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ORIGINAL ARTICLE

The state of marketing analytics in research and practice

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Abstract

This paper presents a systematic review of marketing research on the burgeoning new area of "marketing analytics" and considers the importance of marketing analytics for marketing research and practice. This article contributes to the marketing literature with a systematic review of studies and findings on marketing analytics, which allow for further recommendations. We identify the central themes and concepts related to marketing analytics present in marketing research and provide a comparison between the focus of marketing research, practice, and academics regarding this topic. The study also provides practitioners with a summary of the current findings and a more natural way to translate and apply theoretical findings in practice. Academics can also use these results in the classroom to promote and demonstrate the importance and benefits of marketing analytics.

Keywords Marketing analytics · Big data · Marketing metrics

Introduction

Marketing researchers have noted that marketing science and practice are going through an analytics disruption, considering the explosion of data, the emergence of digital marketing, social media, and marketing analytics (Moorman 2016; Verhoef et al. 2016). A crossroads is also underlined in effect measurement, big data, and online/offline integration, as scholars have pointed to challenging in integrating big and small data and marketing analytics into marketing decision and operations (Hanssens and Pauwels 2016). Experts predict even more extensive development of big data, due to smart technology devices such as watches, cameras, and generally, the Internet of Things (Baesens et al. 2016). Scholars have recommended more research regarding the use of customer analytics in many areas of marketing, including retailing (Hoppner and Griffith 2015), firm performance (Germann et al. 2014), computing technologies, analytical methodologies in marketing (Kannan and Li 2017), predictive analytics (Shmueli and Koppius 2011), and big data analytics (Wamba et al. 2017). Business researchers emphasize the importance of interdisciplinary work to address a major real-world problem that is beyond the capacity of a single discipline. This would involve the application of big data and analytics, such as competitive benchmarking (Ketter et al. 2016).

Researchers also note the advantages of big data and analytics in better understanding shopping patterns using carts with RFIDs, mobile phone apps, or video cameras. These technologies are helpful in managing supply chain and business processes (Davenport 2006; Venkatesan 2017), as well as in the areas of search engine optimization, and social media analytics (Kumar et al. 2017). In the context of social media, researchers have argued that marketers should focus not only on using it as a communication channel with consumers but also as a source of marketing insights (Moe and Schweidel 2017).

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While big data, marketing analytics, and data mining seem to be here to stay in marketing (Jobs et al. 2016), businesses consider data analysis a particularly critical challenge (Verhoef et al. 2016). Marketing analytics play a central role under these circumstances, considering the needs for adequate metrics and analytical methods to improve data-driven marketing operations and decision making (Wedel and Kannan 2016). As studies have concluded, businesses can achieve favorable and sustainable performance outcomes through the higher use of marketing analytics (Germann et al. 2013).

The purpose of this research is to analyze the current state of research in marketing analytics and assess the central study themes, topics of interest, findings, as well as methods of analysis employed. We also have as objective to evaluate the use of marketing analytics in marketing research practice and compare the real-world interests with those of academics in published studies, as well as in university courses. This article contributes to the marketing literature with a systematic review of studies and findings on marketing analytics, which allow for further recommendations. We begin by describing the historical setting, and then we present the results of a comprehensive literature review of marketing journals, comparing co-occurrences of words found in academic research with those inclusive of marketing research firms to represent the practitioner point of view, as well as to business schools to reflect the current status of education and MBA training. We then conclude with recommendations for academics as researchers and as educators, and for practitioners.

Marketing analytics overview

Decades ago, marketing data were usually available at an aggregate level, on a yearly or monthly level. In 1923, Nielsen created one of the first and most well-known market research companies to measure product sales in stores. Between the 1930s and 1950s, Nielsen started measuring radio and television audiences (Wedel and Kannan 2016). Thirty years ago, marketers were getting used to the adoption of the UPCs, scanner data, and bimonthly audit data from AC Nielsen (Bijmolt et al. 2010). Also, in the 1980s, the INFORMS Society of Marketing Science was created.

In the mid-1990s, the field of traditional analytics matured, Internet marketing began to be deployed, and marketers realized the opportunity to measure interactions of website visitors through log files. Also, at that time, CRM software became available, from companies like Oracle and Salesforce (Wedel and Kannan 2016). The first commercial web analytics vendor, I/PRO Corp, was launched in 1994, WebTrends in 1995, Omniture in 2002, and Google Analytics in 2005 (Chaffey and Patron 2012). The 2000s represented an opportunity to develop new data and channels and to create diverse complementary marketing analytics. These advanced with the development of the Internet and the dramatic increase in data processing speed and data storage capabilities, according to Moore's law, stating that electronic storage capacity per unit volume doubles every 2 years (Rust and Huang 2014).

The new analytics have even affected marketing research, providing researchers the opportunity of using web-based interactive survey tools, online qualitative analysis, mining, and analyzing large databases (Hauser 2007). Thanks to the digital platform, companies started having access to large customer databases, with information on purchase behavior, marketing contacts, and other customer characteristics were stored. The Internet and social media brought an explosion of real-time data, coupled with improved data generation and collection, reduction in computing costs, and advances in statistics (Verhoef et al. 2016). In current times, businesses are using analytics as a significant competitive advantage not just because they can, but also because they should (Davenport 2006). Overall, marketers can use analytics in deciding the allocation of marketing resources, customer lifetime value, in identifying and retaining profitable customers and getting more from each transaction. The following section presents the methodology of the systematic review of the marketing analytics research, practice, and essential academic factors.

Marketing analytics systematic review method and data

To analyze the state of research on marketing analytics, we use a three-phase systematic review approach (Barczak 2017; Littell et al. 2008). In phase 1, we performed a search for peer-reviewed articles, including the keywords "marketing analytics" in their title and published between 2007 and 2018 in the following databases: ABI Inform and EBSCO Host. ABI provided a list of 31 articles, and EBSCO provided 60 articles. After eliminating duplicated articles, book reviews, editorials, presentations of special issues, and articles that were not strictly related to analytics, 27 articles were retained for analysis.

We then focused on searching the keywords "marketing analytics" in the full text of top marketing journals, including the *Journal of the Academy of Marketing Science*, *Journal of Consumer Psychology*, *Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *International Journal of Research in Marketing*, *Journal of Retailing*, *European Journal of Marketing*, and the *Journal of Business Research*. From the top marketing journals, we found 35 articles related to the topic of marketing analytics. In total, the sample for analysis consists of 62 articles.

The table summarizing the critical characteristics of each of the 62 total studies analyzed is presented in Appendix Table 5. That summary table shows the 62 articles scrutinized, and the theories and methods of research and data types in the marketing analytics research.

For an overview of marketing analytics in practice and in order to analyze the differences and similarities of this concept with marketing analytics research, we also took into consideration the top 20 market research firms (AMA 2017). We extracted the description these companies use for their marketing analytics offering and services, with specific attention to capture the focus of practitioners and compare it with the priority issues identified by researchers.

The second phase of data collection consists of furthering our understanding of the evolution of marketing analytics with regard to pedagogy, specifically the course and specialization offering of business schools. For this purpose, phase 2 involved performing a search on the websites of the top 25 best global universities for economics and business, as identified by U.S. News (2018), and extracted information regarding their course offerings and specializations on marketing analytics, as well as their course descriptions.

After the literature review was performed, we employed qualitative content analysis and cluster analysis methods to identify the central themes present in the articles analyzed. In the next section, we draw on the results of the systematic literature review and analysis to offer a seeming concurrence of a definition of marketing analytics, to identify the critical themes for marketing research and practice, as well as the current level of knowledge about this topic.

Results and interpretation

In this section, we provide details regarding the results of the systematic literature review, the content analysis and the lexical analysis performed, to offer a seeming concurrence of a definition of marketing analytics, to identify the central themes of interest for research, practice, and academia, as well as to emphasize the key findings of the literature to date.

