

“Embracing AI and Big Data in customer journey mapping: from literature review to a theoretical framework”

AUTHORS	Mario D'Arco  https://orcid.org/0000-0001-9564-6960 Letizia Lo Presti  https://orcid.org/0000-0002-6077-8434 Vittoria Marino  https://orcid.org/0000-0002-3799-8770 Riccardo Resciniti
ARTICLE INFO	Mario D'Arco , Letizia Lo Presti, Vittoria Marino and Riccardo Resciniti (2019). Embracing AI and Big Data in customer journey mapping: from literature review to a theoretical framework. <i>Innovative Marketing</i> , 15(4), 102-115. doi: 10.21511/im.15(4).2019.09
DOI	http://dx.doi.org/10.21511/im.15(4).2019.09
RELEASED ON	Thursday, 19 December 2019
RECEIVED ON	Wednesday, 04 December 2019
ACCEPTED ON	Wednesday, 18 December 2019
LICENSE	 This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Innovative Marketing "
ISSN PRINT	1814-2427
ISSN ONLINE	1816-6326
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

66



NUMBER OF FIGURES

4



NUMBER OF TABLES

2

© The author(s) 2025. This publication is an open access article.



BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

Received on: 4th of December, 2019
Accepted on: 18th of December, 2019

© Mario D'Arco,
Letizia Lo Presti, Vittoria Marino,
Riccardo Resciniti, 2019

Mario D'Arco, Ph.D. in Management
and Information Technology,
Department of Business Science
- Management and Innovation
Systems/DISA-MIS, University of
Salerno, Italy.

Letizia Lo Presti, Research Associate
in Management, Department of Law
and Economics, University of Rome
Unitelma Sapienza, Italy.

Vittoria Marino, Associate Professor
in Marketing, Department of
Business Science - Management
and Innovation Systems/DISA-MIS,
University of Salerno, Italy.

Riccardo Resciniti, Full Professor
in Marketing, Department of Law,
Economics, Management and
Quantitative Methods, University of
Sannio, Italy.



This is an Open Access article,
distributed under the terms of the
[Creative Commons Attribution 4.0
International license](https://creativecommons.org/licenses/by/4.0/), which permits
unrestricted re-use, distribution,
and reproduction in any medium,
provided the original work is properly
cited.

Mario D'Arco (Italy), Letizia Lo Presti (Italy), Vittoria Marino (Italy),
Riccardo Resciniti (Italy)

EMBRACING AI AND BIG DATA IN CUSTOMER JOURNEY MAPPING: FROM LITERATURE REVIEW TO A THEORETICAL FRAMEWORK

Abstract

Nowadays, Big Data and Artificial Intelligence (AI) play an important role in different functional areas of marketing. Starting from this assumption, the main objective of this theoretical paper is to better understand the relationship between Big Data, AI, and customer journey mapping. For this purpose, the authors revised the extant literature on the impact of Big Data and AI on marketing practices to illustrate how such data analytics tools can increase the marketing performance and reduce the complexity of the pattern of consumer activity. The results of this research offer some interesting ideas for marketing managers. The proposed Big Data and AI framework to explore and manage the customer journey illustrates how the combined use of Big Data and AI analytics tools can offer effective support to decision-making systems and reduce the risk of bad marketing decision. Specifically, the authors suggest ten main areas of application of Big Data and AI technologies concerning the customer journey mapping. Each one supports a specific task, such as (1) customer profiling; (2) promotion strategy; (3) client acquisition; (4) ad targeting; (5) demand forecasting; (6) pricing strategy; (7) purchase history; (8) predictive analytics; (9) monitor consumer sentiments; and (10) customer relationship management (CRM) activities.

Keywords

consumer analytics, data-driven, decision support
systems, marketing analytics

JEL Classification

M15, M30, M31

INTRODUCTION

In recent years, the word "Big Data" has become increasingly popular. Both academics and non-academics use this term to designate large volumes of extensively varied data that are generated, captured, and processed at high velocity (Laney, 2001). In concomitance with the rise of Big Data technologies, Artificial Intelligence (AI) is being revitalized and has again become an appealing topic for research. According to Duan, Edwards, and Dwivedi (2019), the term AI is used to designate "the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks" (p. 63). AI tools can support the processing of large amounts of data and turn them into useful information.

As highlighted by Huang (2019), Big Data and AI are widely used in many different fields, "such as robotics, speech recognition, image recognition, machine translation, automatic response, natural language processing and automatic driving" (p. 165). Furthermore, Big Data and AI are transforming the business environment and many areas of marketing. The correlation between these methods and marketing

discipline is related to the technological progress, which enables broad implementation of Big Data and AI applications in practice, such as marketing analytics toolbox based on machine learning (Sun, Huang, Wu, Song, & Wunsch, 2017; Choi, Wallace, & Wang, 2018).

Since consumer behavior is being influenced more and more by digital applications, the generation and availability of data is growing at a faster rate than ever before. The convergence of Big Data, AI, and marketing can create greater customer value and several advantages for companies. For example, marketers and organizations can use Big Data-related analytics techniques to gain important information about transactions, purchase quantities, and customer credentials (Thackeray, Neiger, Hanson, & McKenzie, 2008). Additionally, data are useful to better understand the consumer behavior, purchase preferences, and marketing trends (Yin & Kaynak, 2015). Furthermore, company management, supported by Big Data analytics tools, can make better decision about production quantity, stock control and inventory, sales forecasting, logistics optimization, supplier coordination, and purchase channels selection (Schneider & Gupta, 2016; Bradlow, Gangwar, Kopalle, & Voleti, 2017).

Based on these premises, it is important to investigate how Big Data and AI should be leveraged strategically to plan the customer journey. Customer journey is a metaphor to conceptualize the customer experience during the purchase cycle. Specifically, both researchers and practitioners with this metaphor designate the sequence of customer's direct and indirect encounters with a specific product, service, or brand (Meyer & Schwager, 2007). Such encounters are mediated by different types of touchpoints, namely, online and offline channels that affect the customer's experiences and purchase intentions.

