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A thematic exploration of social media analytics in marketing research and an agenda for future inquiry

Yun Wang, Qi Deng, Michel Rod and Shaobo Ji

Sprott School of Business, Carleton University, Ottawa, ON, Canada

ABSTRACT
This paper aims to present the current social media analytics in marketing research. A bottom-up thematic content analysis of 123 academic papers from 38 top Marketing and Information Systems journals was conducted. Types of social media platform, data, and analytics; marketing themes; and fields of study that are involved in social media analytics research are identified. The match between technological inputs and marketing outputs is presented. The findings reveal the current status of social media analytics in marketing research and identify various untapped areas for further research. This paper proposes that the impact of social media analytics is not restricted as a marketing research method; it fosters or amplifies changes in marketing approach, and structure and culture in organisations. To maximise its benefits, this paper suggests that firms could strategically build a technological knowledge base of social media analytics, and strategically manage and support its use by facilitating IT-marketing and IT-organisation alignments.

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Social media analytics; marketing intelligence; literature review; interdisciplinary research

Introduction

In the Internet age, social media, 'a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of user-generated content' (Kaplan & Haenlein, 2010, p. 61), has become ubiquitous in consumers' daily life. Along with the information search and sharing behaviours and social networking activities online, consumers leave their 'traces' on social media. Enabled by social media analytics, the 'traces' become available and form massive and abundant databases from which researchers and marketers can extract meaningful marketing and business intelligence, such as demand forecasting (Moon et al., 2014) and consumer preference (Abrahams et al., 2013), which have become increasingly important for developing and implementing successful marketing strategies such as resource allocation and product innovation. Unlike traditional methods such as surveys and focus groups, social media analytics, when applied in marketing research, can directly and unobtrusively capture and analyse data generated by customers on their own, allowing organizations to understand their customers better. Through bringing organizations 'closer' to their customers, social media analytics facilitates the data-driven, evidence-based decision-making and allows marketing units to add more value to organizations'

CONTACT Yun Wang yun.wang3@carleton.ca

strategic management. As its basis, social media analytics is simply the practice of gathering data from social media sources and analyzing that data using analytics tools in order to make informed business decisions. A formal definition of social media analytics is that it is the process of extracting useful patterns and intelligence by 'developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data, usually driven by specific requirements from a target application' (Zeng et al., 2010, p. 14). It has been gradually utilised in marketing research. As a new research stream started from around 2011, social media analytics in marketing research is still in its infancy. A comprehensive understanding of its current status is necessary and can provide a solid knowledge base for future research (Wamba et al., 2016). This paper aims at consolidating the knowledge created by academic studies that exploit social media analytics for marketing purposes and enabling an in-depth understanding of social media analytics in marketing research. Specifically, this paper presents a thematic content analysis of 123 academic papers collected from 38 top journals in Marketing and Information Systems fields, with the aim to answer (1) how social media analytics has been used in marketing research and (2) how to further develop its use in marketing and maximize its benefits.

Based on our review results, we suggest that social media analytics should not only be applied for marketing research at a technical level but also be strategically planned, managed, and evaluated. The use of social media analytics as a method in marketing research will inevitably bring changes to higher-level organizational practices because it brings or amplifies some shifts in marketing approaches (e.g. data-driven approach, internal marketing, and holistic marketing approach) and results in organizational cultural and structural adaptations (e.g. cross-departmental collaborations). Moreover, because of the ever-changing technological features of social media analytics, its use urges businesses to build a more flexible and swift marketing strategy to alertly respond to the changing environment. For instance, the emerging real-time analytics might remind firms to address the real-time reactions and behaviours from social media users rather than the historical data for more prompt and accurate prediction and monitoring; the linguistic analytics might assist firms to reveal the context-dependent implicit cultural factors, which aids the top manager's strategic decision-making regarding cross-border merger and acquisition. That is, this paper argues that the impact of social media analytics goes beyond completing marketing research; rather, the use of social media analytics in marketing not only provides marketing insights, but, more importantly, leads to a more dynamic approach to marketing strategy. By recognizing the higher-level organisational impact brought by the use of social media analytics, we further highlight that, in order to exploit its benefit, firms may need to strategically develop a technological knowledge base of social media analytics and strategically foster the social media analytics-marketing alignment and social media analytics-organisation alignment.

The paper is structured as follows. The next section presents the research methodology, including data collection and analysis approach. Then, findings are presented and discussed; research gaps and opportunities are proposed. Lastly, the paper is concluded by presenting final remarks and limitations. This paper contributes to marketing research revolving social media analytics by building a complete knowledge base as a reference for researchers and practitioners, by emphasising its technological and strategic impact on the organization, and by identifying the potential research gaps and suggesting future research directions.

Methodology

To achieve the objectives of the paper, we capitalised on the method proposed by Webster and Watson (2002) for conducting systematic literature reviews. We grounded this research in multiple disciplines (i.e. Marketing and Information Systems) to embrace the premise of interdisciplinary research involving integrated insights gaining, boundary crossing and bridge building (Repko, 2008). This approach is appropriate for our research since social media analytics in marketing research has a cross-disciplinary nature. We believe that the two areas together can provide us with a comprehensive basis for exploration. Regarding data processing, we did a thematic content analysis, which is one of the most common analysis methods in qualitative research with an emphasis on identifying patterns (or 'themes') within a set of data (Braun & Clarke, 2006). This approach is especially useful when examining a theoretically underdeveloped area (Valos et al., 2016) and appropriate for theory construction or proposition development (Warwick & Lininger, 1975).