Marketing analytics definition

Deriving from our systematic review, we begin by clarifying the definition of marketing analytics. Marketing researchers have used different aspects of business analytics in their research, thereof the definitions used also vary, as shown in Table 1.

At the same time, considering the emergence of big data, many marketing studies take into consideration data mining and big data analytics, defined as the capture of data and derivation of insights that act as decisional aids, economically extract value from very large volumes of a wide variety of

Table 1 Analytics definitions

Big data analytics (BDA) is the capture of data and derivation of insights that act as decisional aids (Motamarri et al. 2017; Rust and Huang 2014)
According to Forrester Research, advanced analytics is "any solution that supports the identification of meaningful patterns and correlations among variables in complex, structured and unstructured, historical, and potential future data sets to predict future events and assessing the attractiveness of various courses of action. Advanced analytics typically incorporate data mining, descriptive modeling, econometrics, forecasting, operations research optimization, predictive modeling, simulations, statistics and text analytics" (Leventhal 2010)
Analytics is "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport and Harris 2007)
Social media analytics is the technology used to monitor, measure, and analyze activity by users of the Web 2.0 (and beyond) to provide information for business decisions (Goh and Sun 2015)
According to IDC, BDA is "a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery and/or analysis" (Côrte-Real et al. 2017)
According to the Web Analytics Association, web analytics is "the measurement, collection, analysis, and reporting of Internet data for the purposes of understanding and optimizing Web usage" (Chaffey and Patron 2012; Järvinen and Karjaluoto 2015)
Big data consumer analytics is defined as the extraction of hidden insight about consumer behavior from big data and the exploitation of that insight through advantageous interpretation (Erevelles et al. 2016)
According to Hitachi Consulting Group (2005), marketing analytics is a "focus on coordinating every marketing touch point to maximize the customer experience as customers move from awareness, to interested, to qualified, to making the purchase" (Hauser 2007)
Marketing analytics is a "technology-enabled and model-supported approach to harness customer and market data to enhance marketing decision making" (Germann et al. 2013; Lilien 2011, p. 5)
Marketing analytics involves the collection, management, and analysis—descriptive, diagnostic, predictive, and prescriptive—of data to obtain insights into marketing performance, maximize the effectiveness of instruments of marketing control, and optimize firms' return on investment (ROI) (Wedel and Kannan 2016)

data and the measurement, collection, analysis, and reporting of Internet data (Chaffey and Patron 2012; Côrte-Real et al. 2017; Järvinen and Karjaluoto 2015; Motamarri et al. 2017; Rust and Huang 2014). In this context, whether defining big data consumer analytics or social media analytics, researchers emphasize the benefits and outcomes of using analytics, those of analyzing the activity of consumers, discovering the hidden insight about consumer behavior and using the findings in business decisions (Erevelles et al. 2016; Goh and Sun 2015).

We also employ a conceptual analysis of the definitions of marketing analytics. Leximancer uses a relatively new method for transforming lexical co-occurrence information from natural language into semantic patterns in an unsupervised manner. It is a content analysis emulator which replicates the manual coding procedures using algorithms, machine learning, and statistical processes (Dann 2010; Smith and Humphreys 2006). This analysis goes beyond keyword searching by discovering and extracting thesaurus-based concepts from the text data, with no requirement for a prior dictionary, generating a concept map with thematic clusters and related concepts (Dann 2010; Smith and Humphreys 2006).

In Fig. 1, the concepts are clustered into higher-level "themes" when the map is generated. Ideas that appear together often in the same pieces of text attract one another strongly, and so tend to be close near one another in the map's space. The themes help with the interpretation by grouping the clusters of concepts. The concept map contains the names of the main ideas that occur within the text. These are shown as gray labels on the map. The Leximancer

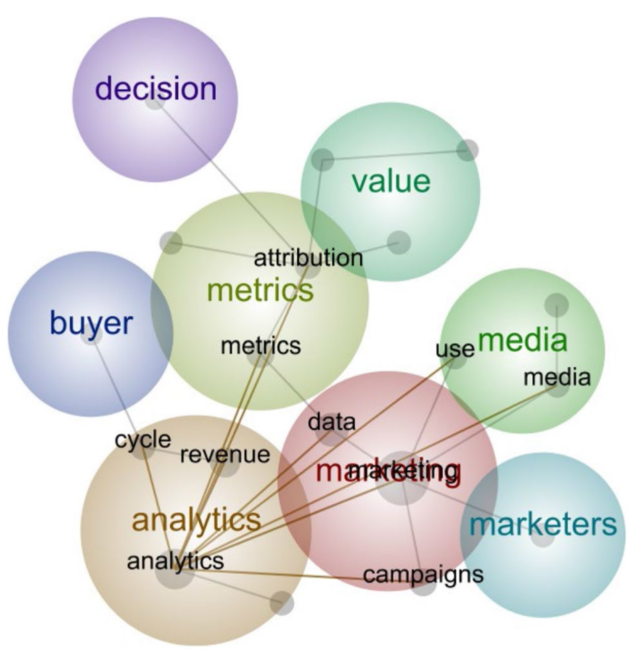

Fig. 1 Marketing analytics definition analysis

analysis performed on the definitions of analytics, as shown in Fig. 1, highlights the significant relationship between analytics and marketing campaigns, as well as media. Note that metrics play a central role in marketing and business decision making. Another function noticed for analytics is that of mediators between buyers and marketers.

Further continuing with the analysis with marketing analytics definitions presented in Table 1, we notice that researchers underline their role in data collection, management, and analysis (descriptive, diagnostic, predictive, and prescriptive) to gain insights related to marketing performance, improve marketing control, and optimize ROI (Wedel and Kannan 2016). Considering all these aspects of analytics, we provide the following definition:

> Marketing Analytics is the study of data and modeling tools used to address marketing resource and customer-related business decisions.

Marketing analytics and academic research

In this section, we offer a deeper understanding of several elements of research in analytics, first characterizing data issues, and then measures and metrics. An overview of the articles analyzed emphasizes the increase in interest in the topic of marketing analytics in the past years, considering that more than half of the studies examined have been published in the past 2 years. The distribution of studies in the top marketing journals exhibits no interest from the part of consumer research journals, but it does show a somewhat fairly evenly distributed focus on analytics from the other marketing publications. The number of empirical journals (37) and technical (3) is higher than the ones that are conceptual and theoretical (21). The studies show the emerging status of the concept and journal interest for articles that are focused on providing overviews of the notion and on developing it from a theoretical standpoint. When it comes to the research focus, many articles are oriented towards big data and social media, followed by a discussion on marketing strategy and marketing channels. Regarding the marketing topics of the articles analyzed, many of them are related to marketing strategy decisions and predictive analytics and online customer behavior.

The methods of analysis used and the data employed emphasize the specific and the benefits of marketing analytics, including content analysis, grounded theory, econometric modeling and simulation, forecasting, lexical semantic analysis (used in this study), SEM, regression, sentiment analysis, and text mining. The methods of quantitative and qualitative data analysis also accentuate the versatile character of marketing analytics and their capacity for dealing with multiple types of data. A large number of review articles (14) underline the state of marketing research related to marketing analytics, regarding the need of more integrative empirical studies in the primary marketing areas, as well as the formulation of comprehensive theoretical models.

We performed an in-depth content analysis of the 62 articles performed in NVivo. The procedure of identifying the central themes in the articles of focus has revealed the essential themes and sub-themes of the articles, as presented in Table 2. The content analysis identifies the same vital themes in marketing analytics, related to data, metrics, and online aspects, as well as consumer and customer behavior, value, and business performance. Table 2 also reveals the sub-themes and some of the concepts discussed in the marketing analytics research.