As highlighted by Lemon and Verhoef (2016), customer journey consists of three phases: the prepurchase phase, the purchase phase, and the postpurchase phase. The first phase encompasses the behaviors such as need recognition, search, and the formation of consideration set assembled from exposure to information found on the web, ads, user-generated contents, words of mouth, or other stimuli. In the second phase, consumers, based on the information provided, select what they want and proceed with the payment. The third phase is characterized by such behaviors as usage and consumption, and positive or negative postpurchase engagement phenomena.

The main objective of this theoretical paper is to systematize the relationship between Big Data, AI, and customer journey map. Starting from an exploration of the extant literature concerning the impact of Big Data and AI on marketing practices, the authors aim at developing a theoretical framework focused on strategic use of Big Data and AI across the customer journey mapping. Specifically, the findings reveal how such data analytics tools can increase the marketing performance (i.e., media spend and touch point selection (see Edelman, 2010), and reduce the complexity of the purchase patterns and consumer activities.

1. THEORETICAL BASIS

As highlighted by Fink (2005), "A literature review is a systematic, explicit, and reproducible design for identifying, evaluating, and interpreting the existing body of recorded documents" (p. 3). Literature reviews are conducted for a variety of purposes. First, they present in a rigorous way the knowledge already available on a specific topic. Second, the collection of previous works helps the researchers to identify new patterns and themes that can contribute to theory development.

In this research, the purpose of the literature review is (1) to define those existing research concerning the usefulness of Big Data and AI adoption in the marketing, (2) to provide a framework for implementing and managing these technologies to understand the customer journey.

Due to the existence in the academic literature of a large number of articles about Big Data and AI, we followed a specific inclusion/exclusion protocol. Firstly, publications were selected from 2014 onwards, since as highlighted by Grover and Kar

(2017) before this date, the number of publications focusing on the benefits of Big Data for marketers and organizations is not so prominent. Secondly, we focused on the articles that appeared in peer-reviewed academic journals, excluding other types of publications, such as books or conference proceedings. Studies that were not written in English were also excluded, as well as those ones that were not published in business and management area.

Searches were carried out on Scopus and Web of Science databases during the period from July 1, 2019 to July 8, 2019. We selected the two aforementioned databases because they are considered the most exhaustive sources of scholarly articles and academic productions in the social sciences (Vieira & Gomes, 2009). At this stage of the review process, we selected the articles by reading the title, abstract and, in some cases, the entire document.

Table 1 illustrates the combinations of keywords and the limitations performed in the Scopus database. The first combination was determined to capture the articles about the use of Big Data in the marketing area. Using this combination, 181 articles were identified, but only 26 documents satisfied the purpose of this research. The second combination was applied to capture the articles about the use of AI in marketing practices. The number of articles identified was 50, but only 15 were selected. The third combination was introduced to extract those documents concerning the relationship between Big Data and customer journey. The total number of articles identified was two, but only one article was selected for further analysis. Finally, the fourth combination was applied to capture the articles about the relationship between AI and customer journey. Two documents emerged from the search. Both documents were considered relevant for this study.

The same combinations of keywords and limitations were used to perform the searches in the Web of Science database (see Table 2). With regard to the first combination, the number of documents identified was 128, but only 21 articles were selected. The second combination, introduced to identify those articles concerning the role of the AI in the marketing functions, revealed 11 documents, but only three were selected for further analysis. The total number of articles identified with the third combination was three, but only two were selected. Finally, with regard to the fourth combination concerning the relationship between artificial intelligence and customer journey, the total number of articles identified was one, but this document was discarded because it did not fit with the topic of our research.

After this searching process, 78 articles in the literature were identified. The next step consisted of manually cleaning the dataset from duplications. The final dataset included 43 articles considered as capable of helping the researchers to better understand the role of Big Data and AI in specific marketing practices such as customer journey mapping. Specifically, 26 articles deal with topics related to the domain of Big Data, other 16 articles explore the relationship between AI and marketing, and one article focuses strictly on the relationship between Big Data and customer journey.

The 43 studies selected for the literature review were subjected to a descriptive analysis in order to collect the information about the distribution of publication over time, the distribution of publications by journals, and the recurring terms in the titles and abstracts.

The year wise publication of the documents selected for this literature review is given in Figure 1. Only eight papers were published in the period 2014–2015. The majority of publications, in fact,

Table 1. Combination of keywords and limitations in the Scopus database

Searches	Combination of keywords and limitations
First combination	TITLE-ABS-KEY ("Big Data" AND "marketing") AND DOCTYPE (ar) AND PUBYEAR > 2013 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (LANGUAGE, "English"))
Second combination	TITLE-ABS-KEY ("Artificial Intelligence" AND "marketing") AND DOCTYPE (ar) AND PUBYEAR > 2013 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (LANGUAGE, "English"))
Third combination	TITLE-ABS-KEY ("Big Data" AND "customer journey") AND DOCTYPE (ar) AND PUBYEAR > 2013 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (LANGUAGE, "English"))
Fourth combination	TITLE-ABS-KEY ("Artificial Intelligence" AND "customer journey") AND DOCTYPE (ar) AND PUBYEAR > 2013 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (LANGUAGE, "English"))

Table 2. Combination of keywords and limitations in the Web of Science database

Searches	Combination of keywords and limitations
First combination	TOPIC: (“Big Data” AND “marketing”) Refined by: LANGUAGES: (ENGLISH) AND RESEARCH AREAS: (BUSINESS ECONOMICS) AND DOCUMENT TYPES: (ARTICLE) AND WEB OF SCIENCE CATEGORIES: (BUSINESS OR MANAGEMENT) Timespan: 2014–2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI.
Second combination	TOPIC: (“Artificial Intelligence” AND “marketing”) Refined by: LANGUAGES: (ENGLISH) AND RESEARCH AREAS: (BUSINESS ECONOMICS) AND DOCUMENT TYPES: (ARTICLE) AND WEB OF SCIENCE CATEGORIES: (BUSINESS) Timespan: 2014–2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI.
Third combination	TOPIC: (“Big Data” AND “customer journey”) Refined by: LANGUAGES: (ENGLISH) AND RESEARCH AREAS: (BUSINESS ECONOMICS) AND DOCUMENT TYPES: (ARTICLE) AND WEB OF SCIENCE CATEGORIES: (BUSINESS OR MANAGEMENT) Timespan: 2014–2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI.
Fourth combination	TOPIC: (“Artificial Intelligence” AND “customer journey”) Refined by: RESEARCH AREAS: (BUSINESS ECONOMICS) AND DOCUMENT TYPES: (ARTICLE) AND WEB OF SCIENCE CATEGORIES: (MANAGEMENT) Timespan: 2014–2019. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI.

appear after 2015, this means that in recent years, there has been growing interest in topics such as the adoption of Big Data and AI tools in the marketing area. The major number of articles about the relationship between Big Data and marketing were published in 2016. Conversely, in the period from January 1, 2019 to July 8, 2019, researches paid significant attention to AI adoption in the marketing. Specifically, in this time-frame, seven articles were published.

