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Abstract

This article is intended to serve as a primer for social media analytics.The paper explores different dimensions of such analytics by drawing on a review of the literature. Specifically, the paper sheds light on the definitional aspects, types of social media data and types of analytics to improve firm performance. The findings of the paper will help the reader to grasp the fundamental of social media analytics.

Introduction

Social media is at the core of the so called “social commerce”, which represents a new form of “Internet-based social media that allows people to participate in the marketing, selling, comparing, and buying of products and services in online marketplaces and communities” (Stephen & Toubia, 2010). Driven by the widespread diffusion and adoption of social media platforms such as Facebook, Twitter and Pinterest as well as mobile devices, social commerce is expected to generate tremendous business value in terms of operational efficiency and improved revenues in the incoming years. Some analysts estimated that the social commerce market will grow from about US$5 billion in 2011, to almost US$30 billion by 2016 (Zhou, Zhang, & Zimmerman, 2011). In a McKinsey Global Institute report, the consulting firm foresaw that in 2012 only, “$900 billion to $1.3 trillion in annual value could be unlocked in just four sectors by products and services that enable social interactions in the digital realm”. According to the same report, “[t]here’s no doubt organizations have begun to realize significant value from largely external uses of social [media]. Yet internal applications have barely begun to tap their full potential, even though about two-thirds of social’s estimated economic value stems from improved collaboration and communication within enterprises. Although more than 80 percent of executives say their companies deploy social technologies, few have figured out how to use them in ways that could have a large-scale, replicable, and measurable impact at an enterprise level” (Chui, Dewhurst, & Pollak, 2013). While business value from social media is emerging as an important field of research (S. Fosso Wamba & L. Carter, 2013), very few empirical studies have been devoted to how to actually co-create and capture value from social media and relevant analytics.

Social media analytics (SMA) has emerged as an innovative research field after years of rapid and increasing adoption of social networks across the entire business. Due to the richness and the most dynamic evidence of social data, there are clear opportunities for theoretical and practical inquiry to create new knowledge and scientific possibilities by leveraging data, technology, analytics, business and society (Culnan, McHugh, & Zubillaga, 2010). There is growing evidence that SMA provides a broader view of consumers, groups and society and creates business value by identifying new patterns and opportunities (Batrinca & Treleaven, 2015; Kaplan & Haenlein, 2010). However, very few studies provide a general taxonomy to explore the types of social media data and analytics. Therefore, this paper identifies different conceptual dimensions of social media data, analytics and their relevance to business value.

The special issue on "Unveiling the Impact of Social Media: Importance of the Co-creation of Business Value during the Adoption and Use Process" of the Journal of Organizational and End User Computing (JOEUC) presents this position paper to encourage more frequent and knowledgeable use of social media analytics. The remainder of this paper is structured as follows. First, the concept of social media analytics is discussed. Second, types of social media data are explained. Third, types of social media analytics are illuminated. Finally, future research directions are provided as well as a conclusion.

Defining Social Media Analytics

The use of social media to engage with customers has increased dramatically in recent years. According to the Pew Research Center (Sheet, 2014), more than 74% of online adults in the U.S use social media to connect, interact, collaborate or engage with others. Social media based recommendations influenced an average of 26 percent purchases across 30 product area and more than 100 brands (Bughin, 2015). The widespread influence of social media as a source of information and marketplace has sparked research interests for social media analytics (SMA) (A. Chen, Lu, Chau, & Gupta, 2014; Qiu, Rui, & Whinston, 2014). Although the impact of social media continues to increase, its measurement remains a challenge.

Social media refers to communication technology platforms where people share information and opinions (Agrawal, Budak, & El Abbadi, 2011), which can connect both existing and potential customers not only with each other but also with companies and organizations (Mangold & Faulds, 2009). Hansen, Shneiderman, and Smith (2010) defined social media as a set of online tools that support social interaction between users that involves monologue (one to one) to dialogue (many to many). Zeng, Chen, Lusch, and Li (2010, p.13) identified social media as "a conversational, distributed mode of content generation, dissemination, and communication among communities". A. Chen et al. (2014) put forward social media as a form of online community to get connected with people from internal and external circles. Such social media platforms let users entertain, learn, and even to make social and political changes through interacting with others on online social connection and networks (Agrawal et al., 2011). All opportunities for various aspects of business lie in the fact that virtually every social interaction among the consumers on social media can be observed and analyzed.