Data collection

Initially, we performed a systematic search to accumulate a relatively complete body of literature. Towards this end, we started with Web of Science, using Boolean Operators, 'TS = ("social media analytics" OR "data analytics" OR "text mining" OR "opinion mining" OR "text analytics" OR "sentiment analysis" OR "network analytics" OR "web analytics") AND TS = marketing'. The preliminary search resulted in 1,974 papers. Given the overwhelming literature on the topic, we instead adopted a purposeful sampling method. We searched Web of Science, using the same searching terms, but restricted to Marketing and Information Systems journals ranked as A* or A in the 2016 Australian Business Deans Council (i.e. ABDC) journal list. For the journals that are not indexed by Web of Science, we searched the journals' catalogues using the same keywords. In total, 88 journals were searched. This approach results in 198 papers, a high-quality and feasible dataset. We examined the titles and abstracts to exclude irrelevant papers (e.g. papers irrelevant to marketing, introduction to special issues, and editorial/commentary papers). This step resulted in a total of 123 empirical papers remaining in our sample. Table 1 shows the distribution of the papers across journals.

Data analysis

Consistent with the seminal works on social media analytics from Zeng et al. (2010) and Fan and Gordon (2014), we apply the *input-process-output* framework to structure our analysis. It is a broadly applied research framework for the use of information systems (Fan & Gordon, 2014). Based on the framework, we further categorise the three elements as (1) *input*: platforms and data; (2) *process*: analytics and stages; and (3) *output*: marketing insights across marketing sub-areas and industries (see Figure 1). The categorisation of the key elements is supported by previous research (see Fan et al., 2015; Lamberton & Stephen, 2016; Valos et al., 2016). Particularly, Misirlis and Vlachopoulou (2018) classified social media analytics in marketing research by media types, analysis types, fields of study and marketing objectives. Similarly, Kalampokis et al. (2013) investigated the prediction power of social media analytics by examining the platforms, analytics, and application areas.

Table 1. Distribution of SMA-in-marketing across journals.

Marketing journal name	No. of articles	Marketing journal name	No. of articles
International Journal of Research in Marketing	5	*Journal of Strategic Marketing*	2
Marketing Science	5	*Psychology & Marketing*	2
European Journal of Marketing	4	*Journal of Advertising*	1
Journal of Marketing	4	*Journal of Consumer Affairs*	1
Journal of Retailing & Consumer Services	4	*Journal of Business & Industrial Marketing*	1
Marketing Intelligence & Planning	4	*Journal of Interactive Marketing*	1
Industrial Marketing Management	3	*Journal of Retailing*	1
Journal of Marketing Research	3	*Journal of Service Research*	1
Journal of Business Research	2	*Marketing Letters*	1
Journal of Consumer Research	2	*Public Relations Review*	1
Journal of Hospitality Marketing & Management	2	*Quantitative Marketing and Economics*	1
IS journal name	**No. of articles**	**IS journal name**	**No. of articles**
Decision Support Systems	18	*Information Systems Frontier*	3
Knowledge-Based Systems	10	*International Journal of Electronic Commerce*	3
Electronic Commerce Research	7	*Enterprise Information Systems*	2
Information & Management	7	*Information Systems Research*	1
International Journal of Information Management	5	*Information, Communication & Society*	1
MIS Quarterly	5	*Behaviour & Information Technology*	1
Journal of Management Information Systems	4	*Business & Information Systems Engineering*	1
Electronic Markets	3	*Journal of Information Systems*	1

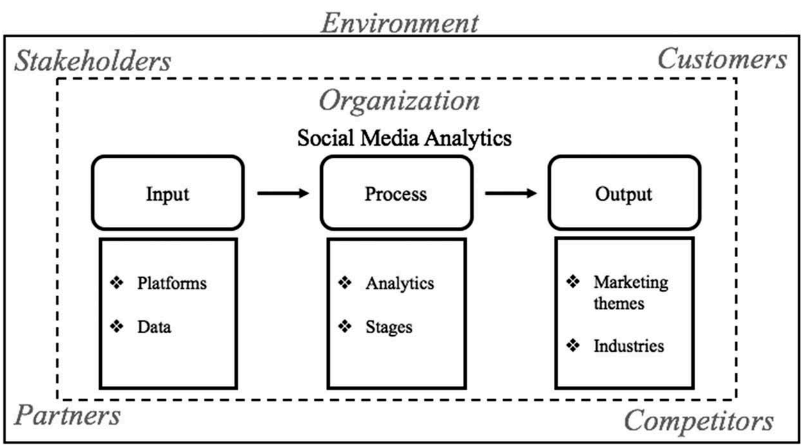

Figure 1. The input-process-output framework of SMA-in-marketing.

Guided by the analysis framework, we conducted a thematic content analysis to code the data. This approach has been widely used in marketing research and social media-related research to achieve the goal of typology analysis (see Das, 2009; McNaughton, 2001; Valos et al., 2016). Specifically, we followed two iterative and ongoing stages. At stage 1, two researchers independently coded the data to extract the keywords/terms/concepts regarding *input* (i.e. platforms and data), *process* (i.e. analytics and stages), and *output* (i.e. marketing sub-areas and industries). In terms of the interrater reliability, overall 92.1% agreement was achieved. Specifically, the coding agreements were 95.9% for *input* (i.e. 97.5% for platform and 94.3% for data), 92.7% for *process* (i.e. 87.8% for analytics and 97.5% for stages), and 87.8% for *output* (i.e. 82.1% for marketing sub-areas and 93.5% for industries). The consensuses were achieved by discussions and deliberations between two coders. At stage 2, the keywords/terms/concepts extracted in the first stage were classified and grouped to form larger and most appropriate themes. This bottom-up clustering approach is especially beneficial and valid for our research, as the terminology and applications of social media analytics are continually evolving and emerging, with alternative terms often used for the same practice and approach.

