis, the voice of customers, churn analysis, competitive intelligence, risk analysis, and document analysis. For example, research suggests that adding unstructured textual information (such as a tweet) into a conventional churn prediction model (i.e., models that identify those customers that are most likely to discontinue using a service or product) resulted in a significant increase in predictive performance (Coussement and Van den Poel 2008). Such predictions can help managers identify customers at risk of switching thus organizing a preemptive customer retention campaigns.

Use by Government—application of SMA in the government sector can vary from counter-terrorism, cybersecurity, bio-surveillance, to health analytics. Increasing governments from around the world use SMA, for example, for national security purposes especially by monitoring and analysis of social networking sites, blogs, forums, and instant messages (Zanasi 2009). In the area of bio-surveillance, government agencies need to develop and properly coordinate responses to potential epidemics (such as the Ebola virus) or acts of bioterrorism (such as anthrax letters). By combining social media data (such as chats and comments) with organizational data from sources such as 911 calls, poison control centers and hospitals, government agencies use text analytics to detect potential epidemics ahead of time. Such early detection enables government agencies to take proactive steps to limit the spread of disease, for instance, by providing early warnings and recommendations to citizens and health care providers.

Use by Academia—one of the key areas academic use SMA is for research analytics to users understand key topics and patterns in previous research and how it applies to a current research endeavor. Understanding previous research in key domain areas researchers focus on new research in unique areas and ensure that future endeavors do not repeat the mistakes of the past.

Use by Financial Institutes—SMA is useful in early warnings for financial crises and fraud. Social media data, for instance, has been used to highlight economic trends (such as extreme reduced spending) as an early signal for impending job loss. Such social media monitoring also serves as a safeguard against illegal, discriminatory, and fraudulent practices, saving government and individuals countless dollars in damages.

6 TYPES OF SOCIAL MEDIA ANALYTICS

Social media analytics help achieve business objectives through describing data to analyze trends, predicting future problems and opportunities, and optimizing business processes to enhance organizational decision making. Like any business analytics (Delen and Demirkan 2013), social media analytics can take four forms (Figure 2): Descriptive analytics, Diagnostic analytics, Predictive Analytics, and Prescriptive analytics.

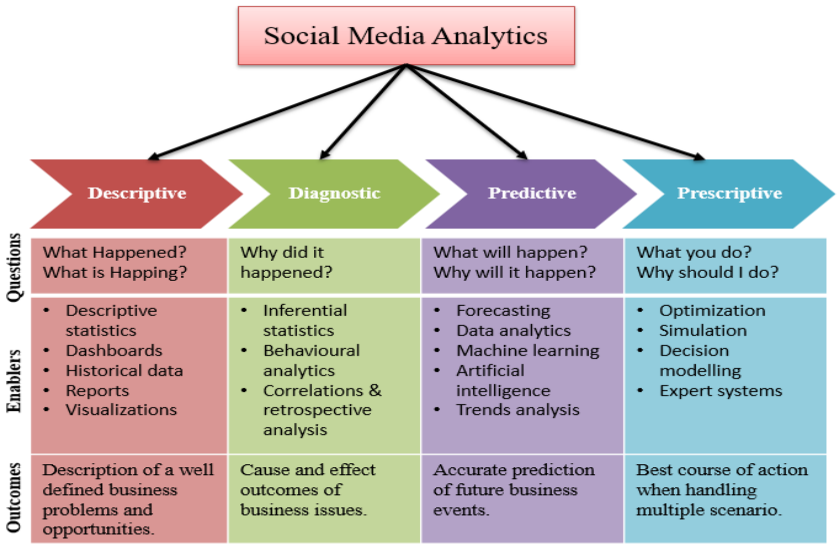

Figure 2 Types of Social Media Analytics

6.1 Descriptive Analytics (Reactive)

Descriptive analytics reactive in nature and deals with the questions of “what happened and/or what is happing?” It is mostly focused on gathering and describing social media data in the form of reports, visualizations, and clustering to understand a well-defined business problem or opportunity. Actions analytics (e.g., no. of likes, tweets, and views) and text analytics are examples of descriptive analytics. Social media text (e.g., user comments), for instance, can be used to understand users’ sentiments or identify emerging trends by clustering themes and topics. Currently, descriptive analytics accounts for the majority of social media analytics.

6.2 Diagnostic Analytics (Reactive)

Also reactive in nature, diagnostic analytics deals with the questions of “why something happened?” Enablers of diagnostics analytics include inferential statistics, behavioral analytics, correlations & retrospective analysis and the outcome being cause and effect analysis of business issues. For example, while descriptive analytics can provide an overview of your social media marketing campaign’s performances (posts, mentions, followers, fans, page views, reviews, pins, etc); diagnostic analytics can distill this data into a single view to see what worked in your past campaigns and what didn’t.