People in various businesses now can derive useful information from social network data to understand their consumers more comprehensively and precisely by utilizing various types of social media analytic tools. H. Chen, Chiang, and Storey (2012) defined Social Media Analytics (SMA) as a method to uncover what customers think and feel by analyzing structured and unstructured online data dispersed across a vast array of online sources. Zeng et al. (2010) highlighted SMA as informatics tools and frameworks to collect, monitor, analyze, summarize and visualize social media data to facilitate conversations and interactions to extract useful patterns and intelligence. Fan and Gordon (2014) identified SMA as interdisciplinary modelling and analytical paradigm consisting of three steps: 1) capturing data from various courses; 2) understanding data using various analytics and models; and 3) summarizing and presenting the findings for decision making. SMA shares similarity with Big Data Analytics (BDA) in that both SMA and BDA involve analysis, management and visualization of the similar types of datasets—accumulated traces of consumers' online activities (Kiron, Perguson, & Prentice, 2013). Also, SMA can be similar to social network analysis as both can aim to understand underlying relational components of consumer activities on social media.

SMA includes various analyses including sentiment analysis or opinion mining—the analytic techniques that analyzes people's opinions, sentiment, evaluation, attitude, judgments and emotions towards various objects, including issues, products, services, organizations, individuals, and so on (Liu, 2012). Thus, SMA can provide organizations with broad senses of customers' current needs (Mosley Jr, 2012), opinions (Eysenbach, 2009), public sentiments and future demands (Lee, Moon, & Salamatian, 2010; Szabo & Huberman, 2010), by incorporating big data and social network analytic tools. Therefore, we identify SMA as more comprehensive analysis tool than BDA social network or sentiment analysis, as SMA can encompass BDA, social network analysis and sentiment analysis to understand consumers.

Types of Social Media Data

Different online social media generate different types of data. Data can be in many different forms, such as text, image, audio, video, click data, mouse movement data, deleted non-posted content, etc. (Batrinca & Treleaven, 2015). Social media data can be broadly categorized into seven categories: 1) Demographic Data, 2) Product Data, 3) Psychographic Data, 4) Behavioral Data, 5) Referrals Data, 6) Location Data and 7) Intention Data (see Table 1). First, demographic data are the publicly open and shared information, including age, race or ethnicity, gender, education, income, and geography (Kaplan & Haenlein, 2010). These data are available in profile information of individuals' social media profile. Although an individual's profile information may not be enough to understand the bigger picture, aggregated information can create a strong direction to make business decision. Second, product data are generated through social media users' mentioning of a particular brand or product on social media (Mangold & Faulds, 2009). This mentioning or discussion of a particular brand or product can appear either in any particular brand's social media page or in personal area of social media user. Third, consumers also share their problems and expectation with a product, and product value and features on social media (Heinonen, 2011). Psychographic data refer to such data that can inform consumers' personality, values, attitude, interests and lifestyle related to a product or a brand. Fourth, behavioral data represent consumers' past buying behavior, such as buying record, in social media platform (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). By analyzing behavioral data from social media pages, companies can identity their target customers and predict future intention. Fifth, referrals data are data from ratings and reviews shared on social media platforms. This type of data comes from positive or negative word of mouth on social media (Trusov, Bucklin, & Pauwels, 2009). Referrals data give a clearer picture that helps organizations or companies to identify reason for sharing the information. In order to generate positive word-of-mouth, analysis on consumers' referral data is crucial. Sixth, location data inform consumers' real time or current information regarding their geographical location (Wagner et al., 2010). Twitter and Facebook both have such features that enable users to share their current location while sharing certain information on social networking sites. Such location data provide a great opportunity for companies to build effective strategies that link virtual and real world. For instance, location data analysis can be helpful for hotel and resort and event management organization to better organize the business by targeting consumers based on their current geographical locations. Finally, intention data are those data that can help organizations and companies to predict consumers' expectation with a product or a brand and future activities related to them (Ballings & Van den Poel, 2015).

As the nature and type of social data represent the unique attributes of big data (i.e., volume, variety, velocity, veracity) (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015), there is possibility of new theory enquiring new challenging problems on better algorithms, infrastructure and data management to create business value and improve firm performance. The emerging social media analytics also indicate that social media data are “relational” and “networked”, thus this stream necessitates new developments in system and data quality, privacy and ethical implications, strategic alignment and corporate culture.