Findings

Following the *input-process-output* framework, we initially categorise the papers based on the *input*, namely, the type of social media platforms employed (Table 2) and the type of social media data analysed (Table 3). Then, we categorise the literature from the *process* perspective, namely, the type of analytics used (Table 4) and the stage of social media analytics involved (Table 5). Lastly, we analyse the papers based on their *output*, namely, the marketing themes emerged and the major domains/industries involved (Figures 2 and 3). In the end, we combine all results to provide integrated and interpretive insights into the fit between social media analytics and marketing.

Input: social media platform

Ten types of social media are identified as the platforms for marketing intelligence (see Table 2). Three outstanding patterns regarding the platforms examined in current marketing research are (1) research centers on e-commerce and third-party review sites (nearly half of the papers), while little attention has been paid to content communities, wikis or social tagging systems (less than 5% of papers); (2) both consumer-controlled and firm-controlled social media are employed; (3) organisational systems have potentials for exploiting social media intelligence.

Input: social media data

Seven major types of social media data have been mined in previous marketing research (see Table 3). Our categorisation takes the three major entities in social media into consideration, namely the consumers, firms, and social media platforms. Social media intelligence is affected by the behaviours of consumers and firms, but also the affordances and constraints of the platforms. Platform-based structured data, profile data, and consumption data are differentially presented due to the unique technological capabilities of different platforms. The sub-categories of each type of data, their use frequencies, and example articles are shown in Table 3. We see an unevenly developed pattern for the use of data. Among the sub-categories, consumer-generated textual data are the most widely used data type, followed by platform-based structured data, network data, and post-level metadata. Little attention has been paid to consumer-generated linguistic data, rich media data, and temporal data.

Table 2. Articles' classification concerning input – Social media platform.

Platforms	Sub-types	Example articles	% of total
E-commerce sites	-Amazon, group buying, auction, crowdfunding	Felbermayr and Nanopoulos (2016); Ghose et al. (2012); Hu and Winer (2017); Ordenes et al. (2017); Singh and Tucker (2017).	26.02%
Third-party review sites	-TripAdvisor, Epinions, Expedia, IMDB	Calheiros et al. (2017); Moon and Kamakura (2017); Moon and Song (2015); Moon et al. (2014); Lash and Zhao (2016); Zhang et al. (2018).	19.51%
Microblog	-Twitter, Weibo	Liu et al. (2016); Makarem and Jae (2016); Alp and Öğüdücü (2018); Aswani et al. (2018).	15.45%
User-controlled online community	-Blog, forum	Onishi and Manchanda (2012); Schweidel and Moe (2014); Agarwal et al. (2012); Homburg et al. (2015).	13.01%
Firm-controlled online community	-Firm's website/forums	Järvinen & Karjaluoto (2015); Wilson (2010); Abrahams et al. (2013); Jabr et al. (2014).	12.2%
Social network sites	-Facebook, LinkedIn	Ding et al. (2017); Wang et al. (2017).	4.07%
Organizational systems	-Innovation systems	Toubia and Netzer (2017); Shi et al. (2016).	2.44%
Content community	-Flickr, YouTube	Miah et al. (2017).	1.62%
Wikis	-Wikipedia	Liu et al. (2016); Moon and Song (2015).	1.62%
Social tagging	-Delicious	Nam et al. (2017)	0.81%

Table 3. Articles' classification concerning input – Social media data.

Data	Sub-types	Example articles	% of total
Consumer-generated data	• CG-textual data (reviews, comments, posts, inquiries, tweets, Wikipedia pages)	Calheiros et al. (2017); Felbermayr and Nanopoulos (2016); Ghose et al. (2012); Homburg et al. (2015); Kumar et al. (2016); Liu et al. (2016); Makarem and Jae (2016)	69.92%
	• CG-linguistic data	Siering et al. (2016); Tang et al. (2016)	3.25%
Platform-based data	• Structured data (ratings, stars, rankings)	Felbermayr and Nanopoulos (2016); Moon and Kamakura (2017); Moon and Song (2015); Moon et al. (2014); Ordenes et al. (2017)	26.02%
	• Profile data (gender, age, followers)	Singh and Tucker (2017); Ikeda et al. (2013); Jabr et al. (2014); Miah et al. (2017)	13.01%
	• Consumption data	He et al. (2016)	1.63%
Metadata	• Post-level (volume, length)	Liu et al. (2016); Chen and Xu (2017)	14.63%
	• Webpage-level (web traffic)	Hu and Winer (2017); Wilson (2010)	6.50%
Network data	• Links between users	Alp and Öğüdücü (2018); Wang et al. (2017); Toubia and Netzer (2017)	15.45%
	• Links between words		
Firm-generated data	• Webpages, posts, comments, Product descriptions	Kumar et al. (2016); Lash and Zhao (2016); Lau et al. (2014); Risius and Beck (2015)	10.57%
Temporal data	• Real-time data, posting time	Ikeda et al. (2013); Ding et al. (2017)	5.69%
Rich media data	• Geotag, image	Ghose et al. (2012); Miah et al. (2017)	2.44%

Table 4. Articles' classification concerning process – Analytics.