6.3 Predictive Analytics (Proactive)

Predictive analytics involves analyzing large amounts of accumulated social media data to predict a future event. It is also reactive in nature and an essence deals with the question of “what will happen and/or why will it happen?” The primary outcome of predictive modeling is an accurate projection of the future happenings and the reasoning underlying such an event. For example, an intention expressed over social media (such as buy, sell, recommend, quit, desire, or wish) can be mined to predict a future event (such as a purchase). Alternatively, a business manager can predict sales figures based on historical visits (or in-links) to a corporate website.

6.4 Prescriptive Analytics (Proactive)

While predictive analytics help to predict the future, prescriptive analytics suggest the best action to take when handling a scenario (Lustig et al. 2010). For example, if you have groups of social media users that display certain patterns of buying behavior, how can you optimize your offering to each group? Like predictive analytics, prescriptive analytics has not yet found its way into social media data. The main enablers of prescriptive analytics include optimization and simulation modeling, multi-criteria decision modeling, expert systems, and group support systems. Whereas, the main outcome of prescriptive modeling is either the best course of action when handling multiple scenarios, or expert opinions provided to a decision-maker that could lead to the best possible course of action.

7 CURRENT VS. POTENTIAL USE OF SOCIAL MEDIA ANALYTICS

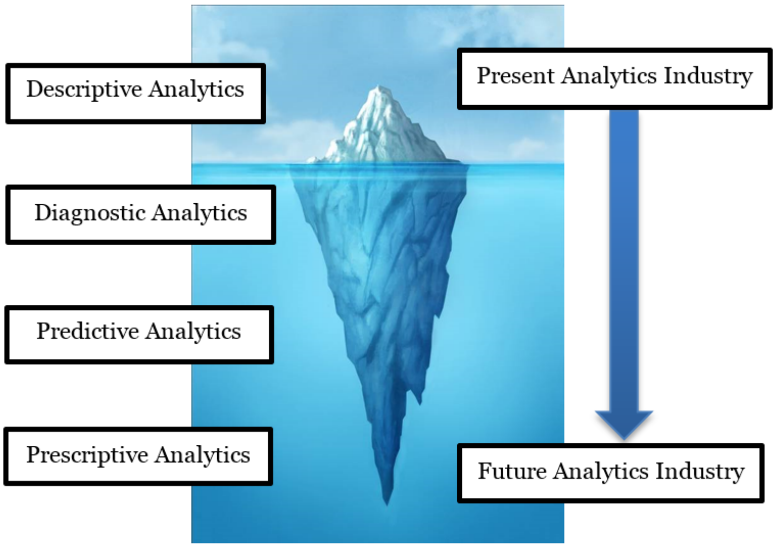

Figure 3 Current versus Potential Use of Social Media Analytics

The current social media analytics discourse suggests that at present the majority of the analytics industry and practice revolves around descriptive analytics. And if there is any use of predictive and prescriptive analytics, it is limited to structured data only. According to Gartner (2012), only 3 percent of companies used prescriptive analytics, but with structured data only. However, the use of social media data for descriptive analytics is just the tip of an iceberg (see Figure 3). Its true potential is in predictive and prescriptive analytics. The future of the analytics industry is in the use of predictive/prescriptive analytics thus unleashing the true potential of social media analytics.

8 KEY PERFORMANCE INDICATORS (KPIs)

When it comes to social media return on investment (ROI), a vast majority of business managers find it hard to quantitatively measure such returns. This becomes problematic as top management often demands concrete measures on their return on social media marketing investment (Weinberg and Pehlivan 2011). The question of measuring social media ROI is a highly controversial issue. Due to nature of social media, some researchers suggest that social media returns should not always be measured in monetary instruments, instead business managers should use platform-specific social metrics (Likes; Shares; Comments; Views; Posts; Dislike) to gauge the effectiveness of social media engagement efforts (Cronin 2014; Hoffman and Fodor 2010). Similarly, Khan et al. (2019) has showed that social media returns should be measured from the network point of view taking into account the network effect. One way to measure returns on social media investment is through the use of key performance indicators (KPIs). KPIs are quantifiable measures used to gauge a company's success at reaching targets. The value of having KPIs is that they help a business stay focused on achieving their goals and objectives. Once the key business goals have been identified, KPIs are then developed to measure how effectively a company is achieving these goals. The eight layers of social media concepts introduced earlier can be used to developed business-specific KPIs. Table 2 provides a list of business goals and the potential social media to measure these goals.