Table 1: Types of Social Media Data for analytics

Types	Descriptions	Applications
Demographic Data	Consumers' demographic information in social media, which includes age, gender, education, geography etc.	• Amazon provides customized offer by name to its customers with specific product suggestions that ultimately lead to a long run relationship (Nemschoff, 2013). • Honda Japan offered login name to 630,00 people to their site to have a chance a newly launching vehicle CR-Z and the data collected from social media information where people asked for new product CR-Z's information. That ultimately took the prelaunch order to 4,500 units with 10,000 unit sales in first month (Edelman & Salsberg, 2010)
Product Data	Product data in social media, which are generated when a particular brand or product name is mentioned.	• Coca-Cola gained significant sales uplift by broadcasting a consumer made video, which was initially shared in YouTube and was gaining popularity there. The title of the video was, "The Extreme Diet Coke and Mentos Experiments"(Kaplan & Haenlein, 2010). • Just two weeks before launching iPhone5, Apple used various media channels to share products features with attractive commercials and media communication. With the help of social media conversation data, Apple found some most popular topics for promotion and to increase consumers' purchase intention(Moore, 2014). • Using Twitter, the car company Ford directly interacts with the consumers and responds in real time which ultimately helps the company to understand what's happening around the brand and helps to stop negative word-of-mouth before it gets viral (Balwani, 2009). • BBVA sets their communication strategy for responding to positive or negative comments in the Facebook, Twitter, blogs, online forums etc. Using this system, BBVA has increased customers' positive feedback more than one percent and decreased negative feedback by 1.5 percent with more delighted consumer experience(IBM, 2014). • Car Company Ford initiated a social media campaign while launching a new car, Fiesta Model, through which they received 50,000 requests for information regarding Fiesta Model and those were initially from non-Ford drivers. Later, after product lunching in late 2010, within first 6 days they sold around 10,000 cars. One of the major parts of the campaign was providing a European model of the car to 100 social media influencers completing "missions" and telling themselves to documenting and sharing experience to different social media sites. Only in YouTube the videos received 6.5 million views (Muñoz & Strotmeyer, 2010). • McDonald's sets an example of protecting brand image by regularly monitoring social media. They did it by responding to a hoax through quick social media response and responding individuals' tweets in some cases. The hoax was, the company was charging additional charging from African-Americans and that majorly appeared in Twitter. The reward of responding that hoax attack successfully in social media was, five percent stock price rise of McDonald's(Muñoz & Strotmeyer, 2010).

Psychographic Data	The type of social media data that indicate consumers' personality, interest and lifestyle.	• Helps to build content strategy with proper understanding of what consumers like and dislike. • Based on tracking information of consumers' web visiting device whether it is PC, mobile or Tablet, companies can take decision whether to go for technical update of their website for mobile friendly version (Schlagwein, 2014) • Based on the understanding of behavioral information, Starbucks has developed ''My Starbucks Idea'' platform where consumers provide new ideas for the company and the best ideas are voted by other members (Kaplan & Haenlein, 2010). • The research company Nielsen considers real-time twitter data to build TV Audience Rating using its 140 million members. It helps to give more accurate TV rating information to its clients(Kiron, Palmer, Phillips, & Berkman, 2013). • Through DEWmocracy promotion, PepsiCo gathered customer insight from Social Media to create new verities of Mountain Dew brand which has been sold 36 million cases since 2008(Muñoz & Strotmeyer, 2010). • PepsiCo's sports drink Gatorade regularly started monitoring social media with major focus to various related terms including their brand, competitors and sportsmen they sponsored through real time customized data visualization and console. They analyze emotional responses around launched products and promotions, and they integrate all these finding to the product and marketing. To maintain all these, the company made a "war room" in their marketing department at Chicago. The visit to online resources of the brand, visitors' length of interaction and sharing from campaign - all have turned doubled due to all these monitoring and integration done by the company (Muñoz & Strotmeyer, 2010). • The software company Intuit made important changes in their Quicken and QuickBooks personal finance software based on direct consumer experience collected from online forum. The company initially made that forum so that one user can help another, and the company utilized and implemented the learning gained from consumers' comments in the forum (Muñoz & Strotmeyer, 2010).
Behavioral Data	Past behavioral information in social media that supports to predict future action.	• A bank in Australia, UBank maintains a dedicated team which monitors non-consumers' dissatisfaction on rival banks in social media and based on that information they make them their customer (Schlagwein, 2014) • Pursway, a social media monitoring company provides helpful consumer insights to its client firms. Pursway identifies 10-25 closest individuals of client companies' clients and monitor their transactions based on their spending pattern and provide insights through building social graph on that data (Technologies, 2013). • Using IBM Business Analytics Solutions, a global financial group BBVA analyses social data to monitor brand perception, find opportunities to make new clients, monitor existing clients' activities to retain them and create delighted customers(IBM, 2014)