With regard to the journals that contributed to the development of such issue, it is possible to notice that 43 collected articles appear in 36 different academic journals (see Figure 2). The journals with the major number of articles are Applied Marketing Analytics (3), Journal of Destination Marketing and Management (3), Decision Support Systems (2), Journal of Travel and Tourism Marketing (2), and Journal of Travel Research (2).

The publications collected for this review have appeared principally in the journals focusing on

substantive issues in the domain of marketing and management, such as theories in the support of enhanced decision-making, aspects concerning the measurement and analysis of marketing performance to improve its effectiveness, and researches in the field of manufacturing operations management. It is interesting to note that six journals deal with tourism and hospitality topics. The importance given to the application of Big Data analytics in the tourism industry is also confirmed by the text analysis of the titles and abstracts of the collected documents for the literature review. The word cloud used to illustrate those terms with the higher frequency reveals the presence of words such as “tourism,” “travels,” and “tourists” (see Figure 3). Other prominent words that appear in the text corpus are “analysis,” “analytics,” “customer,” “knowledge,” and “management.” This means that the main researches about how Big Data and AI can help marketing are focusing on themes like customer analytics, and the importance of knowledge in decision-making.

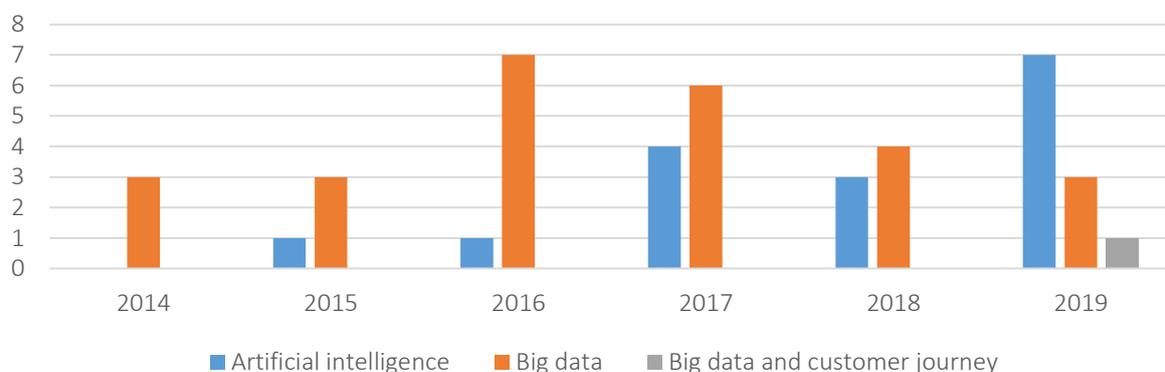


Figure 1. Distribution of publications by year

ing level (i.e., Wiencierz & Röttger, 2016). Fourthly, this literature review does not investigate separately Big Data and AI (i.e., Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; Nassirtoussi, Aghabozorgi, Wah, & Ngo, 2014), but its main objective is to combine these two technologies in order to understand how they can be used by marketers to analyze and model the customer journey. Reviewing the existing literature, the authors found out that marketers and organizations can use Big Data analytics and AI systems to collect the consumer data from many sources and deliver the important insights to support marketing decision-making. Specifically, several areas of application were identified and further described.

2.1. Customer profiling

Marketers can use Big Data and AI to support customer profiling. The customer profiling is possible thanks to the enormous availability of data that individuals voluntarily and involuntarily leave in almost all their online actions. Verhoef et al. (2017) highlight that thanks to the advances in information and communication technology, consumers are capable of connecting with three components: (1) People (other consumers and firms' representatives), (2) Objects, and (3) their Physical environments. This framework called POP allows both researchers and practitioners to create the customer profiles by aggregating and synthesizing very heterogeneous data coming from different sources, such as environmental sensors, smartphones, and wearables. According to Trusov, Ma, and Jamal (2016), processing the massive records of user online activity coming from search engines, web visits, and display advertising enables to identify the consumer behavioral profiles. Unlike traditional retailer, pure-click companies such as Google, Facebook, eBay/PayPal, and Amazon have at their disposal specific apps that help them to profile their customers and use data-driven marketing to make specific decision (Pousttchi & Hufenbach, 2014). Liu, Huang, Bao, and Chen (2019) highlight that user-generated content (UGC), that is, "media content created by users to share information and/or opinions with other users" (Tang, Fang, & Feng, 2014, p. 41), such as online reviews in the tourism sector, represents another source of information about consumers. Utilizing lexicon filtering and machine learning enables to conduct a

sentiment analysis of Big Data in the form of UGC and collect the information on a specific theme. Finally, a decision support system (DSS) that uses of AI techniques can help managers to improve the client acquisition and development. For example, the main purpose of the BIG CHASE, a DSS tool experimented in the financial context by Banco Santander S.A., as highlighted by Quijano-Sanchez and Liberatore (2017), using the social structure obtained from client relations and operations, is to identify "the most reliable sequence of clients that a manager should contact to reach a defined target (a client or a non-client)" (p. 51).

2.2. Promotion strategies

The information obtained from customer profiling can be used to support sales promotion and other promotion strategies (Buhalis & Foerste, 2015). In order to reach potential customers, Miralles-Pechuán, Ponce, and Martínez-Villaseñor (2018) suggest the adoption of micro-targeting techniques based on a machine-learning based click-through rate model to program the display advertising campaigns. The information retrieved from the web and processed through the specific algorithm proposed by Miralles-Pechuan et al. (2018) is useful to configure the parameters of a campaign, such as age, time, browser, operating system, and device type. In this way, advertisers can increase the performance of online publicity (i.e., more conversions) by selecting a very specific public.