After coding the main themes and sub-themes in each article based on sentences, a cluster analysis was performed in NVivo to visualize patterns in by grouping sources that are coded similarly by nodes (Alves, Fernandes, and Raposo 2016; Raich et al. 2014). This analysis extracts the similarities and differences across the articles analyzed, and it shows how similar are the research studies from the various authors and journals downloaded. The coding at the selected sources was compared, and sources that have been coded similarly are clustered together in an unsupervised machine learning procedure in NVivo, while those that have been coded differently are displayed further apart on the cluster analysis diagram, based on the Pearson correlation coefficient (-1 = least similar, 1 = most similar). The correlation coefficients in the main six clusters obtained are included in Appendix Table 6, while the six clusters, with their components and themes, are reflected in Table 3.

The six clusters identified in the NVivo analysis reflect the six most important areas of research in connection to marketing analytics, as well as the most significant findings presented by the literature in this domain. The first cluster, related to *marketing strategy and data mining*, includes studies related to social media analytics, models, and mining unstructured, large digital datasets. These studies underline the benefits of marketing analytics in the social media world for understanding consumers' perceptions of the brand and marketing communications (Chandrasekaran et al. 2017; Culotta and Cutler 2016; Martens et al. 2016).

The second cluster focuses on *marketing research and metrics*, and it underlines the capacity of a business to use marketing analytics and metrics as an efficient way to gain market insights, to track and optimize performance and to be competitive (Krush et al. 2016; Wilson 2010). Businesses can make use of different types of metrics, including attitudinal, behavioral, and financial. In this context, studies have emphasized the importance of adapting the

Table 2 Main research themes derived from analysis of 62 marketing publications found in "Appendix"

Analytics: advanced analytics, analytical methods, analytical modeling, analytical tool, analytics culture, big data analytics, customer analytics, data analytics, marketing analytics, marketing analytics deployment
Brand: advertised brand, brand equity, brand loyalty, brand management, brand managers, brand names, brand sales, branded keywords, cumulative online brand search volume, focal brand, prior media publicity, brand website prominence
Consumer: consumer behavior, consumer response, individual consumers, online consumer activity
Customer: attractive customers, customer acquisition, customer behavior, customer insights, customer needs, customer profitability, customer relationship management, customer spending, customer value, individual customer, prospective customers, right customers
Data: aggregate data, available data, big data, big data analytics, data collection, data mining, data quality, data set, data sources, data warehouses, large data sets, online search data, search data, social media data, structured data, unstructured data, using data
Effects: advertising effectiveness, direct effects, long-term effects, main effects, marketing effectiveness, moderating effects, permanent effects, positive effect, total effects.
Information: information overload, product information, relevant information, subscription information
Marketing: digital marketing, direct marketers, market environment, market response modeling, marketing activities, marketing analytics, marketing budget, marketing campaign, marketing department, marketing efforts, marketing literature, marketing managers, marketing practice, marketing research, marketing scholars, marketing scientists
Model: analytical modeling, conceptual model, market response modeling, measurement model, predictive modeling, scoring models, structural models
Online: available online, cumulative online brand search volume, online consumer activity, online environment, online products, online purchases, online retailing, online reviews, online search data, online search volume, online shopping
Performance: business performance, firm performance, firm performance, key performance indicators, objective performance measures, organizational performance, predictive performance
Product: customer product return behavior, focal product, online products, product features, product information, product positioning, product quality, product use, purchasing products
Research: academic research, first research question, future research, international marketing channels research, marketing research, operations research, previous research, recent research, research question
Sales: brand sales, sales data, sales evolution, sales force, sales lead, sales revenue, secondary sales
Value: commercial value, customer lifetime value, customer value, customer value management, firm value, future value metrics, lifetime value, monetary value, strategic value, valuable information

Table 3 Main research clusters

Cluster 1	Marketing strategy and data mining
Chandrasekaran et al. (2017)	Effects, online, brand, research
Coursaris et al. (2016)	Research, product, effects, data
Culotta and Cutler (2016)	Data, marketing research
Kumar et al. (2017)	Data, marketing, model, effects
Martens et al. (2016)	Data, performance, value, research, product
Netzer et al. (2012)	Data, marketing, product, consumer, analytics
Cluster 2	Marketing research and metrics
Bijmolt et al. (2010)	Marketing, data, value, analytics
Chung et al. (2016)	Data, information, product
Fluss (2010)	Marketing, customer
Furness (2011)	Data, marketing, analytics, value
Hofacker et al. (2016)	Marketing, research, value, data, customer
Krush et al. (2016)	Marketing, model, effects, value
Kumar et al. (2016)	Marketing, customer, product, value, performance
Martin and Murphy (2017)	Marketing, data, effects, analytics
Miles (2014)	Marketing, performance, model, analytics
Ozimek (2010)	Marketing, analytics, effects, model
Persson and Ryals (2014)	Marketing, customer, online, sales
Wilson (2010)	Customer, marketing, online, product, sales
Cluster 3	Big data in retail and services
Bradlow et al. (2017)	Customer, data, product, marketing, analytics
Germann et al. (2014)	Customer, value
Huang and Rust (2017)	Data, analytics, customer
Järvinen and Karjaluoto (2015)	Sales, performance
Jobs et al. (2015)	Data, analytics, customer
Lau et al. (2014)	Data, online, consumer
Wedel and Kannan (2016)	Data, consumer, customer, marketing, model
Xu et al. (2016)	Analytics, customer, marketing, product
Cluster 4	Digital analytics and social media
Atwong (2015)	Marketing, research, data
Hair Jr. (2007)	Data, information, research, consumer, marketing
Ho et al. (2010)	Customer, marketing, product, research
Kerr and Kelly (2017)	Research, product, online, marketing
Liu et al. (2016)	Data, information, research, consumer
Moe and Schweidel (2017)	Effects, data, information, consumer, online
Nair et al. (2017)	Marketing, research, data, information
Quinn et al. (2016)	Marketing, data, analytics, performance, value
Ringel and Skiera (2016)	Data, information, research, consumer, online
Trusov et al. (2016)	Data, information, research, consumer, online
Vorvoreanu et al. (2013)	Marketing, data, effects
Cluster 5	Value-added
Chaffey and Patron (2012)	Value, brand, customer, data, marketing, research
Hanssens and Pauwels (2016)	Marketing, sales, model
Hanssens et al. (2014)	Marketing, brand, effects, performance, customer
Hauser (2007)	Customer, model, marketing
Kumar et al. (2016a, b)	Customer, brand
Maklan et al. (2015)	Customer, marketing, performance
Roberts et al. (2014)	Marketing, brand, data, customer, effect

Table 3 (continued)

Cluster 5	Value-added
Sridhar et al. (2017)	Sales, model, online, brand
Cluster 6	**Modeling and business performance**
Aggarwal et al. (2009)	Online, brand, customer, marketing, research
Alcaraz (2014)	Analytics
Corrigan et al. (2014)	Customer, data, marketing, model.
Côrte-Real et al. (2017)	Model, data, effects
Erevelles et al. (2016)	Data, marketing, research, consumer
Germann et al. (2013)	Performance, analytics
Gunasekaran et al. (2017)	Performance, effects, analytics
Hoppner and Griffith (2015)	Research, analytics, online
Jobs et al. (2016)	Data, value, marketing, performance
LaPointe (2012)	Analytics, brand, marketing, online
Leventhal (2010)	Data
Lilien (2016)	Data, effects, online
Motamarri et al. (2017)	Customer, effects, data, online
Pauwels (2015)	Effects, brand, data, research, customer
Petersen et al. (2009)	Value, research, data, product, marketing, model
Saboo et al. (2016)	Online, value, effects, customer, data
Salehan and Kim (2016)	Research, data, analytics, online

parameters to the new environment, connecting metrics and reconciling multiple perspectives on marketing metrics (Ayanso and Lertwachara 2014; Bendle et al. 2015; Ozimek 2010; Wilson 2010). Researchers have noted that the use of metrics in the study of small-business success is essential for researchers and practitioners, considering the advantage of predictive analytics and statistics (Miles 2014; Wilson 2010). The analyzed studies underline that marketing analytics can help collect and analyze data about customers' brand preference, shopping frequency, and buying patterns (Miles 2014). Our model generated based on previous marketing analytics research emphasizes their importance for firms and managers regarding business performance, providing value, as well as achieving and measuring results. As noted in the conceptual map in Fig. 2, marketing metrics are essential to measuring marketing performance in different areas of marketing, including sales and advertising.