Analytics	Sub-types	Example articles	% of total
Text mining	• Keyword retrieval • Topic isolation • Topic modeling • Cluster analysis	Felbermayr and Nanopoulos (2016); Liu et al. (2017); Moon and Kamakura (2017); Moon and Song (2015); Leong et al. (2004); Nam et al. (2017); Schweidel and Moe (2014); Singh and Tucker (2017); Alp and Öğüdücü (2018); Aswani et al. (2018); Chen and Xu (2017)	46.34%
Sentiment analysis	• Opinion mining • Aspect-oriented classification	Calheiros et al. (2017); Homburg et al. (2015); Kumar et al. (2016); Makarem and Jae (2016); Ordenes et al. (2017); Lee et al. (2016)	42.27%
Web analytics	• Cloud computing	Hu and Winer (2017); Järvinen and Taiminen (2016)	9.76%
	• Web crawling	Moon and Song (2015); Ordenes et al. (2017)	19.51%
Network analytics	• Social network	Debreceny et al. (2017); Ikeda et al. (2013)	10.57%
	• Semantic network	Toubia and Netzer (2017)	4.88%
Descriptive analysis	• Statistical analysis	Liu et al. (2016); Aswani et al. (2018)	8.13%
Image analytics	• Image classification	Ghose et al. (2012); Miah et al. (2017)	1.63%

Table 5. Articles' classification concerning process – SMA stages.

Stage	Sub-types	Example articles	% of total
Collect	• Web scraping • API • Web crawler	Moon and Song (2015); Ordenes et al. (2017); Jabr et al. (2014); Singh and Tucker (2017); Alp and Öğüdücü (2018); Lash and Zhao (2016); Van Heijst et al. (2008)	19.51%
Understand	• All analytics	All articles	100%
Present	• Maps	Nam et al. (2017); Moon and Kamakura (2017)	5.69%

Figure 2. Marketing themes and time trends.

Process: analytics

Six major types of analytics are identified (see Table 4). *Text mining* refers to the content-based analysis, such as topic modelling and clustering (Gandomi & Haider, 2015). *Sentiment analysis* (e.g. opinion mining) is based on *text mining* but separated as an independent type of analytics because of its wide application (Fan & Gordon, 2014). *Web analytics* refers to web page-based analysis such as website crawling/spidering and search log analysis (Chen et al., 2012). Different from the content-based analytics, *network analytics* (e.g. centrality and community analysis) is structure-based, extracting intelligence from the relationships and structures (Gandomi & Haider, 2015). Two sub-types of network analytics are identified: semantic and social network analysis. The former examines the networks among products/objects, while the latter targets the more traditional human networks. *Descriptive analysis* refers to the quantitative statistical analysis (e.g. frequency and counts) (Chae, 2015). In addition, *image analytics*, which represents the analysis specifically treating images and visual contents (e.g. visual content representation and feature descriptor), is identified. However, the very limited number of research has involved image analytics (Ghose et al., 2012; Miah et al., 2017) whereas the most research attention has been paid to text mining and sentiment analysis.

Process: stages of social media analytics

Regarding stages of social media analytics, we followed Fan and Gordon (2014) and Zeng et al. (2010) to categorise the papers into three stages, namely, collect, understand, and present. Particularly, if a paper mentions the method/process of collecting/analysing/presenting social media data, we tag the paper as collect/understand/present. In the end, we found all of the papers discussed how they understand the data; 19.5% of the papers described how they collect the data (e.g. by using web scraping techniques, making use of APIs or web crawler services); only 5.69% of the papers introduced how they present the data (e.g. maps). The details and example articles are demonstrated in Table 5.

Output: marketing themes and industries

In this section, we delve into the output of social media analytics in marketing research, aiming to uncover the marketing themes (i.e. the application areas of social media analytics in marketing) and the domains/industries addressed in previous research. Nine major marketing themes are identified (see Figure 2). Among them, consumer behaviour is the most developed and popular theme, involving various sub-themes such as consumers' purchase decision, experience, and satisfaction, and social media behaviours. The strategy revolves around external market intelligence (e.g. competitive analysis, marketing structure/positioning, consumer profiling/segmentation) and internal business intelligence (e.g. media mix, ecosystem building, IT integration). It ranks as the second hottest theme, followed by e-WOM, which includes the research on the effect of e-WOM/e-emotion, the antecedents, and key influencer identification. The social media analytics is also utilized for product management (e.g. component diagnostics, innovation, feature adjustment, and deception detection), performance measurement (e.g. effectiveness of advertising/digital marketing/social media strategies), branding (e.g. brand perception/image, association consistency, community building, and brand metrics), personalized marketing (e.g. ranking algorithms, recommendation systems, and filtering), pricing (e.g. elasticity of demand and fluctuation prediction) and sales (e.g. sales forecasting). Figure 2 demonstrates the distribution of papers across themes and years. Consumer behaviour and strategy are the first-tier areas (the fastest-growing areas and with the largest number of articles). Branding, product management, and e-WOM are the second-tier themes. Pricing and sales prediction, personalised marketing and performance measurement are not fully developed.