2.3. Demand forecasting

Companies can utilize Big Data and AI to forecast the sales of products. Some researches (Chong, Li, Ngai, Ch'ng, & Lee, 2016; Chong, Ch'ng, Liu, & Li, 2017; Park, Yang, & Wang, 2019) highlight the importance to investigate online reviews, sentiments, customer questions and answers, and online promotional variables, such as free delivery and price discount offerings. The information obtained from the analysis of this type of data can be used for developing the models capable of predicting the sales products online. Other information concerning the demand forecasting can be obtained from the analysis of the web traffic volume data. Specifically, Yang et al. (2014) found out that in the tourism sector, it is possible to predict the demand

for hotel rooms at a destination, and potentially even local businesses' future revenue and performance, analyzing web traffic data. Huge amount of data from consumers can be also collected through mobile apps. According to Trabucchi, Buganza, and Pellizzoni (2017), "this data represents a powerful new source of value" (p. 43), because companies can use them to predict consumer product demands and "to build deep understanding of customers' needs and wants, and of how products are used" (p. 50).

2.4. New product/service development

Cao, Duan, and El Banna (2019) show that Big Data can support the product development process. Generally, product development is a very long and delicate process that requires as much information as possible on the target markets' shopping preferences. One of the main risks for companies belonging to sectors with a high rate of innovation is the long time it takes to develop a new product. The use of Big Data analytics tools offers the opportunity to reduce the product development time by 20 to 50% because it allows the marketing managers to collect the insights about the customers' needs and expectations, as well as competitors' new designs, and key product features. Xu, Frankwick, and Ramirez (2016) highlight that by adopting Big Data analytics tools, firms can determine if a new product will become successful. For example, Netflix examines vast quantities of real-time data produced by its users to predict if a pilot will become a successful new show. To understand the consumer preferences regarding the different features and different configurations of a new product, the most commonly used method is conjoint analysis. The results obtained from this method sometimes do not provide the clear indications. That is why López, Maldonado, and Montoya (2017) introduced a novel choice-based conjoint approach based on Support Vector Machines, a branch of AI. This novel approach has "superior predictive performance and computational efficiency [...] Additionally, the method can be further extended to deal with clusters of consumers instead of an unimodal representation of preference heterogeneity" (Lopez et al., 2017, p. 15). Kühl et al. (2019) underline the importance to monitor on social media the consumer needs and

wants in order to design customer-centric products and services and control marketing activities. Specifically, the authors stated that it is possible to utilize machine learning algorithms "to detect characteristics ("needs") in n instances ("tweets")" (p. 14). Big Data analytics, as highlighted by some researchers (Marine-Roig & Clavé, 2105; Önder, 2017), can be adopted in the tourism sector to predict the travels destination too. Tourism and hospitality industry can use this information to understand the tourist trend, create the specific travel product, and provide the sufficient local transportation options.

2.5. Pricing strategy

According to Danaher, Huang, Smith, and Telang (2014) Big Data analytics techniques can be adopted to optimize the pricing strategies of specific products that are influenced by periods, trends, and fashions, for example, in digital music market, it is possible to determine own- and cross-price elasticities for songs and albums. Both Weber and Schütt (2019) and Wirth (2018) are interested in the potential of AI to inform the marketing decisions with regard to four areas of the marketing mix, that is, "product," "price," "place", and "promotion." Specifically, according to Wirth (2018) "AI is powerful enough to inform decisions such as will person A like product B and will consumer X purchase the car Y at price Z" (p. 436). Thanks to AI, retail is changing. For example, using the automatic algorithms is possible to perform such an operation as dynamic pricing, namely, a pricing strategy in which companies adjust the prices for products or services in real-time based on the current market demand. This model of calculating the price would be difficult for a human being, but with the help of AI this task can be automated and completed very quickly.

2.6. Distribution choices

As highlighted by Wu, Ho, Lam, and Ip (2015) AI approach can be adopted to analyze the competitiveness and profitability of specific distribution channels. For example, the authors propose a franchising decision support system capable of collecting the data from the external environment and help the franchisor in formulating the marketing strategies.

2.7. Customer service

Big Data analytics can help the firms to understand how to serve customers better. Specifically, from a service delivery point of view, Big Data analytics can help the frontline employees to interact with customers (Motamarri, Akter, & Yanamandram, 2017). Services are complex to define because they have many dimensions, and differ from each other. For example, some services require low interactions and low customization; others, instead, are based on the customer's active involvement. Companies, to better understand the consumers' preferences and develop the schemes of service contexts that facilitate the frontline employees in service delivery, can use the information collected from the web (i.e., internet searches, click stream, Facebook chats, Twitter exchanges, peer networking sites, etc.). Nevertheless, as highlighted by Montamarri et al. (2017), one of the risks is to violate the consumers' privacy.

Pradana, Sing, and Kumar (2017) suggest that companies, to facilitate the interaction with the consumers on the corporate or e-commerce websites, can utilize Intelligent Conversational Bot, that is, "an implementation of Artificial Intelligence (AI) in a form of software or application which users can interact by having conversations" (Pradana et al., 2017, p. 265). Such a tool can act as a salesperson to help the companies advertise their products. Furthermore, consumers can pose simple questions to the bot in order to gain specific information.

2.8. Analysis of consumer behavior

The emergence of user-generated content on the internet has provided a new source of data concerning the human behavior. As highlighted by Hofacker, Malthouse, and Sultan (2016), consumers provide on social media information about their relationship with a brand or a company. An examination of what is being said online can help the marketers to identify the warning signs of consumer dissatisfaction, such as negative word of mouth, or complaints about the product, the service or the brand in general. Furthermore, text mining and other emerging technologies, such as Automated Sentiment Analysis, offer the possibility to measure the customer satisfaction (i.e.,

Kirilenko, Stepchenkova, Kim, & Li, 2018; Park, Ok, & Chae, 2016; Park et al., 2019), loyalty and commitment (Hofacker et al., 2016). McColl-Kennedy et al. (2019) introduce a conceptual framework for measuring and understanding the customer experience that takes into consideration the customer perspective, such as emotions (i.e., joy, love, surprise, anger, sadness, and fear), and cognitive response to the different touchpoint that occur during the purchase decision journey (i.e., complaints, compliments, and suggestions). Specifically, they recommend to utilize linguistics-based text mining model to capture the details about consumers that matter for making the marketing decisions.