Referrals Data	Ratings, reviews and non-verbal attitudes generate referral data.	• A radio station in Australia, “triple j” uses its Twitter data to understand whether listeners like their programs or not by monitoring the rate of re-tweets and responses (Schlagwein, 2014) • IKEA uses interactive catalogue to engage potential customers who share posts of relevant products within their social media circle. It resulted into a big spike into its sales figure (Scott, 2013). • McDonald’s Japan promotes new products through utilizing fan base in blog and Twitter. These fans talk about their preferences of foods and the company and occasionally receive offers of free food (Edelman & Salsberg, 2010)
Location Data	Real time location data of consumer.	• Using social media, Levi Strauss offered location specific deals by generating word-of-mouth by their customers. And in one particular case, 400 customers’ word-of-mouth brought 1600 people to the stores (Muñoz & Strotmeyer, 2010).
Intention Data	Data in social media that indicate consumers' future buying intentions and activity.	• By semantic analysis of Facebook status updates, Shift (an American company) measures people's purchase intent and sharing the data with their client companies as service (Beckland, 2011). • Hornall Anderson, a marketing company, generates purchase intention score for their client companies through analyzing social media data; clients include a big number of retail and consumer companies (Gleanster, 2013). • By analyzing intention data, companies can design better offer and plan for consumers, better example can be set for real estate, bank, insurance etc.

Types of Social Media Analytics

Table 2 shows that Social Media Analytics (SMA) can be classified into many types based on the objectives. First, topic modeling can be used to detect dominant themes topics from a large body of texts captured from social media platforms such as web usage including social media sites (e.g. Facebook, Twitter, Flicker) (Bollen, Mao, & Zeng, 2011; J. Chen, Nairn, Nelson, Bernstein, & Chi, 2010; Dou, Wang, Chang, & Ribarsky, 2011), news article reading (Teitler et al., 2008) and purchase behaviors (Hennig - Thurau, Gwinner, Walsh, & Gremler, 2004; Kozinets, 1999). Topic modeling can be used to identify user interests and key topics in forums or social media postings (Aggarwal & Wang, 2011; Lariscy, Avery, Sweetser, & Howes, 2009; Taboada, Brooke, Tofiloski, Voll, & Stede, 2011; Zailskaite-Jakste & Kuvykaite, 2012). Second, opinion mining or sentiment analysis plays a vital role in SMA which uses computational linguistics and natural language processing to extract insights from text data. They are typically used to determine brand image, track stock market, identify trends and manage crises (Fan & Gordon, 2014). Third, social network analysis is used to model connections, growth and dynamics of networks and activities in social media platforms, such as Facebook and Twitter. Opinion mining or sentiment analysis a critical tool for viral marketing because it enables identification of influential groups or predictive modelling that identifies customer groups who have high purchase intentions. Fourth, trend analysis is used to uncover industry trends, such as product demands, consumer insights, and service quality of an industry. SMA can help business managers or decision makers to predict the future behaviors or trend of an entity (e.g. individual, group, community, events etc) based on historical data. For instance, e-commerce companies such as Amazon, e-Bay, Pandora, Last.fm, iLike, and many others predict the customer side demand based on frequency and sentiments of customers' recommendations and reviews left on the commercial sites. Fifth, popularity prediction is also becoming an important analytics tool because it predicts future demands of products and services analyzing, likes, comments and shares. Sixth, consumer engagement analysis has become another key practice in SMA since consumers increasingly interact with organizations, brands, and product through various social media channels. It can be used to assess consumers' engagement with a brand (Baird & Parasnis, 2011), advertising (Phillips & McQuarrie, 2010), service development process (Claycomb, Lengnick-Hall, & Inks, 2001; Graf, 2007), and online brand communities (Algesheimer, Dholakia, & Herrmann, 2005). Finally, Visual analytics can be defined as "the science of analytical reasoning facilitated by interactive visual interfaces"(Thomas & Cook, 2006). The ultimate goal of this analysis is to gain insights by identifying patterns, structures and trends through analysis of a vast amount of data aggregated from social media platforms. Overall, firms in the digital economy increasingly extract value from social commerce either by identifying opportunities or solving problems. This new development in the realm of data driven social commerce paves the path for innovative, nontraditional research.