Social Media Analytics Layer	**Business Goal**	**Potential KPI**
Action Analytics	Engagement; Popularity;	-*Re-tweet %:* Percentage of re-tweets in the total tweets. The higher the percentage the more a customer's interacts with your company. -*Replies %*: Percentage of replies in the total tweets. The higher the percentage the more your company is responsive. -*Mentions*: the average number of customers mentioned per tweet by a candidate. The higher the percentage of mentions the more interaction is happening.
Text Analytics	Customer Sentiment Analysis; Lead generation; Idea generation;	-% of positive opinion expressed in Tweets or comments; -% of Negative opinion expresses in tweets or comments; -No. of users' intention (e.g., buy, recommend) expressed in Tweets or comments; -No. of new topics/idea expressed in a tweet;
Network Analytics	Network Expansion; Network Structure;	-No. new nodes added to a network; -No. of Key nodes in a network; -The proportion of direct ties in a network relative to the total number possible (density); -Average no. of links in a network (degree)
Search Engines Analytics	Search Engine Optimization;	-No. of quality in-links to your website; -No. of people searching for your brand; -No. of new topics/idea researched related to your brand; -The ratio between organize VS. paid search results; -No. of referrals; -The volume of search engine traffic;
Location Analytics	Geo-targeting; location-based advertising; Tracking activity and interest;	-No. of people entered a store per period of time (arrival metrics); -The ratio of people entering the store to the people passing by (Capture Rate); -The ratio between people lingering close to the display (or sensor or exhibit) and total visitors to the store (Drew Rate); -No. of triggered actions (or messages) delivered; -The ration between the total no. of triggered actions delivered vs., the customer responded to; -No. of potential customers in a geographic location;

Social Media Analytics Layer	Business Goal	Potential KPI
Apps Analytics	App optimization; Customer engagement;	-No. of times the application is opened; -No. of first-time users; -Total time spent using the application divided by total user count; -How often mobile users open the application;
Hyperlink Analytics	Website hyperlink environment;	-No. of incoming hyperlinks originating from other websites; -No. of out-links generated out of a website; -No. of co-links with important websites;

Table 2 Social Media Analytics KPIs

9 SOCIAL MEDIA ANALYTICS VALUE CREATION CYCLE

Social media analytics business value creations is a six-step iterative process (involving both the science and art) of harnessing the desired business value from social media (Figure 3). At the centre of the analytics is the organizational goals and objectives that we want to achieve with social media analytics. The following are the six general steps, at the highest level of abstraction, that involves both the science and art of achieving business insights from social media data.

Step 1: Identification—the identification stage is the art part of social media analytics and is concerned with searching and identifying the right source of information for analytical purposes. The numbers and types of users and information (such as text, conversation, and networks) available over social media are huge, diverse, multilingual, and noisy. Thus, framing the right question and knowing what data to analyze is extremely crucial in gaining useful business insights. The source and type of data to be analyzed should be aligned with business objectives.

Step 2: Extraction—once a reliable and mineable source of data are identified, next comes the extraction of the data. The type (e.g., text, numerical, or network) and size of data will determine the method and tools suitable for extraction. Small-size numerical information, for example, can be extracted manually (e.g., going to your Facebook fan page and counting likes and copying comments), and a large-scale automated extraction is done through an API (application programming interface). APIs, in simple words, are sets of routines/protocols that social media service companies (e.g., Twitter and Facebook) have developed that allow users to access small portions of data hosted in their databases. The greatest benefit of using APIs is that it allows other entities (e.g., customers, programmers, and other organizations) to build apps, widgets, websites, and other tools based on open social media data. Some data, such as social networks and hyperlink networks, can only be extracted through specialized tools.

Step 3: Cleaning—this step involves removing the unwanted data from the automatically extracted data. Some data may need cleaning, while other data can go into analysis directly. In the case of the text analytics cleaning, coding, clustering, and filtering may be needed to get rid of irrelevant textual data using natural language processing (NPL). Coding and filtering can be performed by machines (i.e., automated) or can be carried out manually by humans. For example, Discovertext combines both machine learning and human coding techniques to code, cluster, and classify social media data.

Step 4: Analyzing—at this stage, the clean data is analyzed for business insights. Depending on the layer of social media analytics under consideration and the tools and algorithm employed, the steps and approach to take will greatly vary. For example, nodes in a social media network can be clustered and visualized in a variety of ways depending on the algorithm employed. The overall objective at this stage is to extract meaningful insights without the data losing its integrity.

Step 5: Visualization—in addition to numerical results, most of the eight layers of social media analytics will also result in visual outcomes. The science of effective visualization known as visual analytics is becoming an important part of interactive decision making facilitated by solid visualization (Wong and Thomas 2004). Effective visualization is particularly helpful with complex and large data sets because it can reveal hidden patterns, relationships, and trends. It is the effective visualization of the results that will demonstrate the value of social media data to top management.