2.9. Customer relationship management

The online contexts create the challenges and opportunities for customer relationship management (CRM). For example, e-commerce, AI technologies (i.e., chatbots, avatars, and virtual assistants), and Big Data analytics used for generating the enhanced customer insights that can be used to personalize the products and services constitute an important building block for online relationships (Steinhoff, Arli, Weaven, & Kozlenkova, 2019). George and Wakefield (2018) highlight that both marketers and researchers should use Big Data "to better understand how consumers respond to contact strategies over time" (p. 113), such as direct mail, email, telephone and salesperson contacts. Specifically, service firms can adopt Big Data analytics to leverage useful information to more effectively attract, serve, and retain the customers.

2.10. Brand analysis

Brand managers and marketers can adopt the intelligent systems based on fuzzy logic, an area of AI, for modelling and evaluating the branding strategies. For example, Identimod is a decision support system proposed by Chica, Córdón, Damas, Iglesias, and Mingot (2016) appropriate to analyze the intangible variables related to the brands (i.e., brand loyalty, brand awareness, perceived quality, brand associations, and other proprietary assets). Putting all the available linguistic or numerical data in the system, Identimod can simulate different scenarios and support the marketing decision-making. For example, this

technology can help brand managers to take important decision such as keep the current brand image, rebrand the company, restyle the current brand, reduce the size of a brand portfolio, etc.

3. DISCUSSION

The task of understanding the customer journey is complex because there are many factors and variables that need to be considered (i.e., sociodemographic and psychographic characteristics, consumer buying motives, duration of the journey, buying frequency, number of the different touchpoints used during the search, etc.). Fortunately, according to Erevelles, Fukawa, and Swayne (2015), consumers have become an “incessant generator of both structured, transactional data as well as contemporary unstructured behavioral data” (p. 898). Therefore, with the help of Big Data and AI, marketers and organizations can collect the consumer data from many sources and deliver the important insights about his/her path to purchase.

Assuming that the customer journey consists of three different phases, namely prepurchase, purchase, and postpurchase (Lemon & Verhoef, 2016), the proposed framework illustrates the type of data that researchers or practitioners can collect from different sources to better understand and manage the customer journey at any stage. Furthermore, the framework shows different specific tasks concerning the customer journey modelling that can be improved by Big Data and AI utilization (see Figure 4).

The prepurchase phase includes “customer’s entire experience before purchase” (Lemon & Verhoef, 2016, p. 76). Generally, the “journey” starts with the consumer intention to purchase something he/she needs or desires. If in the traditional offline world, the consumer had trouble finding the alternatives, nowadays, with the explosion of the digital markets, the problem has too many alternatives (Hofacker et al., 2016). Therefore, the customer decision process is not linear anymore, but it is iterative and sometimes very long. Thanks to Big Data analytics consumer search activities on website, e-commerce, and shopping app are recorded and ana-

lyzed (Trusov et al., 2016). Marketers can easily retrieve the information regarding which items have been searched, clicked on, added to a shopping cart or wish list, abandoned, or purchased. Furthermore, as highlighted by Hofacker et al. (2016), it is possible to know “which search terms attracted prospective customers from search engines, and whether it was a paid search term or an organic one” (p. 91). All the information collected at this stage can be used to create the customer profiles. Customer profiling will help the marketers to understand their customers, highlighting who they are, what their interests are, and what they want. This insight will help the companies to recognize their customer’s characteristics (demographics), and behavior (psychographics). In addition, collecting the customer data gives the researchers and practitioners the possibility to map the touchpoints that occur throughout the journey from the customers’ perspective. Having a better understanding of the customers helps the marketers to allocate their resources efficiently, such as advertising spend (Edelman, 2010) and ad targeting (Miralles-Pechuan et al., 2018). Furthermore, leveraging customer data organization is useful to know each customer more individually and deliver better value to the customers because they get things they want. This means happier customers, reduced client churn, and bigger profits. Finally, accessing to a vast and growing ocean of data retailers have the ability to quickly gain the information that can be utilized for pricing strategies. For example, the automatic tracking of metrics such as page views, cart abandonment, and conversion rates can signal to retailers if their pricing strategy is wrong.

Purchase is the second phase of the customer journey. According to Lemon and Verhoef (2016), this phase “covers all customer interactions with the brand and its environment during the purchase event itself. It is characterized by behaviors such as choice, ordering, and payment” (p. 76). Generally, this phase of the journey is “the most temporally compressed” (Lemon & Verhoef, 2016, p. 76), but it is reach of detailed data about transactions, geographic location of the client, influence of price on customer’s purchase decision, and bestseller products. Choosing the right technology, data collected

Source: Built by the authors.