The third cluster identifies a topic of significant interest for contemporary business research, ***big data***, in the context of retail and services, and it underlines the capacity of a business to use marketing analytics and metrics as an efficient way to gain market insights, to track and optimize performance and to be competitive (Huang and Rust 2017; Järvinen and Karjaluoto 2015). Some of the studies analyzed emphasize the benefits of big data analytics in retailing (Bradlow et al. 2017; Germann et al. 2014), services (Huang and Rust 2017), new product success (Xu et al. 2016), and marketing communications (Jobs et al. 2015).

Cluster 4 refers to *digital analytics and social media*. It refers to the benefits of marketing analytics in collecting consumer information and providing a user profile that can lead to innovations in the way marketers communicate with consumers (Kerr and Kelly 2017; Moe and Schweidel 2017; Trusov et al. 2016).

The articles in cluster 5 are focused on *the value added* that marketing analytics could bring, in a collaborative context that takes a macro-level approach and considers marketing research, practice, and academia (Chaffey and Patron 2012; Hanssens and Pauwels 2016; Roberts et al. 2014). An overview of the articles included in this group emphasizes the value of marketing in the world of analytics for each of these stakeholders (Hauser 2007).

Finally, cluster 6 includes studies that emphasize, in general, aspects focusing on *modeling and business performance*. These articles show the positive implications of marketing analytics for business decision making, strategizing and performance, and how organizations can benefit from it to increase profitability and shareholder value (Germann et al. 2013; Jobs et al. 2016; Petersen et al. 2009).

To summarize the most significant findings from the literature review and analysis we performed, Fig. 2 presents the main points regarding the emergent themes derived from the marketing analytics research framework. It covers the essential elements present in the definition of marketing analytics, including its measurement, data collection, and analysis purpose and the close relationship

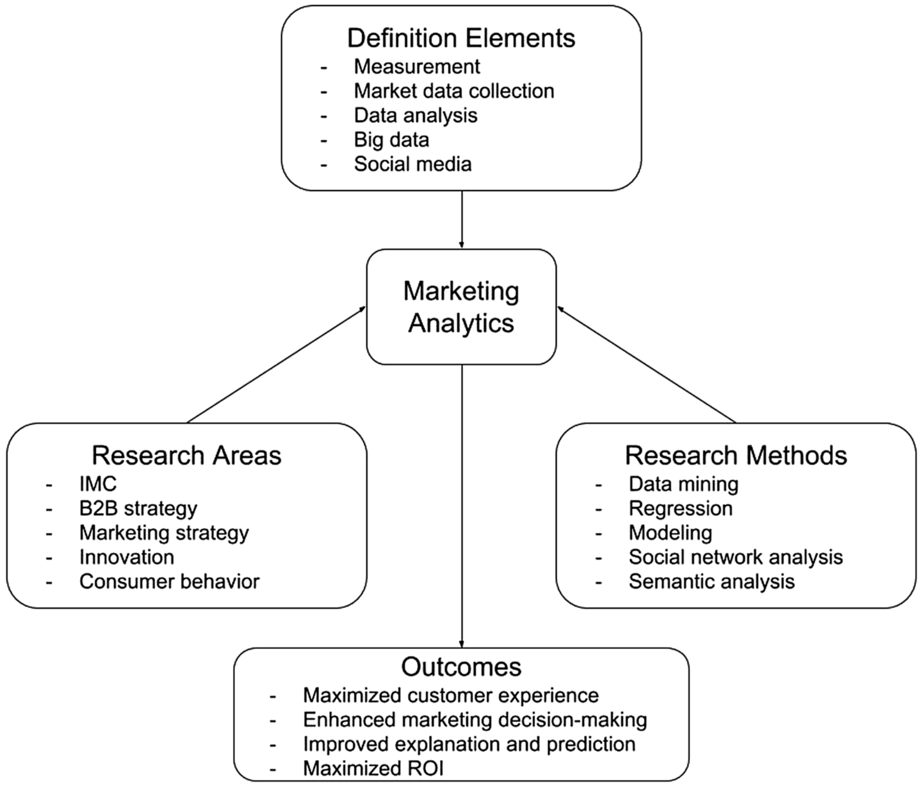

Fig. 2 Marketing analytics research framework

with the recent developments in big data and social media.

Figure 2 presents the most critical areas of marketing that were included in earlier marketing analytics research, which can also benefit from additional studies that can clarify the use of analytics in domains such as consumer behavior, B2B, and innovation. The most used research methods are also presented, and they depict a connection with the specifics of the data studied, including social media and big data, which fare well with methods such as data mining, sentiment analysis, and social network analysis. These articles provide an overview of the critical elements of the marketing analytics output, including value for consumers and marketers, such as a maximized customer experience and a higher ROI.

Marketing analytics in practice

To assess the differences and similarities of the way marketing analytics is perceived in marketing research, practice, and academia, we performed a content analysis in NVIVO, combining the abstracts of the research articles, the description of marketing analytics services from research companies, as well as the course descriptions from business schools. Table 4 shows the primary topics connected to marketing analytics and their degree of importance for marketing researchers, practitioners, and academics.

Customers are in the center of our practice-related part of the model in Table 4, which underlines their essential role in engaging with businesses and as a target and recipient of services (Hanssens and Pauwels 2016). Thanks to modern technology, the Internet, and social media, companies can

Table 4 Theme importance

	Analytics (%)	Customer (%)	Data (%)	Management (%)	Marketing (%)
Courses	21.9	5.9	26.7	6.1	39.4
Practice	13.9	23.8	12.5	6.5	43.3
Research	20.2	12.5	20.8	9.3	37.1

provide personalized services and employ customer relationship management (CRM) to deliver higher use-value for customers (Maklan et al. 2015). The digital environment has changed the way marketers communicate and engage with consumers, as well as the methods of gaining insights in consumers' behavior, as a result of marketing analytics (Huang and Rust 2017; Kerr and Kelly 2017). Customers play a central role in the results of our systematic review, related to analytics, marketing, social media, and online data.

Marketing studies have shown a widespread increase in the use of marketing analytics and intelligent agent technologies, even from companies such as IBM, Amazon, eBay, and Netflix, for collaborative filtering, personalization, recommendation systems, and price-comparison engines (Kumar et al. 2016a, b; Verhoef et al. 2016). Total global expenditures in marketing dashboards, analytic software, and other marketing software systems reach about $24 billion annually, and substantial investments have been made in big data start-ups in the past years (Jobs et al. 2015; Krush et al. 2016). For many practitioners, big data has become the norm and a way to maintain competitiveness in the marketplace (Chaffey and Patron 2012; Krishen and Petrescu 2017; Petrescu and Krishen 2017). Articles have underlined that even B2B practitioners see vast potential in using B2B customer analytics to solve business problems, although they do not yet seem to be benefitting from the tools nor the guidance to achieve this (Lilien 2016). Studies show that businesses employ cloud-based predictive analytics providers (such as Lattice and Mintigo) to draw on both inside data sources and outside data sources to identify new leads (Lilien 2016). In addition, managers seem to have difficulties regarding the selection of the right metrics, the interpretation of the results and their integration, which leads to frustration and disappointment, which requires more analysis and reflection in research and academics (Pauwels 2015; Petrescu and Krishen 2017; Verhoef et al. 2016; Wedel and Kannan 2016).