Table 2: Types of Social Media Analytics (SMA)

Study	Area of Influenced Discussed	Definition	Purpose
Topic Modelling (Aggarwal & Wang, 2011; Claycomb et al., 2001; Fan & Gordon, 2014)	Politics (e.g., measuring and managing public opinion), Public Health (e.g. health related awareness) and Business (e.g. brand mentioned, product recommendation etc.)	Detecting dominant themes or topics by sifting through large body of captured text.	Using advanced statistics and machine learning, it helps to identify latent themes/topics.
Opinion Mining (Pang & Lee, 2008; Saggion & Funk, 2009)	E-commerce (e.g., forecasting demand and future event), Finance (e.g. stock market prediction) HR (hiring, retain and promotion of the right person), marketing (brand recognition, share of voice) etc.	Opinion mining is similar to Sentiment analysis, but it more focuses on the views, believes and judgment rather considering positive or negative sentiment at first place.	Opinion Analysis measures the views, and beliefs based on the criteria that depend on the purpose of analysis.
Sentiment analysis (Taboada et al., 2011; Weichselbraun, Gindl, & Scharl, 2010)	E–commerce (e.g., product/brand recommendation, product improvement needs), PR (e.g., public opinion and emotion), Politics (public sentiments and appraisal, popularity, new idea acceptance etc.), Marketing (consumer insights and emotions, share of voice, campaign design), service (e.g., service recommendation and word of mouth, service improvement), Supply chain (e.g., product demand forecast), Finance (e.g., stock market price).	Sentiment analysis is similar to opinion mining but its refers to more in-depth interpretation of data of public/consumer/user sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, Individuals, issues, events, topics, and their attributes.	Sentiment analysis measures the individual, group, communities emotions towards any types of events, products, services, brand etc.
Social Network Analysis (Hanneman & Riddle, 2005; Hansen et al., 2010; Sarner et al., 2011; Weinstein, Campbell, Delaney, & O'Leary, 2009)	CRM (e.g., relationship between groups and other community and brands), Politics (e.g., relationship between groups and community), Marketing (e.g., Brand influencer or sentiment influencer or community leader identification), Functional areas including production and operations (sales forecast, operation forecast, delivery channels etc.).	Analysis of the social network that made up of individuals call nodes and connected with other nodes with similar interest, knowledge, opinion, etc. Data analysis technique includes number of nodes, frequency of edges and eigenvectors (i.e., page rank algorithm).	Social Network Analysis measures the types and depth of relationship between the networks. Many scholars considered Social Network analysis as foundation of Social Media analytics.

Trend analysis (Fan & Gordon, 2014)	Customer or sales number, effectiveness of ad campaign, Shifts in consumer sentiment, stock markets etc.	Predicting market trends or customer behavior using historical data.	Forecasting sales, market share, customer growth or movements in stock market based on time series and regression analysis.
Popularity Prediction (Lee et al., 2010; Szabo & Huberman, 2010)	Business (e.g. forecasting demands and new product), Marketing (e.g. brand awareness, brand recognition, Brand popularity, consumer insights), PR (e.g. e- word of mouth), Entertainment (e.g. movie and record popularity, buzz marketing etc.), Politics (e.g. candidate selection, modifying election manifesto, awareness etc.) e-Governance (e.g. awareness and public reaction)	Popularity prediction is the methods of collecting positive and negative opinion/ranks/feedbacks, shares and likes on certain subjects or events and to understand the level of current popularity and forecast the future based on the current evidence.	The popularity prediction allows organization to forecast the future demand of product, services, or events.
Customer engagement analysis (Greenberg, 2010; Kim, 2014; Zailskaite-Jakste & Kuvykaite, 2012)	E- commerce and Marketing (e.g. campaign development, new sells channel development, new product development etc.), Business (e.g. new customer segment development, new area/ distribution channel development etc.), politics (e.g. share of voice, information dissemination, opinion and concept testing, popularity measurement and increase etc.), e-Government (e.g. public awareness creation, public sentiments management etc.), Entertainment (e.g. movie or records e-word of mouth and promotion etc.)	Consumer engagement is the process to prolong the conversation or events or activities with social media participants or users. Without proper incentives it difficult to create engagement for long time, thus proper incentives and understanding the online consumer insights/behavior is very important.	The purpose of the consumer engagement is to measure the success of the online activities whether it is a commercial campaign on non-profit activities. It helps organization to understand the current situation and next action needed to be successful in online environment.
Visual analytics (Fan & Gordon, 2014; Keim, Mansmann, Schneidewind, Thomas, & Ziegler, 2008; Thomas & Cook, 2006)	Marketing, Sales, E-commerce, Big data etc.	Visual analytics is very popular in the era of big data. It is an iterative process that involves information gathering, processing and decision making.	The purpose of visual analytics is to use graphical interfaces (e.g., dashboards) to present, explore and confirm relationships among variables.