As for major domains, Figure 3 shows the results. Four domains are identified, and the percentages they occupied in the total papers are calculated: business-to-consumer (B2 C) (51.22%), e-marketplace (17.07%), service (8.94%), and business-to-business (B2B) (5.69%). Two main clusters emerge under the B2 C domain: experience goods and search goods. Under experience goods, movie, and hospitality & tourism are the industries that attract the greatest attention; under search goods are electronics and automobiles. E-marketplace includes e-commerce (e.g. Amazon), which dominates this domain, and some emergent forms like online auction (e.g. eBay), online agency (e.g. e-travel agency), crowdfunding site (e.g. Kickstarter), and group-buying site (e.g. Groupon). Under the domain of service are industries like health, education, banking, transportation, and telecommunication. B2B is the most under-researched field in social media analytics research in marketing.

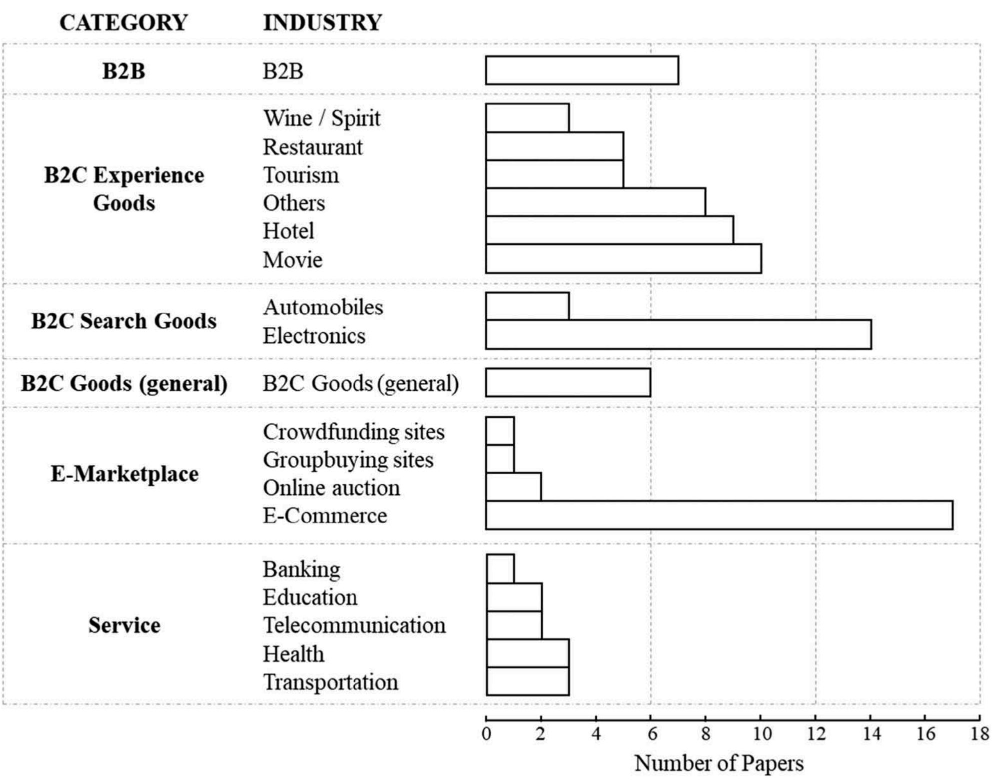

Figure 3. Number of articles per domain.

Integrated insights: social media analytics in marketing

By synthesising Tables 2–5 and Figures 2 and 3, we can further analyse the empirical studies and integrate the insights to develop a deeper and more holistic understanding of social media analytics in marketing research. That is, we discuss the match patterns between social media platform/data/analytics and marketing themes/industries (see Table 6).

Consumer behaviour

This is the most broadly researched theme that covers various sub-themes, including consumer purchase decision for search goods (e.g. automobiles and electronics), consumer experience and satisfaction for experience goods (e.g. hotels, restaurants, movies, and wines), and consumer's social media behaviours (e.g. sentiment expression, motivations for posting and sharing, preferences, and attitudes). Consumer-generated textual data and platform-based data (including structured, profile, and consumption data) from third-party review sites and E-commerce sites are the major source for understanding consumer attitudes and opinions (Calheiros et al., 2017; Ordenes et al., 2017; Xu et al., 2017). We also identified some less used but promising data that could be utilized to produce in-depth understandings of consumer consumption behaviours as well as social media/online behaviours, including consumer-generated linguistic data (Siering et al., 2016), temporal data (Jabr et al., 2014), network data (Chen & Xu, 2017), and metadata (Hu & Winer, 2017).

Strategy

Sub-themes in this category include competitive analysis and benchmarking, market structure and positioning, consumer profiling and segmentation in the B2 C context, as well as digital marketing strategy and ecosystem building in the B2B context. Specifically, search goods industries (e.g. electronics) prefer to use consumer-generated and firm-generated data to extract intelligence about competitors and the whole industry (Lee et al., 2016; Shi et al., 2016) and to understand brand positioning and create product/brand maps (Nam et al., 2017). Experience goods industries (e.g. tourism, movie, wines, and hotels) prefer to use consumer-generated textual data, supplemented by platform-based profile data, and network data, to extract intelligence about consumer profiling and to do the consumer segmentation accordingly (Hoontrakul & Sahadev, 2008). On the B2B side, research focused on the improvements of digital marketing and online communications (Järvinen & Taiminen, 2016), market surveillance (Debreceny et al., 2017), as well as the decision support for mergers and acquisitions (Lau et al., 2012). The social media platforms used under the three sub-themes are evenly scattered across a wide range. However, it is worth to notice that social tagging system and social tagging data are emphasised as highly neglected but highly valued sources (Nam et al., 2017). Moreover, we want to highlight two different types of network analytics: the semantic network analytics, which is focusing on the product/brand relationships and networks (Chen & Xu, 2017; Toubia & Netzer, 2017), and the social network analytics, which is focusing on the user relationships and networks (Alp & Öğüdücü, 2018; Aswani et al., 2018). They both aim to identify the 'nodes' and 'edges' and build network graphs, but function for different aspects and purposes (products/brands and users).