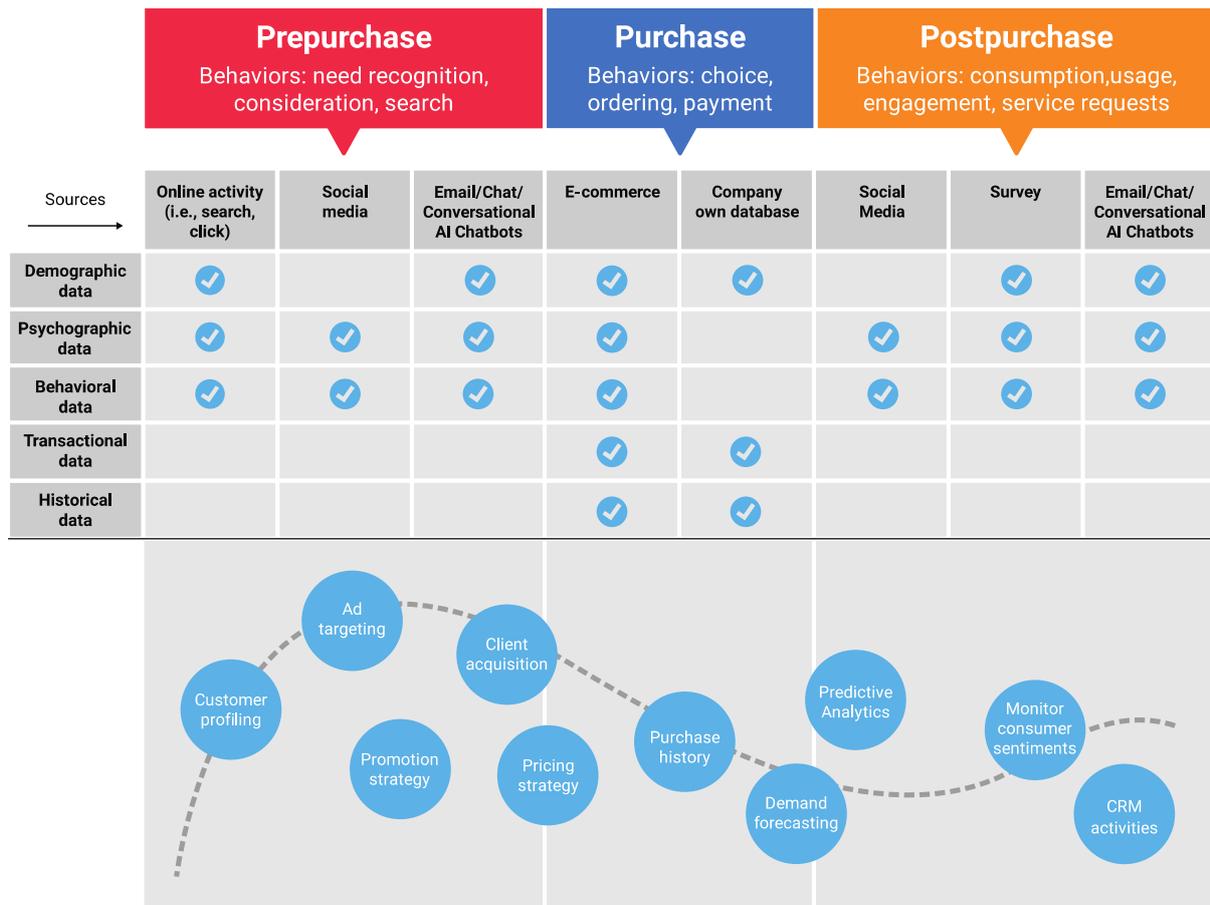


Figure 4. Big Data and AI framework for the customer journey mapping

during this phase of the journey can be analyzed “in terms of purchase history, credit and return history available” (Chauhan, Mahajan, & Lohare, 2017, p. 486). Therefore, all the information collected in this phase is useful for customer profiling, demand forecasting and profit optimization. Such data, in fact, could be the source of a decision support system and help marketers to make better decision.

The postpurchase phase, as highlighted by Lemon and Verhoef (2016), “encompasses customer interactions with the brand and its environment following the actual purchase. This stage includes behaviors such as usage and consumption, post-purchase engagement, and service requests” (p. 76). Theoretically, this phase of the journey can last from the purchase to the end of the customer’s life. During this phase, customers “evaluate the gap between their expectations and their consumption experience during and after consumption” (Hofacker et

al., 2016, p. 92). Therefore, e-word of mouth, reviews, tweets, shared pictures or videos about a product represent a large amount of data capable of producing the knowledge about customer satisfaction, commitment, and attitudinal loyalty. For example, if people complain about a product/service on social media or on a review site, marketers should treat this data as the material to investigate. Understanding how consumer feel about the product features or the service experience, if they are satisfied or not, is fundamental in the development of sustainable competitive advantage of brands and companies. During this phase of the customer journey, Big Data analytics and AI can be used to monitor the consumer sentiments (Marine-Roig & Clavé, 2015; Culotta & Cutler, 2016; Kirilenko et al., 2018; Buhalis & Sinarta, 2019), or to automatically quantify the customer needs from social media (Kühl, Mühlthaler, & Goutier, 2019). In addition, during this phase, marketers can utilize Intelligent Conversational Bot (Pradana

et al., 2017) to enhance the customer service and simultaneously collect the useful data. Finally, as highlighted by George and Wakefield (2017), Big Data analytics can be used to plan the CRM strategy. For example, implementing the data into a predictive model could help the marketers readily identify the at-risk customers and adopt the specific strategies in reactions.

CONCLUSION

As we could conclude from the literature review carried out in this article, Big Data analytics tools and AI find large application in the marketing field, especially in the domain of customer analytics and decision support systems. An interesting observation was noted that only two studies (i.e., George & Wakefield, 2017; McColl-Kennedy, 2019) deal about how Big Data analytics and AI can be applied to explore and manage the customer journey. Therefore, the theoretical contribution of this paper consists of proposing a Big Data and AI framework (Figure 4) capable of illustrating how such technologies can be used for customer journey modelling. Specifically, we suggest ten main areas of application of Big Data and AI technologies in the customer journey modelling: (1) customer profiling; (2) promotion strategy; (3) client acquisition; (4) ad targeting; (5) demand forecasting; (6) pricing strategy; (7) purchase history; (8) predictive analytics; (9) monitor consumer sentiments; and (10) customer relationship management (CRM) activities. Each one supports a specific task, such as understanding the customer needs and wants at each stage of the “journey” or at each touchpoint; identifying the different buyer personas in order to provide the specific pricing strategy or customer engagement solutions; collecting information to create better products or service, to improve the customer experience, and to make advertising more relevant.

The proposed framework poses a new perspective on Big Data and AI literature since it essentially focuses on the customer journey mapping. Furthermore, it can be very useful for managers and decision-makers. Creating a good customer journey represents one of the main sources of competitive advantage. Therefore, it is important for practitioners to learn how to turn the data into insights that can be used to solve the problems and improve their capabilities of increasing the customer value and competitive performance.

Future studies should explore more deeply the relationship between Big Data, AI and customer journey map. This is, in fact, a relatively unexplored area. Specifically, researchers should highlight the main technologies behind Big Data and AI, that is, the platforms or software useful to collect the data, analyze the data, and produce the knowledge to solve the complex problems.