Future Research Directions

Social media represents an embryonic and fascinating field of research for both practitioners and academics. Even if the emergent literature on the topic has identified various contributions of social media in transforming customers experiences, marketing processes (Bianchi & Andrews, 2015; Chang, Yu, & Lu, 2015; Hall-Phillips, Park, Chung, Anaza, & Rathod, 2015; Michaelidou, Siamagka, & Christodoulides, 2011; Kevin J. Trainor, Andzulis, Rapp, & Agnihotri, 2014), information diffusion (Park, Lim, & Park, 2015; Zhang, 2015), government practices and government-citizen relationship (Klischewski, 2014; Pieri, 2014; Stamati, Papadopoulos, & Anagnostopoulos, 2015), firm performance (Kevin J. Trainor et al., 2014), many research questions are still unanswered, and thus justifying more research on social media.

The importance of IT in facilitating information sharing has been echoed by many scholars, including from the emerging literature on social media regarding information diffusion using Twitter and YouTube (Park et al., 2015) and firm’s voluntary information disclosure (Zhang, 2015) . However, exploring the role of social media in information diffusion within organisation, industry and society, as well as across these entities is still interesting valuables for future research. Since social media tools are diverse and varied, it will be interesting to explore the best mechanism to be used for each type of social media (e.g., Twitter vs YouTube or Twitter vs Facebook, or Facebook vs YouTube) for improved information sharing for competitive advantage.

While traditional IT adoption research theories (e.g., TAM, UTAUT) have advanced our understanding of studying the adoption and use of IT at various levels, it will be interesting to see if these theories are still relevant in the context of social media adoption at the individual, organizational, and inter-organizational levels? Indeed, the emerging literature on social media points to a different direction. For example, when studying the adoption of social media in general by small and medium sized enterprises (SMEs), Fosso Wamba and Carter (2014) found that “firms’ geographic location does not impact the adoption of social media tools by SMEs” (p. 8). However, the same authors found a significant positive relationship between firms’ geographic location and the SMEs intention to adopt Twitter (S. Fosso Wamba & L. Carter, 2013). Considering that social media research is highly inter-disciplinary investigating different theoretical bases, the foundation of such research will be valuable to academics in general and more relevant findings from the research will then also eventually impact practitioners. It will also shed light on methodological trends in this stream of research. It will be interesting to see whether the trend in social media research is data driven or theory driven analyzing existing research.

In addition, social media-enabled business analytics at the individual, organizational and interorganizational levels is an interesting future research avenue. Additionally future research on developing roadmaps and frameworks towards better design, technical, and financial decision to appropriate social media technologies is the current demand. Finally, one of the most important future research directions is in the area of privacy, security, and trust issues involved in the use of social media technologies.

Conclusions

When different types of analyses are properly applied, SMA can deliver transaction, strategic and transformative business values to firms. SMA can be a very useful tool to understand the customers and build relationships with customers based on their real-time activity and location data collected and shared through various social media channels (Greenberg, 2010; Sarner et al., 2011; Kevin J Trainor, 2012). Also, because SMA help firms to map the needs of the broader market, it will ultimately help them to improve market intelligence, scale and speed of production, flexibility of distribution, and effectiveness of supply chain and promotion (Chamlertwat, Bhattarakosol, Rungkasiri, & Haruechaiyasak, 2012; Kiron, Palmer, Phillips, & Kruschwitz, 2012; Zeng et al., 2010). Thus, SMA can provide sustainable business values to different areas of business, such as marketing, e-commerce, public relations, supply chain, and finance.

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