Table 6. Integrated insights: SMA-in-marketing.

Theme	Industry	Platform	Data	Analytics
Consumer behaviour Purchase decision, experience and satisfaction, social media behaviour.	• B2 C • E-market	• Third-party review sites • E-commerce • Online community • Microblog/social network sites	• CG-textual data • PB-structured/ consumption/ profile data • Network/temporal/linguis-tic/metadata	• Text mining • Sentiment analysis • Network analytics • Descriptive analysis
Strategy Competitive analysis and positioning, consumer profiling and segmentation, M&A, ecosystem.	• B2 C • B2B	• Microblog • E-commerce/third-party review sites • Firm-controlled community • Social tagging	• CG-/FG-textual data • PB-profile/Network data • Social tagging/ temporal data	• Network analytics • Text mining • Sentiment analysis
Branding Perception, association, metrics, community.	• B2 C-Experience goods • Service	• Microblog and blog • Firm-controlled community	• CG-textual data • FG-textual data	• Text mining • Sentiment analysis
Product management Component diagnostics, feature design and adjustment, deception detection, innovation.	• B2 C-Search goods • E-market	• E-commerce • Third-party review sites • User-controlled community • Organizational systems	• CG-textual data • PB-structured data	• Text mining • Sentiment analysis
e-WOM Effect of e-WOM, antecedents, key influencers.	• B2 C-Experience goods • E-market	• E-commerce • Third-party review sites	• CG-textual data • PB-structured/ profile data • Metadata • Network data	• Text mining • Sentiment analysis • Descriptive analysis • Network analytics
Pricing Elasticity of demand, fluctuation, demand forecasting.	• E-market • B2 C-experience goods	• E-commerce • Content community/Wikis/ Twitter	• PB-structured data • CG-textual data • Rich media	• Text mining • Sentiment analysis • Image analytics
Sales Sales forecasting.	• B2 C-Experience goods	• Third-party review sites • Wikis	• CG-textual data • FG-textual data • Metadata	• Text mining • Sentiment analysis • Descriptive analysis
Personalized marketing Ranking systems, recommendation systems.	• E-market	• E-commerce • Third-party review sites	• CG-textual data • PB-structured/ consumption data • Rich media	• Text mining • Sentiment analysis • Web analytics • Image analytics
Performance measurement Measures of social media strategies.	• B2B • B2 C • Service	• Firm-controlled community	• CG-textual/ linguistic data • PB-structured data • Metadata	• Text mining • Sentiment analysis • Web analytics • Descriptive analysis

CG, consumer-generated; FG, firm-generated; PB, platform-based.
- Refers to the widely used items;
- Refers to the widely used items;
- Refers to the limited used items.
- Refers to the limited used items.

Branding

Business-to-consumer experience goods are largely applying social media analytics to extract branding-related intelligence, by employing both user-controlled and firm-controlled social media (Homburg et al., 2015) including Twitter, blogs, and firm's forums/websites and by mining both consumer-generated textual data and firm-generated textual data (Kumar et al., 2016), to understand consumers' brand perception and keep brand association consistency. Text mining and sentiment analysis are prominent techniques to use in this area. Besides, services like transportation and telecommunication are also using Twitter, blog, and forum to build brand knowledge (Schweidel & Moe, 2014).

Product management

Search goods like automobiles and electronics are exploiting the potential of social media analytics for product management. E-commerce, third-party review sites (e.g. mobile phone review sites) and user-controlled online communities (mainly forums) are adopted. Consumer-generated textual data and platform-based structured data are examined to do component diagnostics (Abrahams et al., 2013), facilitate product designs (Singh & Tucker, 2017) and adjust product features (Zhang et al., 2018). Moreover, those data are utilised for deception detection (Siering et al., 2016). It is worth to mention that researchers suggest the use of social media analytics in organisational systems (a.k.a. intra-/inter-organizational social media) for idea identification and facilitation, which is beneficial to product innovation (Toubia & Netzer, 2017).

e-WOM. Experience goods and e-marketplace are the major areas that apply social media analytics for e-WOM. The platforms concentrate on e-commerce and third-party review sites, which provide tons of consumer reviews. Data include consumer-generated textual data (the review contents), platform-based structured data (e.g. 'likes', 'stars') and profile data (e.g. followers), network data (e.g. links between users), and metadata (e.g. review volume/length). Different combinations of those data could be monitored to examine different aspects of e-WOM, such as consumer attitudes to e-WOM (Tang & Guo, 2015), identification of key influencers (Alp & Öğüdücü, 2018), and effect of emotion (Felbermayr & Nanopoulos, 2016). Moreover, combined with offline sales/revenue data, online reviews could be exploited to validate the effect of e-WOM (Moon et al., 2014). Accordingly, in addition to text mining and sentiment analysis, network and descriptive analytics are employed.