Thus, to better understand the situation of marketing analytics in practice and to analyze the differences and similarities of this concept with marketing analytics research, we looked at the top 20 market research firms (AMA 2017). We extracted the description these companies use for their marketing analytics offering and services, with specific attention to capture the focus of practitioners and compare it with the priority issues identified by researchers.

The focus of marketing research companies with regard to marketing analytics is more concentrated on two main factors: the business, and its consumers. The significantly higher importance awarded to consumers is also evident in Table 4. The interest is related to using marketing analytics to formulate marketing strategies and make decisions on pricing and product. At the same time, customer lifetime value, a vital ROI aspect, is also featured by marketers. The relation between practice and research is mainly based on performance and strategies, points that have been identified as needing development for marketing analytics. Regarding practice and marketing academia, the model shows the prominence awarded to business decisions by both categories, which will be further discussed in the next section. Also, in this context, practitioners are much more oriented towards the technical side of marketing analytics and the use of specialized software.

Marketing analytics in academia for educators

Research has emphasized different academic developments that affect marketing practice, including companies that were founded by academics or on academic work (Wedel and Kannan 2016). One of the significant contributors to the diffusion and evolution of marketing analytics in practice and research is represented by the academics, through the teaching and mentoring offered by business schools. For this purpose, we performed a search on the websites of the top 25 best global universities for economics and business, as identified by U.S. News (2018), and extracted information regarding their course offerings and specializations on marketing analytics, as well as their course descriptions. Most of the top universities have some course related to marketing analytics, many at the graduate level, and some also at the undergraduate level. Some colleges also have degrees in marketing analytics, such as a Master's in Marketing Analytics at the University of Chicago and a B.S. in Marketing Analytics at New York University. The University of Pennsylvania has developed the Wharton Customer Analytics Initiative, an academic research center focusing on the development and application of customer analytics methods and has the Marketing Analytics: Data Tools and Techniques course on the free MOOC platform EdX. Other universities, such as the University of California at Berkeley and Columbia University also offer free marketing analytics courses, besides there are house courses, on EdX. We also wanted to evaluate the level of interest in marketing analytics in business schools perceived to be less modern and not included in the U.S. News ranking. For this purpose, we analyzed ten of the business schools recently accredited by the AACSB in the past year. Only one of them included mentions of a marketing analytics course on its website.

Regarding the conceptual focus in the marketing analytics courses, Table 4 shows that data analysis is central, including business models, business decisions, marketing metrics, and knowledge. While regression appears as the most common method even in the conceptual map, there are various software packages used, including Excel, SPSS, R, as well as different tools, such as competitive analysis, quantitative strategic planning matrix (QSPM) decision model, Monte

Carlo analysis decision model, conjoint analysis, promotion analytics, and budgets for traditional and social media. As the model and Table 4 underline, the focus is on teaching students the basics of data analysis, to make decisions and come up with models from the analytics collected.

Recommendations

This systematic review on the state of marketing analytics in research, practice, and higher education has provided findings regarding the priorities and interests for each of the three parties, the differences, and commonalities among them, as well as information regarding the central research answers on this topic. There are still many questions that need to be answered and issues that should be clarified regarding marketing analytics, especially considering their widespread use and fast-paced development.

Academic research

To date, what the analysis of marketing analytics research suggests is that the concepts and terminologies as yet appear somewhat fragmented concerning the different areas of marketing and their uses or benefits from marketing analytics. For example, recall the varieties even in defining marketing analytics (Table 1), and the array of coverage across the literature (in "Appendix") of research foci, theoretical approaches, and types of data requiring analyses.

Current marketing analytics seem to represent a somewhat higher tendency toward practical and concrete marketing aspects, yet these studies could also benefit from the consideration of a more rigorous theoretical base when developing a conceptual model. Perhaps this focus on practical over theoretical is understandable given the influx of big data from the real (non-academic) world, hence bringing with the accompanying practical questions. We echo a call from leading marketing analytics scholars who encourage that academics provide theory-based criteria for managers concerning marketing metrics use and interpretation (Hanssens et al. 2014).

Given the close relationship between academia and industry for marketing analytics, perhaps closer than for many other topics areas within marketing, academics and practitioners might benefit from still closer links to further improve research (Martin and Murphy 2017; Petrescu and Krishen 2017). Part of the distance to date is likely attributable to the natural differential speeds in these two worlds, with the fast pace of marketing analytics development in practice and the slower rate of marketing academic scholarship.

Many data analysis methods have gained popularity due to big data and online content, including sentiment analysis, semantic analysis, and social network analysis, some of them used in the papers analyzed. The role of these methods in marketing research needs to be made clear, as well as the requirements regarding the rigor criteria for them. In addition, it is equally important to use marketing analytics concepts, principles, and metrics, even when the data are not particularly “big.” That is, marketing analytics offer a rigorous way of thinking about relationships, in addition to its many useful analytical tools, and most marketing questions could be better addressed using marketing analytics.

Academia in its role as educator

Academic marketing departments should include marketing analytics into their overall curriculum to provide students with a compelling career advantage, considering the research and especially practitioner (and job market) interest in this area. This line of coursework presumably begins with a solid statistics class, another in marketing research, and then could span out to cover different types of models for different kinds of data, at least for MBAs and possibly also for advanced undergraduates.

Academic marketing departments should also provide their students with real-world opportunities to practice marketing analytics, data collection, analysis, interpretation, and decision making. This can include collaboration with local businesses on practical projects, internships, and student business incubators. Doing so would help students understand our usual cautions in generalizing results, dealing with populations (as opposed to samples) and biased samples as the basis for understanding customers, in making decisions and developing theory. Much like interpreting qualitative research, the results of non-random samples cannot be generalized.

Exposure to one or more big data datasets will help students understand that with large samples and populations, every effect becomes statistically significant despite being of no importance whatsoever. There are also many proprietary performance measurement models available that are subjective and have no theoretical basis.

Finally, one element of education that can be implemented relatively quickly is executive programs. Traditionally, changes in full-time programs require more bureaucracy and vetting, whereas executive programs can be developed, advertised, staffed, and run with relatively little delay. There is likely a currently unmet demand for such retraining and retooling among marketing practitioners, who would not have been exposed to such material during their MBA or undergraduate days but who can appreciate the need to be facile with the concepts and analytical tools to be part of today's marketing dialog.

Managerial practice

The data and requisite technology are valuable, yet it is not just about data and technology. Our models showed a decided practitioner focus on business decisions and prescriptive information, yet we all know the data and the technology are useful only to the extent to which they are efficiently and rigorously employed to draw insights and conclusions from the data. The interpretation and the theory behind it are critical.

As the multitude of marketing metrics and methods of analysis in the reviewed articles shows, there are no universal metrical or analytics or agreed upon standards. That diversity is fine and should be encouraged, at least until some types of data or models make apparent breakthroughs. Marketing analytics requires a holistic approach, a combination of techniques, ideally with different types of data, fitting the profile of the company, and interpreted in conjunction.

As many market research companies were founded by academics (Wedel and Kannan 2016), it is a possibly fruitful endeavor to collaborate with researchers and professors on different market analytics topics, especially at universities where this area is developed.

Conclusions

We presented a systematic review of marketing research on the topic of marketing analytics. In a semantic and cluster analysis, we identified the central themes and concepts related to marketing analytics in marketing research, including big data, marketing metrics, and marketing analytics value. We also provided an analysis framework for elements of marketing analytics as viewed by marketing research, practice, and educators.

Drawing from the results of the analysis, we presented recommendations for researchers, regarding future research needs related to marketing analytics. The principal focus in this aspect should be theory building and development, as well as the formulation of integrative models. Regarding practitioners, they could also benefit from a more systematic, theoretical-based approach and the use of a holistic strategy. Academic educators can contribute to the development of both these fields and the training of competent managers.