REFERENCES

- Booth, D. (2019). Marketing analytics in the age of machine learning. *Applied Marketing Analytics*, 4(3), 214-221. Retrieved from <https://www.ingentaconnect.com/content/hsp/ama/2019/00000004/00000003/art00004>
- Bradlow, E. T., Gangwar, M., Kopal, P., & Voleti, S. (2017). The role of Big Data and predictive analytics in retailing. *Journal of Retailing*, 93(1), 79-95. <https://doi.org/10.1016/j.jretai.2016.12.004>
- Buhalis, D., & Foerste, M. (2015). SoCoMo marketing for travel and tourism: Empowering co-creation of value. *Journal of Destination Marketing and Management*, 4(3), 151-161. <https://doi.org/10.1016/j.jdmm.2015.04.001>
- Buhalis, D., & Sinarta, Y. (2019). Real-time co-creation and nowness service: lessons from tourism and hospitality. *Journal of Travel and Tourism Marketing*, 36(5), 563-582. <https://doi.org/10.1080/10548408.2019.1592059>
- Cao, G., Duan, Y., & El Banna, A. (2019). A dynamic capability view of marketing analytics: Evidence from UK firms. *Industrial Marketing Management*, 76, 72-83. <https://doi.org/10.1016/j.indmarman.2018.08.002>
- Chauhan, P., Mahajan, A., & Lohare, D. (2017). Role of Big Data in retail customer-centric marketing. *National Journal of Multidisciplinary Research and Development*, 2(3), 484-488. Retrieved from https://www.researchgate.net/publication/315471275_The_Role_of_Big_Data_and_Predictive_Analytics_in_Retailing

7. Chiang, L.-L. L., & Yang, C.-S. (2018). Does country-of-origin brand personality generate retail customer lifetime value? A Big Data analytics approach. *Technological Forecasting and Social Change*, 130, 177-187. <https://doi.org/10.1016/j.techfore.2017.06.034>
8. Chica, M., Cordon, O., Damas, S., Iglesias, V., & Mingot, J. (2016). Identimod: Modeling and managing brand value using soft computing. *Decision Support Systems*, 89, 41-55. <https://doi.org/10.1016/j.dss.2016.06.007>
9. Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big Data analytics in operations management. *Production and Operations Management*, 27(10), 1868-1883. <https://doi.org/10.1111/poms.12838>
10. Chong, A. Y. L., Ch'ng, E., Liu, M. J., & Li, B. (2017). Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews. *International Journal of Production Research*, 55(17), 5142-5156. <https://doi.org/10.1080/00207543.2015.1066519>
11. Chong, A. Y. L., Li, B., Ngai, E. W. T., Ch'ng, E., & Lee, F. (2016). Predicting online product sales via online reviews, sentiments, and promotion strategies: A Big Data architecture and neural network approach. *International Journal of Operations and Production Management*, 36(4), 358-383. <https://doi.org/10.1108/IJOPM-03-2015-0151>
12. Danaher, B., Huang, Y., Smith, M. D., & Telang, R. (2014). An empirical analysis of digital music bundling strategies. *Management Science*, 60(6), 1413-1433. <https://doi.org/10.1287/mnsc.2014.1958>
13. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data –evolution, challenges and research agenda. *International Journal of Information Management*, 48, 63-71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.021>
14. Edelman, D. C. (2010). Branding in the digital age. *Harvard Business Review*, 88(12), 62-69. Retrieved from <https://hbr.org/2010/12/branding-in-the-digital-age-youre-spending-your-money-in-all-the-wrong-places>
15. Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897-904. <http://dx.doi.org/10.1016/j.jbusres.2015.07.001>
16. Even, A. (2019). Analytics: Turning data into management gold. *Applied Marketing Analytics*, 4(4), 330-341. Retrieved from <https://medium.com/@even.alon/analytics-turning-data-into-management-gold-fee172191508>
17. Fan, S., Lau, R. Y., & Zhao, J. L. (2015). Demystifying Big Data analytics for business intelligence through the lens of marketing mix. *Big Data Research*, 2(1), 28-32. <https://doi.org/10.1016/j.bdr.2015.02.006>
18. Fink, A. (2005). *Conducting Research Literature Reviews: From the Internet to Paper* (2nd ed.). Thousand Oaks, California: Sage Publications. Retrieved from <https://us.sagepub.com/en-us/nam/conducting-research-literature-reviews/book259191>
19. Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How “Big Data” Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study. *International Journal of Production Economics*, 165, 234-246. <https://doi.org/10.1016/j.ijpe.2014.12.031>
20. Gardé, V. (2018). Digital audience management: Building and managing a robust data management platform for multi-channel targeting and personalisation throughout the customer journey. *Applied Marketing Analytics*, 4(2), 126-135. Retrieved from https://www.researchgate.net/publication/330161486_Digital_audience_management_Building_and_managing_a_robust_data_management_platform_for_multi-channel_targeting_and_personalisation_throughout_the_customer_journey
21. George, M., & Wakefield, K. L. (2018). Modeling the consumer journey for membership services. *Journal of Services Marketing*, 32(2), 113-125. <https://doi.org/10.1108/JSM-03-2017-0071>
22. Grover, P., & Kar, A. K. (2017). Big Data analytics: a review on theoretical contributions and tools used in literature. *Global Journal of Flexible Systems Management*, 18(3), 203-229. <https://doi.org/10.1007/s40171-017-0159-3>
23. Hofacker, C. F., Malthouse, E. C., & Sultan, F. (2016). Big Data and consumer behavior: imminent opportunities. *Journal of Consumer Marketing*, 33(2), 89-97. <https://doi.org/10.1108/JCM-04-2015-1399>
24. Huang, A. (2019). The Era of Artificial Intelligence and Big Data Provides Knowledge Services for the Publishing Industry in China. *Publishing Research Quarterly*, 35(1), 164-171. <https://doi.org/10.1007/s12109-018-9616-x>
25. Kirilenko, A. P., Stepchenkova, S. O., Kim, H., & Li, X. (2018). Automated Sentiment Analysis in Tourism: Comparison of Approaches. *Journal of Travel Research*, 57(8), 1012-1025. <https://doi.org/10.1177/0047287517729757>
26. Kühl, N., Mühlthaler, M., & Goutier, M. (2019) Supporting customer-oriented marketing with artificial intelligence: automatically quantifying customer needs from social media. *Electronic Markets*. <https://doi.org/10.1007/s12525-019-00351-0>
27. Laney, D. (2001). *3D Data management: controlling data volume, velocity, and variety*. Retrieved from <https://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf> (accessed on August 3, 2019).
28. Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69-96. <https://doi.org/10.1509/jm.15.0420>
29. Liu, P., & Yi, S.-P. (2017). Pricing policies of green supply chain