Step 6: Interpretation or Consumption—this step relies on human judgments to interpret valuable knowledge from the visual data. Meaningful interpretation is of particular importance when we are dealing with descriptive analytics that leaves room for different interpretations. While companies are quickly mastering sophisticated analytical methods, skills, and techniques needed to convert big data into information, there seems to a gap between an organization's capacity to produce analytical results and its ability to effectively consuming it. For example, a study of 2,719 business executives, managers, and analytics professionals from the world found that that the greatest problem to creating business value from analytics is not data management issues or complex data modeling skills. But it was translating analytics into business actions and making business decisions based on the results, not producing the results per se (Kiron et al. 2013). The study also identified three levels of analytical maturity in organizations:

Analytically Challenged—these organizations lack sophisticated data management and analytical skills and generally rely more on management experience in decision making.

Analytical Practitioners—such organizations tend to use analytics for operational purposes, have "just good enough data" and are working to become more data-driven.

Analytical Innovators—analytical innovators organization are more strategic in their use and application of analytics, place greater value on data, and have higher levels of data management and analytical skills. These are the organization that is most successful in translating analytics results into business actions and decisions making.

10 CHALLENGES TO SOCIAL MEDIA ANALYTICS

Social media data is high volume, high velocity, and highly diverse, which, in a sense, is a blessing regarding the insights it carries; however, analyzing and interpreting it presents several challenges. Analyzing unstructured data requires new metrics, tools, and capabilities, particularly for real-time analytics that most businesses do not possess. Some social media analytics tools are listed in a later section.

Volume and Velocity as a Challenge—Social media data is large and generated swiftly. Capturing and analyzing millions of records that appear every second is a real challenge. For example, on Twitter, three hundred forty-two thousand tweets appear every minute, and on Facebook, one million likes are shared every twenty minutes. Capturing all this information may not be feasible. Knowing what to focus on is crucial for narrowing down the scope and size of the data. Luckily, sophisticated tools are being developed to handle high-volume and high-velocity data.

Diversity as Challenge—Social media users and the content they generate are extremely diverse, multilingual, and vary across time and space. Not every tweet, like, or user is worth looking at. A tweet or mention coming from an influential social media user is more valuable than a tweet from a non-influential user. Due to the noisy and diverse nature of social media data, separating relevant content from noise is challenging and time-consuming.

Unstructured Data as a Challenge—Unlike the data stored in the corporate databases, which are mostly numbers, social media data is highly unstructured and consists of text, graphics, actions, and relations. Short social media text, such as tweets and comments, has a dubious grammatical structure and is laden with abbreviations, acronyms, and emoticons (a symbol or combination of symbols used to convey emotional expressions in text messages), thus representing a significant challenge for extracting business intelligence.

Social media Analytics Accuracy—Owing to the challenges of volume, velocity, and diversity, the accuracy of Social Media Analytics is questionable. As the huge unstructured data (also known as 'dirty' data) is generated over social media, the accuracy of social listening is decreasing. For example, text analytics (one of the main component of social media analytics) cannot capture many of the ways people use language. Most of the tools have developed by Western and English speaking countries. The tools often translate the text into English, apply sentiment analysis, then assign it to the original post its native language.

Privacy and Ethical Issues—Two important issues to bear in mind are privacy and ethical issues related to mining data from social media platforms. Privacy advocacy groups have long raised serious concerns regarding large-scale mining of social media data and warned against transforming social spaces into behavioral laboratories. The social media privacy issue first came into the spotlight particularly due to the large-scale "Facebook Experiment" carried out in 2012. In this experiment, Facebook manipulated the news feeds feature of thousands of people to see if emotion contagion occurs without face-to-face interaction (and absence of nonverbal cues) between people in social networks (Kramer et al. 2014). Though the experiment was consistent with Facebook's Data Use Policy (Verma 2014) and helped promote our understanding of online social behavior, it does, however, raise serious concerns regarding obtaining informed consent from participants and allowing them to opt-out.

11 CONCLUDING REMARKS

No doubt, social media data provides tremendous opportunities for businesses. It is, however, not enough to simply have a social media analytics tool ready to mine data. Analytics should be strategically aligned to support existing business goals (Khan 2018). Without a well-crafted and aligned social media strategy, the business will struggle to get the desired outcomes from social media analytics. If the business goal, for instance, is to understand customer sentiments expressed over social media, social media analytics should be designed to facilitate this objective. It may require, for example, tools and skills for extracting and analyzing tweets or comments posted on a Facebook fan page. Alternatively, if the business objective is to identify influential social media customers and their position in the network, the focus should be on social media networks.

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