This article contributes to the marketing literature by integrating critical marketing analytics studies and providing an overview of the state of research. Practitioners receive recommendations and a summary of the review, for a more natural way to apply theoretical findings in practice. Academics can also use these results in the classroom to present and demonstrate the application and benefits of marketing analytics.

Appendix

See Tables 5 and 6. To date, what the analysis of marketing analytics research suggests is that the concepts and terminologies as yet appear somewhat fragmented concerning the different areas of marketing and their uses or benefits from marketing analytics. For example, recall the varieties even in defining marketing analytics (Table 1), and the array of coverage across the literature (in Appendix Table 5) of research foci, theoretical approaches, and types of data requiring analyses.

Current marketing analytics seem to represent a somewhat higher tendency towards practical and concrete marketing aspects, yet these studies could also benefit from the consideration of a more rigorous theoretical base when developing a conceptual model. Perhaps this focus on practical over theoretical is understandable given the influx of big data from the real (non-academic) world, hence bringing with the accompanying practical questions. We echo a call from leading marketing analytics scholars who encourage that academics provide theory-based criteria for managers concerning marketing metrics use and interpretation (Hanssens et al. 2014).

Table 5 Content summarization of marketing analytics literature review

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Aggarwal et al.	2009	*Journal of Retailing*	Empirical	Big data	Lexical semantic analysis of online data	Lexical semantics	Lexical semantic analysis	Information stored in online search engine databases		Proposes a method to assess a brand's positioning relative to that of its competitors' in the online environment
Alcaraz	2014	*Journal of Brand Strategy*	Conceptual	Marketing analytics	Marketing analytics and marketing science		Theoretical			Three reasons for delayed progress in marketing science: syndication, academic, and practitioner (addressing only the demand side, overlooking the supply chain side)
Atwong	2015	*Marketing Education Review*	Empirical	Marketing analytics education	Marketing analytics practicum	Experiential learning	Case study approach	Class data		Social media practicum creates a learning environment in which students can apply marketing principles and prepare for collaborative work in social media marketing and analytics
Bijmolt et al.	2010	*Journal of Service Research*	Conceptual	Marketing analytics	Analytics and customer engagement	Customer equity, decision trees, WOM	Review			The state of the art of models for customer engagement and the problems with calibrating and implementing them

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Bradlow et al.	2017	*Journal of Retailing*	Empirical	Big data	Big data and predictive analytics in retailing		Field experiment, A/B testing	Store data		The importance of theory in guiding any systematic search for answers and for streamlining analysis, even as the role of big data and predictive analytics in retailing is rising
Chaffey and Patron	2012	*Journal of Direct, Data and Digital Mkt. Pract.*	Conceptual	Web analytics	Commercial value of digital analytics		Review			Opportunities for companies to better apply web analytics to improve digital marketing performance
Chandrasekaran et al.	2017	*JAMS*	Empirical	Advertising	Offline ad content and online brand search	Consumer search theory	Quasi-experimental study, regression	Online brand search		The informational content of a TV ad increases online brand search, while attentional content elements decrease this effect
Chung et al.	2016	*JAMS*	Empirical	Social networks	Personalization using social networks	Social networks	Simulation	Field studies with consumers		Mobile automated adaptive personalization systems that use social networks make personalization more effective

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Corrigan et al.	2014	*Marketing Education Review*	Technical	Marketing analytics education	Marketing analytics strategic decisions	Experiential learning	Case study approach			The types of data needed to identify changes in consumer behavior, privacy issues in data mining, and how customer analytics support marketing decisions
Côrte-Real et al.	2017	*Journal of Business Research*	Empirical	Big data	Assessing the value of big data analytics	Knowledge-based view, dynamic capabilities	PLS	Survey IT and business execs		Big data analytics provide business value to several stages of the value chain and can create organizational agility through knowledge management
Coursaris et al.	2016	*Online information review*	Empirical	Social media	Social media analytics	Multi-Grounded Theory, media richness theory	ANOVA and regression analysis	Longitudinal data from three Fortune 200 companies	SPSS	Transformation appeal and richer media have a significant positive effect on engagement
Culotta and Cutler	2016	*Marketing Science*	Empirical	Big data	Brand-consumer social media relationships	Social network	Mining the brand's connections on Twitter, survey	Twitter data		A reliable, flexible, and scalable method for monitoring brand perceptions

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Erevelles et al.	2016	*Journal of Business Research*	Conceptual	Marketing analytics	Big data consumer analytics	Resource-based theory	Theoretical			Physical, human, and organizational capital moderate: collecting and storing evidence of consumer activity as big data, extracting consumer insight from big data, and utilizing it to enhance dynamic/adaptive capabilities
Fluss	2010	*JDDDMP*	Technical	Marketing analytics	Speech analytics		Case study approach		Autonomy etalk, Aurix Limited, CallMiner, Nexidia, NICE Systems, UTOPY and Verint	Speech analytics solutions help enterprises retain customers and generate incremental revenue through a differentiated customer experience
Furness	2011	*JDDDMP*	Empirical	Marketing analytics	Monte Carlo Simulation in marketing analytics	CRM	Case study	Simulation	SAS, SPSS, Excel, SIMUL8, Simscript, Powersim, Vensim, Hugin Expert, BUGS	Monte Carlo Simulation increasing role in (CRM)
Germann et al.	2013	*IJRM*	Empirical	Marketing analytics	Firm performance	Pper echelons theory, the resource-based view	SEM	Survey	Mplus	Firms attain favorable and sustainable performance outcomes through use of marketing analytics

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Germann et al.	2014	*Journal of Retailing*	Empirical	Retailing	Customer analytics in retailing	Repetitive decisions	Hierarchical Bayesian regression	Survey		Firms in the retail industry have the most to gain from deploying customer analytics
Gunasekaran et al.	2017	*Journal of Business Research*	Empirical	Big data	Big data and predictive analytics for supply chain	RBV, assimilation, routinization	Multiple regression	Email survey		Connectivity and information sharing with top management commitment are related to big data and predictive analytics acceptance
Hair Jr.	2007	*European Business Review*	Conceptual	Marketing analytics	Predictive analytics		Theoretical			Data mining and predictive analytics are increasingly popular because of the contributions to converting information to knowledge
Hanssens and Pauwels	2016	*Journal of Marketing*	Conceptual	Marketing metrics	The value of marketing		Theoretical			The use of marketing analytics can improve marketing decision making at different levels of the organization
Hanssens et al.	2014	*Marketing Science*	Empirical	Marketing strategy	Consumer Attitude Metrics for Marketing Mix Decisions	Memory theory, habit formation theory, utility theory, attitude behavior theory	Econometric Modeling	Brand performance tracker	HLM	Combining marketing and attitudinal metrics criteria improves the prediction of brand sales performance

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Hauser	2007	*Direct Marketing: An Intern/ Journal*	Conceptual	Marketing analytics	Marketing analytics	Theory of subject-object transformation	Review	Customer aggregated information DNA		Analytics requires marketers to use data to understand customers at every touch point
Ho et al.	2010	*IJRM*	EMPIRICAL	BIG DATA	Unfolding large-scale marketing data	Information visualization, Multidimensional unfolding	Simulation, EIDP	Experimental	SPSS	A new approach to unfold customer-by-brand transaction data and customer-by-customer network data
Hofacker et al.	2016	*Journal of Consumer Marketing*	Conceptual	Big data	Big data and consumer behavior		Theoretical			Big data have the potential to further our understanding of each stage in the consumer decision-making process
Hoppner and Griffith	2015	*Journal of Retailing*	Conceptual	Marketing Channels	Evolution of research in international marketing channels	Channels, cross-cultural	Review			Customer analytics have the potential to change channel approaches across markets
Huang and Rust	2017	*JAMS*	Conceptual	Services	Technology-driven services	Relationship marketing, personalization	Review			A typology and positioning map for service strategy, in the context of rapid technological change