Pricing

E-marketplace (mainly the online auctions) and consumer experience goods (mainly the media and tourism) are utilizing social media analytics for pricing related tasks such as demand forecasting (Miah et al., 2017), elasticity of demand (Chevalier & Goolsbee, 2003), and price fluctuation prediction (Van Heijst et al., 2008), for a better resource allocation. Data centres on the platform-based structured data and consumer-generated textual data gathered from E-commerce reviews. Interestingly, Wikis (Wikipedia) is applied to predict the demand for TV shows (Liu et al., 2016), while content community (Flickr) is adopted in the tourism industry (Miah et al., 2017). Accordingly, image analytics are used for analysing the messages hidden in rich media data (photos from Flickr).

Sales forecasting

Research suggests that experience goods companies could exploit the capabilities of social media analytics for sales forecasting. Specifically, research illustrates the prediction power of social media analytics by predicting the box office of movies (Lash & Zhao, 2016; Moon & Song, 2015; Onishi & Manchanda, 2012). Movie-focused third-party review sites like IMDb and RottenTomatos are main data source, and consumer-/firm-generated textual data (e.g. reviews and product descriptions) are main data sample. Research found that, in addition to metadata (e.g. volumes of posts), unstructured textual data are effective for prediction (Onishi & Manchanda, 2012). Furthermore, cultural elements are found to be important antecedents of international retailing success; Wikipedia is one the effective resources for producing cultural information and knowledge (Moon & Song, 2015).

Personalized marketing

E-marketplace dominates this area. E-commerce sites and online agencies are making use of consumer data retained in online reviews and search engines to improve ranking algorithms (Ghose et al., 2012), build recommendation systems (He et al., 2016) and develop personalized filtering functions (Lee et al., 2016) to support consumers' information searching and decision-making. In addition to the normally used consumer-generated textual data and platform-based structured data, platform-based consumption data (e.g. consumption duration) and rich media data (e.g. geo-data, image) are also mined since hospitality & tourism industry is largely involved in this theme, in order to upgrade the quality of personal recommendations for tourists and travellers (Ghose et al., 2012). Correspondingly, web analytics and image analytics play an important role in this theme.

Performance measurement

B2B, B2 C, and service domains are evenly distributed in this theme. Platforms centre at firm-controlled online community (firm's websites/official accounts). Data mainly consist of consumer-generated textual and linguistic data and platform-based structured data, complemented by web page-level metadata (e.g. website traffic, click-stream) and post-level metadata (e.g. post/blog volumes). By using text mining/sentiment analysis to examine unstructured textual and linguistic data (Risius & Beck, 2015; Tang et al., 2016), and by using web analytics and descriptive analysis to extract web-level and post-level metadata (Ding et al., 2017; Wilson, 2010), researchers successfully create measures and metrics for evaluating performances of social media strategies, digital marketing, and advertising.

Discussion

Our review identified that, currently, marketing research mainly employs social media analytics to extract marketing insights for certain marketing purposes at the tactical level. We suggest that future research could go beyond this level to examine social media analytics in marketing from a strategic perspective.

Strategically developing social media analytics: building a technological knowledge base

Our review illustrated some unevenly developed trends of social media analytics in marketing research. As Table 2 shows, nearly half of the research focuses on e-commerce and third-party review sites. However, the current popular social media platforms, such as Twitter and Facebook, have received far less attention. Even fewer studies target content communities (e.g. Instagram and YouTube), wikis (e.g. Wikipedia), and social tagging systems (e.g. Delicious). Similarly, as Table 3 shows, consumer-generated textual data and platform-based structured data are widely exploited by marketing researchers, whereas network data, linguistic data, rich media data, and temporal data are largely neglected. However, these less examined social media platforms and data types are valuable and impactful. For instance, wikis and social tagging systems may have stored a large amount of cultural and/or consumer behavioural information (Moon & Song, 2015; Nam et al., 2017). Linguistic data are suggested to be more predictive than textual data (Siering et al., 2016). Moreover, firms are using content communities to generate real-time updates of consumers' attitudes and opinions and using temporal data (e.g. real-time data) to improve consumer feedback quality. Hence, the uneven investigation of social media platforms and data types may cause a loss for both marketing research and practice. One possible reason for this situation is the lack of a strategic perspective that facilitates a systematic and comprehensive knowledge development of social media analytics. Specifically, we identified two aspects of the knowledge gap: (1) the knowledge of the technological foundations of social media analytics, including social media platforms, data types, and analytics techniques; (2) the view of social media analytics as a dynamic process (Risius & Beck, 2015) rather than a static method (Park et al., 2016).

First, current technological knowledge of social media analytics is highly fragmented and fuzzy. For example, analytics techniques such as text mining and sentiment analysis attract most of the research attention but emerging techniques such as real-time and image analytics are rarely addressed; some papers described analytics techniques on a functional level (e.g. prediction analytics and trend analysis) whereas others on a computational level (e.g. Latent Dirichlet Allocation and Bayes). By systematically and continuingly accumulating technological-level knowledge of social media analytics, researchers could build a complete and up-to-date knowledge base of social media analytics and recognize the varying capabilities and constraints of different social media analytics technologies, and through which, more emerging technologies could be examined and more suitable matches between technologies and marketing purposes could be identified.

Second, we suggest researchers view social media analytics as a three-stage dynamic process that involves data collection, data understanding and data presentation (Zeng et al., 2010) and pay more attention to the data presentation stage and the effective use of data visualization. Our review showed that while most papers focused on data understanding and data collection, little research investigated data presentation. However, in marketing practices, data presentation is a critical social media analytics function because effective data presentation (e.g. knowledgeable and straightforward reports and interactive dashboards) could facilitate persuasive and actionable insights going up to aid top managers' decision-making and flowing smoothly across the organization (Fan & Gordon, 2014). While social media analytics services providers have come up with some practical solutions (e.g. Instagram Profile Report from Sprout Social and customised Analytic Dashboard from Hootsuite), marketing academics have not paid enough attention to data presentation. Thus, we suggest that marketing researchers should better understand social media analytics as a complete process that involves not only data capturing and understanding but also data presentation.