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Järvinen and Karjaluoto	2015	*Industrial Marketing Mgt.*	Empirical	Marketing analytics	Digital marketing performance measurement	Marketing performance measurement theory	Case study approach	Interviews		Considering the reasoning behind the chosen metrics, the processing of metrics data, and the organizational context surrounding the use of the system
Jobs et al.	2016	*AMSJ*	Empirical	Big data	Big data advertising analytics		Content analysis	Interviews		Big data firms can potentially add value if properly matched with the right digital client
Jobs et al.	2015	*International Academy of Mkt. Studies Journal*	Empirical	Big data	Big data marketing analytics		Content analysis	Interviews		A consolidated framework and typology intended to help companies and researchers understand the structure of this ecosystem
Kerr and Kelly	2017	*European Journal of Marketing*	Empirical	IMC	IMC education	Digital disruption, IMC	Delphi	Panel		Digital disruption provides many challenges including updating curriculum and up skilling staff

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Krush et al.	2016	*European Journal of Marketing*	Empirical	Marketing strategy	Marketing dashboards	Knowledge-based view (KBV) theory	SEM	Survey		Marketing strategy implementation speed and market information management capability are key integration mechanisms that leverage the marketing dashboard resources
Kumar et al.	2016a	*JAMS*	Empirical	Marketing strategy	Marketing strategy	Intelligent agent technologies	Grounded theory	Interviews		The importance of understanding IAT applications and adopting them
Kumar et al.	2016bb	*Journal of Marketing*	Empirical	Social media marketing analytics	Firm-Generated Content in Social Media	Customer relationship management	Econometric Modeling	Customers social media, transaction data, survey attitudinal data		Firm-generated content has a positive and significant effect on customers' behavior
LaPointe	2012	*Journal of Advertising Research*	Conceptual	Marketing analytics	Marketing analytics in advertising		Theoretical			Areas of potential marketing improvement: stronger relative product value proposition and more effective advertising copy—are not in models

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Lau et al.	2014	*Decision Support Systems*	Empirical	Social analytics	Sentiment analysis	Sentiment analysis	Sentiment analysis	Social media data		Proposed social analytics methodology to tap into the collective social intelligence on the Web, and improve product design and marketing strategies
Leventhal	2010	*JDDDMP*	Conceptual	Data mining	Data mining and marketing analytics	Social network theory	Review			The use of data mining for extracting patterns from large databases
Lilien	2016	*IJRM*	Conceptual	B2B marketing	B2B research gaps	B2B	Review			B2B Innovation, B2B Buying, and B2B Analytics recommendations
Liu et al.	2016	*Marketing Science*	Empirical	Big data	Forecasting of sales/consumption		Methods from cloud computing, machine learning, and text mining	Twitter, Nielsen, Google Trends, Wikipedia, IMDB Reviews, Huffington Post News	LingPipe, DynamicLMClassifier Amazon Elastic MapReduce Hadoop MapReduce	The information content of Tweets and their timeliness significantly improve forecasting accuracy
Maklan et al.	2015	*European Journal of Marketing*	Conceptual	Marketing strategy	CRM return measurement	CRM, structuration, media richness, actor network, variance	Review			A broader epistemological framework, better suited to observing how organizations benefit from IT-led management initiatives, for CRM investment

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Martens et al.	2016	*MIS Quarterly*	Empirical	Predictive analytics	Fine-grained behavior data	Behavioral similarity	Response modeling	Customer transactions		Larger firms may have substantially more valuable data assets than smaller firms, when using their transaction data for targeted marketing
Martin and Murphy	2017	*JAMS*	Conceptual	Data privacy	Information privacy in marketing		Review			Contemporary privacy questions in marketing
Miles	2014	*AMSJ*	Empirical	Marketing analytics	Customer behavior and profitability	SME market behavior	Discriminant analysis	Survey	SAS, SPSS	The marketing behavior analytic is moderately significant in predicting customer behavioral patterns
Moe and Schweidel	2017	*Journal of Product Innovation Mgt.*	Conceptual	Social media analytics	Innovation in social media analytics		Review			Framework that views social media data as a source of marketing insights
Motamarri et al.	2017	*Business Process Mgt. Journal*	Conceptual	Big data analytics	Big data analytics in services marketing	Co-creation, service typology	Review			The primary thrust for BDA is to gain customer insights, resource optimization, and efficient operations
Nair et al.	2017	*Marketing Science*	Empirical	Big data and marketing analytics	Big data and marketing analytics in gaming	Targeting	Econometric Modeling	Transaction data		The value of using empirically relevant marketing analytics solutions for improving outcomes for firms

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Netzer et al.	2012	*Marketing Science*	Empirical	Data mining	Market-Structure Surveillance	Brand-associative network	Text-mining and semantic network analysis, mds, crf	Discussions in user-generated content, survey		Compared a market structure based on user-generated content data with a market structure derived from more traditional sales
Ozimek	2010	*Journal of Database Mkt. & Customer Strategy Mgt.*	Empirical	Marketing analytics	Statistical forecasting and marketing analytics	Basic binomial theory	Modeling and forecasting	Climate change data		In classic direct marketing an over-reliance on statistical modelling techniques and the use of simplistic models
Pauwels et al.	2016	*IJRM*	Empirical	Electronic WOM	Marketing, eWOM content, search, online and offline store traffic	Flow theory	Time series analysis	Social media data		Over a third of the offline store traffic effects materialize indirectly through eWOM and organic search
Persson and Ryals	2014	*Journal of Business Research*	Empirical	Customer management	Customer relationships decisions and analytics	Customer lifetime value, heuristics	Content analysis	Interviews		The use of managerial heuristics is widespread and it frequently outweighs measures such as customer lifetime value
Petersen et al.	2009	*Journal of Retailing*	Conceptual	Customer management	Metrics for profitability and shareholder value	Customer lifetime value, customer equity, referral	Review			Framework that identifies key metrics for a better picture of the company's evolution and future growth potential

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Quinn et al.	2016	*European Journal of Marketing*	Conceptual	Marketing evolution	Marketing in a digital world	Marketing strategy, marketing theory	Review			An increasingly digitalized marketplace and the associated impact of big data for the function of marketing; the changing scope of strategic marketing practice and functional accountability
Ringel and Skiera	2016	*Marketing Science*	Empirical	Big data	Big search data	Network analysis and graph theory	Modeling and two-dimensional mapping	Big search data		Big search data from product- and price-comparison sites provide higher external validity than search data from Google and Amazon
Roberts et al.	2014	*IJRM*	Empirical	Marketing science	Marketing science value chain	Marketing, behavioral, game theory	Exploratory	Survey data managers, intermediaries and academics		The increased importance of big data and the rise of digital and mobile communication, using the marketing science value chain as an organizing framework
Saboo et al.	2016	*MIS Quarterly*	Empirical	Big data	Big data and marketing resource (re) allocation	Time-varying effect model, dynamic marketing resource allocation	Econometric Modeling	Transaction data from a retailer with demographic information		Time-varying effects model handles the complexities associated with big data analytics and provides novel insights for data-driven decision making

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Salehan and Kim	2016	*Decision Support Systems*	Empirical	Big data analytics	Online consumer reviews	Sentiment analysis	Sentiment mining	Online reviews	SentiStrength	Reviews with higher levels of positive sentiment in the title receive more readerships; sentimental reviews with neutral polarity in the text are also perceived to be more helpful
Sridhar et al.	2017	*IJRM*	Empirical	Marketing metrics	Marketing metrics and spending	Kalman filtering theory	Simulation	Store data		Marketing overspending increase as metrics unreliability increases
Trusov et al.	2016	*Marketing Science*	Empirical	Big data	User profiling	The CTM model	Economic simulation, MCMC, Mape	Website browsing information		Proposed model for individual-level targeting of display ads
Vorvoreanu et al.	2013	*JDDDMP*	Empirical	Social media marketing analytics	Case study of SuperBowl	Social media analytics, consumer monitoring	Sentiment analysis	Social media data		Method of using social media analytics that enable broad overall assessment and in-depth understanding of the topics that emerge around a marketing campaign