Based on the discussions above, we propose a strategic knowledge development of social media analytics. Our proposition is supported by social media and big data research, both of which have made efforts to build ontological and epistemological understandings of social media and big data (Chen et al., 2012; Kaplan & Haenlein, 2010). Consistently, we argue for a systematic knowledge development of the technological dimensions of social media analytics. Accordingly, we propose research questions such as but not limited to: what are the categories of social media platforms, data, and analytics? What are their respective affordances and constraints? What are the social media analytics techniques that could be used for data capturing, data understanding and data presentation? This knowledge accumulation will build a solid foundation for daily operations of social media analytics in marketing research; to do that in a strategic way will enable marketers to recognise and utilise emerging technologies in a timely manner, to strategically match social media analytics techniques and marketing purposes, and to effectively and efficiently share and circulate social media intelligence inside and across businesses.

Strategically developing social media analytics: IT-organization alignment

Current research treats social media analytics as a research technique and focuses on its use in marketing research. However, as an IT resource, its use is inevitably bringing changes to higher-level organisational practices. Firstly, rooted in big data analytics, social media analytics has been touted as a new research paradigm that utilises diverse sources of data and analytics tools to make inferences about reality (Boyd & Crawford, 2012). This paradigm shift to computational social science reflects a data-driven approach (Xiang et al., 2017) and requires a re-visit of marketing paradigms (Quinton, 2013) – Should marketing research be guided by a data-driven or theory-driven approach? How to integrate deductive and inductive reasoning? How to overcome the sampling biases? In addition to the debate of data-driven and theory-driven approach, we highlight the shift to a holistic marketing paradigm. Current marketing research mainly focuses on using social media analytics to mine external marketing intelligence (i.e. consumer/market insights). However, given its ability in non-intrusively examining various online data, social media analytics has potential to facilitate value co-creation inside, outside, and across organisations (Wamba et al., 2016), which highlights the necessity of a marketing paradigm shift to building a holistic ecosystem for all stakeholders and maximise the benefits brought by collaboration and co-creation (Chae, 2015). Therefore, social media analytics could and should be applied beyond simply mining external marketing intelligence to other marketing areas, such as supply chain and distribution channel management, knowledge management, and internal marketing. We specifically advocate the inquiries of employee-generated data given that social media are increasingly implemented in organizations as tools for internal, external, and inter-organizational communications (Treem & Leonardi, 2013) and the employee-involved social media analytics has a larger effect on organizational outcomes than the consumer-centric social media analytics (BrandWatch, 2017a). Hence, this review calls for attention to the marketing paradigm shifts that might be brought by the use of social media analytics.

Secondly, instead of treating social media analytics solely as a technique, marketing researchers should view it as one of the IT capabilities that need to be developed strategically in organizations. The integration of social media analytics into an organization is a mutually reinforcing process. On the one hand, the implementation of social media analytics could bring substantial changes to the mechanisms and hierarchies in the organization, creating opportunities for new forms of organizational structures and processes, such as talent and individual skill improvement and department-level capability support (Akter et al., 2018; Järvinen & Taiminen, 2016). On the other hand, the organizational structure and strategies impact the effectiveness of social media implementation. For example, Akter et al. (2018) suggested that a firm's strategic alignment moderated the relationship between data analytics capabilities and firm performance. This mutual-reinforcing relationship urges organizations to promptly respond at a strategic level and align social media analytics implementation with their organizational goals and strategies, so as to effectively manage and support the operational use of analytics. All of the above evidence suggest that marketing researchers should take a step further and examine social media analytics at a strategic level, such as discussing the adjustment in organizational structure and culture along with the implementation of social media analytics in marketing, and investigating the strategic alignment of social media analytics with organizations.

Based on the discussions above, we propose to strategically developing social media analytics in marketing by facilitating its alignment with marketing and organization. Accordingly, we propose research questions such as but not limited to: What are the strategic approaches and organizational cultural/structural/process changes needed for social media analytics-organization integration? What are the marketing paradigm shifts needed for social media analytics-marketing integration? How to measure and evaluate the impact of social media analytics on firm performance? By answering these questions, marketing research could further assist businesses to form more suitable organizational strategic plan and resource allocation for implementing social media analytics (Zeng et al., 2010).

Conclusion and limitation

In this paper, the current status of social media analytics in marketing research is reviewed, and the relevant knowledge is consolidated. We present our findings from three perspectives, namely, input (social media platform and data), process (social media analytics stage and analytics), and output (marketing themes and sub-themes, involved industries). We identify current use patterns between social media analytics technologies and marketing applications. Moreover, we discuss the research gaps and propose potential research opportunities and research questions. Through the review, this paper aims to provide a knowledge base for marketing researchers, to facilitate the understanding of social media analytics in marketing discussions, and to foster more research into this area. That said, this study and its findings are limited by the scope of the literature reviewed. As mentioned, in this paper, we only focus on the papers published in top marketing and information systems academic journals. Considering that social media analytics in marketing research is at its early stage, it is possible to find more relevant papers in conference proceedings and industrial magazines. Future research could further address the research questions by broadening the dataset to include more academic sources and industrial publications such as business magazines, industry reports, and white papers.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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