Table 5 (continued)

Author	Year	Journal	Article type	Research focus	Article topic	Main theories	Research method	Data type	Software	Findings
Wedel and Kannan	2016	*Journal of Marketing*	Conceptual	Marketing analytics	Marketing analytics	Bayesian decision theory	Review	Observational, surveys, field experiments, lab experiments	Excel, SAS, SPSS, Stata, MySQL, Apache, Hadoop, MapReduce, Dremel, Spark, Hive, Matlab, Python, R	Directions for new analytical research methods: (1) analytics for optimizing marketing-mix spending in a data-rich environment, (2) analytics for personalization, and (3) analytics in the context of customers' privacy and data security
Wilson	2010	*Journal of Business and Industrial Marketing*	Technical	Website performance	Clickstream data and website performance	B2B strategy, ecommerce	Web traffic conversion funnels	Experiment website usage data		The analysis of clickstream data using web analytics procedures as a useful tool in the enhancement of a B2B web site
Xu et al.	2016	*Journal of Business Research*	Conceptual	Marketing analytics	Analytics and new product success	Knowledge fusion, complexity	Theoretical			Knowledge fusion taxonomy to understand the relationships among traditional marketing analytics (TMA), big data analytics (BDA), and new product success (NPS)

Table 6 Theme Cluster Correlations

	Cluster 1	1	2	3	4	5
1	Chandrasekaran et al. (2017)					
2	Coursaris et al. (2016)	0.213				
3	Culotta and Cutler (2016)	0.011	0.370			
4	Kumar et al. (2017)	0.225	0.099	0.048		
5	Martens et al. (2016)	−0.046	0.152	0.098	−0.028	
6	Netzer et al. (2012)	0.125	−0.046	−0.057	0.137	−0.057

	Cluster 2	1	2	3	4	5	6	7	8	9	10	11
1	Bijmolt et al. (2010)											
2	Chung et al. (2016)	0.031										
3	Fluss (2010)	0.255	−0.032									
4	Furness (2011)	0.168	−0.032	−0.039								
5	Hofacker et al. (2016)	0.172	−0.040	0.237	−0.049							
6	Krush et al. (2016)	0.023	−0.061	0.124	0.124	0.071						
7	Kumar et al. (2016a, b	0.032	0.188	0.232	−0.073	0.161	0.093					
8	Martin and Murphy (2017)	0.120	−0.037	0.256	0.256	0.192	0.259	0.092				
9	Miles (2014)	0.147	0.092	0.055	0.171	0.116	0.283	0.090	0.131			
10	Ozimek (2010)	0.084	−0.042	0.220	0.220	0.160	0.292	0.144	0.414	0.102		
11	Persson and Ryals (2014)	0.222	−0.035	0.440	−0.043	0.345	0.103	0.110	0.231	0.041	0.197	
12	Wilson (2010)	0.083	0.312	0.130	−0.073	0.077	0.035	0.222	0.003	0.022	−0.016	0.204

	Cluster 3	1	2	3	4	5	6	7
1	Bradlow et al. (2017)							
2	Germann et al. (2014)	0.100						
3	Huang and Rust (2017)	0.180	0.220					
4	Järvinen and Karjaluoto (2015)	0.116	0.171	0.102				
5	Jobs et al. (2015)	0.124	0.380	0.497	0.116			
6	Lau et al. (2014)	0.124	0.237	0.160	0.212	0.175		
7	Wedel and Kannan (2016)	0.084	0.111	0.046	0.261	0.059	0.296	
8	Xu et al. (2016)	0.066	0.182	0.206	0.231	0.125	0.225	0.079

	Cluster 4	1	2	3	4	5	6	7	8	9	10
1	Atwong (2015)										
2	Hair Jr. (2007)	0.288									
3	Ho et al. (2010)	0.431	0.330								
4	Kerr and Kelly (2017)	0.532	0.256	0.390							
5	Liu et al. (2016)	−0.044	−0.057	−0.040	−0.049						
6	Moe and Schweidel (2017)	−0.047	−0.060	−0.042	−0.052	0.273					
7	Nair et al. (2017)	0.288	0.210	0.330	0.256	0.441	0.296				
8	Quinn et al. (2016)	−0.049	0.050	−0.044	0.206	−0.067	−0.071	−0.063			
9	Ringel and Skiera (2016)	0.059	−0.078	0.079	−0.067	0.370	0.344	0.305	−0.009		

Table 6 (continued)

	Cluster 4	1	2	3	4	5	6	7	8	9	10
10	Trusov et al. (2016)	0.085	−0.066	−0.046	0.068	0.445	0.220	0.370	−0.078	0.221	
11	Vorvoreanu et al. (2013)	−0.033	−0.042	−0.029	−0.036	−0.044	−0.047	−0.042	0.235	0.059	−0.052

	Cluster 5	1	2	3	4	5	6	7
1	Chaffey and Patron (2012)							
2	Hanssens and Pauwels (2016)	0.031						
3	Hanssens et al. (2014)	0.097	0.137					
4	Hauser (2007)	0.395	0.009	0.047				
5	Kumar et al. (2016a, b)	0.206	0.009	0.155	0.413			
6	Maklan et al. (2015)	0.358	−0.034	0.216	0.154	0.154		
7	Roberts et al. (2014)	0.220	0.203	0.118	0.175	0.175	0.099	
8	Sridhar et al. (2017)	−0.081	0.183	0.095	0.271	0.271	0.188	0.403

	Cluster 6	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Aggarwal et al. (2009)																
2	Alcaraz (2014)	−0.020															
3	Corrigan et al. (2014)	0.080	−0.017														
4	Côrte−Real et al. (2017)	0.068	−0.018	−0.050													
5	Erevelles et al. (2016)	0.136	−0.023	0.054	0.043												
6	Germann et al. (2013)	0.057	−0.020	−0.053	0.317	0.033											
7	Gunasekaran et al. (2017)	−0.057	−0.018	−0.050	0.210	0.043	0.192										
8	Hoppner and Griffith (2015)	−0.057	−0.018	−0.050	0.078	0.152	0.068	0.078									
9	Jobs et al. (2016)	−0.057	−0.018	0.091	0.078	0.261	−0.057	−0.053	−0.053								
10	LaPointe (2012)	−0.040	0.495	−0.035	0.147	0.106	0.134	0.147	0.147	−0.037							
11	Leventhal (2010)	−0.034	−0.011	−0.030	−0.032	0.310	−0.034	−0.032	0.179	0.179	−0.022						
12	Lilien (2016)	−0.060	−0.020	−0.053	0.317	0.033	0.175	0.192	0.068	0.068	0.134	−0.034					
13	Motamarri et al. (2017)	0.057	−0.020	−0.053	0.068	0.136	0.057	−0.057	−0.057	−0.057	0.134	−0.034	0.057				
14	Pauwels (2015)	−0.082	−0.027	0.132	0.114	0.062	0.008	0.114	0.210	0.018	0.213	−0.047	0.008	0.008			
15	Petersen et al. (2009)	0.193	−0.035	0.159	−0.021	0.138	0.043	0.058	−0.021	−0.100	−0.070	0.067	0.043	0.043	−0.088		
16	Saboo et al. (2016)	−0.070	−0.023	−0.062	−0.066	−0.082	−0.070	−0.066	−0.066	−0.066	0.106	−0.040	−0.070	0.136	−0.017	0.007	
17	Salehan and Kim (2016)	0.019	0.019	0.041	0.131	0.163	0.019	0.131	0.233	0.030	0.092	−0.043	0.116	−0.077	0.264	−0.013	0.079

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