- considering targeted advertising and product green degree in the Big Data environment. *Journal of Cleaner Production*, 164, 1614-1622. <https://doi.org/10.1016/j.jclepro.2017.07.049>
30. Liu, Y., Huang, K., Bao, J., & Chen, K. (2019). Listen to the voices from home: An analysis of Chinese tourists' sentiments regarding Australian destinations. *Tourism Management*, 71, 337-347. <https://doi.org/10.1016/j.tourman.2018.10.004>
 31. López, J., Maldonado, S., & Montoya, R. (2017). Simultaneous preference estimation and heterogeneity control for choice-based conjoint via support vector machines. *Journal of the Operational Research Society*, 68(11), 1323-1334. <https://doi.org/10.1057/s41274-016-0013-6>
 32. Mariani, M., Baggio, R., Fuchs, M., & Höepken, W. (2018). Business intelligence and Big Data in hospitality and tourism: a systematic literature review. *International Journal of Contemporary Hospitality Management*, 30(12), 3514-3554. <https://doi.org/10.1108/IJCHM-07-2017-0461>
 33. Marine-Roig, E., & Clavé, S. A. (2015). Tourism analytics with massive user-generated content: A case study of Barcelona. *Journal of Destination Marketing and Management*, 4(3), 162-172. <https://doi.org/10.1016/j.jdmm.2015.06.004>
 34. McColl-Kennedy, J. R., Zaki, M., Lemon, K. N., Urmetzer, F., & Neely, A. (2019). Gaining Customer Experience Insights That Matter. *Journal of Service Research*, 22(1), 8-26. <https://doi.org/10.1177/1094670518812182>
 35. Meyer, C., & Schwager, A. (2007). Understanding customer experience. *Harvard Business Review*, 85(2), 116-126. Retrieved from <https://hbr.org/2007/02/understanding-customer-experience>
 36. Miralles-Pechuán, L., Ponce, H., & Martínez-Villaseñor, L. (2018). A novel methodology for optimizing display advertising campaigns using genetic algorithms. *Electronic Commerce Research and Applications*, 27, 39-51. <https://doi.org/10.1016/j.elerap.2017.11.004>
 37. Moncrief, W. C. (2017). Are sales as we know it dying ... or merely transforming? *Journal of Personal Selling and Sales Management*, 37(4), 271-279. <https://doi.org/10.1080/08853134.2017.1386110>
 38. Motamarri, S., Akter, S., & Yanamandram, V. (2017). Does Big Data analytics influence front-line employees in services marketing? *Business Process Management Journal*, 23(3), 623-644. <https://doi.org/10.1108/BPMJ-12-2015-0182>
 39. Nassirtoussi, A. K., Aghabozorgi, S., Wah, T. Y., & Ngo, D. C. L. (2014). Text mining for market prediction: A systematic review. *Expert Systems with Applications*, 41(16), 7653-7670. <https://doi.org/10.1016/j.eswa.2014.06.009>
 40. Önder, I. (2017). Classifying multi-destination trips in Austria with Big Data. *Tourism Management Perspectives*, 21, 54-58. <https://doi.org/10.1016/j.tmp.2016.11.002>
 41. Park, S. B., Ok, C. M., & Chae, B. K. (2016). Using Twitter Data for Cruise Tourism Marketing and Research. *Journal of Travel and Tourism Marketing*, 33(6), 885-898. <https://doi.org/10.1080/10548408.2015.1071688>
 42. Park, S., Yang, Y., & Wang, M. (2019). Travel distance and hotel service satisfaction: An inverted U-shaped relationship. *International Journal of Hospitality Management*, 76, 261-270. <https://doi.org/10.1016/j.ijhm.2018.05.015>
 43. Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2019). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Journal of Business & Industrial Marketing*, 34(7), 1410-1419. <https://doi.org/10.1108/JBIM-10-2018-0295>
 44. Pousttchi, K., & Hufenbach, Y. (2014). Engineering the value network of the customer interface and marketing in the data-rich retail environment. *International Journal of Electronic Commerce*, 18(4), 17-41. <https://doi.org/10.2753/JEC1086-4415180401>
 45. Pradana, A., Sing, G. O., & Kumar, Y. J. (2017). SamBot – Intelligent conversational bot for interactive marketing with consumer-centric approach. *International Journal of Computer Information Systems and Industrial Management Applications*, 9, 265-275. Retrieved from http://mirlabs.org/ijcisim/regular_papers_2017/IJCISIM_61.pdf
 46. Quijano-Sanchez, L., & Liberatore, F. (2017). The BIG CHASE: A decision support system for client acquisition applied to financial networks. *Decision Support Systems*, 98, 49-58. <https://doi.org/10.1016/j.dss.2017.04.007>
 47. Quinn, L., Dibb, S., Simkin, L., Canhoto, A., & Analogbei, M. (2016). Troubled waters: the transformation of marketing in a digital world. *European Journal of Marketing*, 50(12), 2103-2133. <https://doi.org/10.1108/EJM-08-2015-0537>
 48. Schneider, M. J., & Gupta, S. (2016). Forecasting sales of new and existing products using consumer reviews: A random projections approach. *International Journal of Forecasting*, 32(2), 243-256. <https://doi.org/10.1016/j.ijforecast.2015.08.005>
 49. Soon, K. W. K., Lee, C. A., & Boursier, P. (2016). A study of the determinants affecting adoption of Big Data using integrated technology acceptance model (TAM) and diffusion of innovation (DOI) in Malaysia. *International journal of applied business and economic research*, 14(1), 17-47. Retrieved from https://www.researchgate.net/publication/304622794_A_study_of_the_determinants_affecting_adoption_of_big_data_using_integrated_Technology_Acceptance_Model_TAM_and_diffusion_of_innovation_DOI_in_Malaysia
 50. Steinhoff, L., Arli, D., Weaven, S., & Kozlenkova, I. V. (2019). Online relationship marketing. *Journal of the Academy of Marketing Science*, 47(3), 369-393. <https://doi.org/10.1007/s11747-018-0621-6>
 51. Sun, F., G., Huang, Q. M. J., Wu, S., Song, D. C., & Wunsch, D. C. (2017). Efficient and rapid machine learning algorithms for Big Data and dynamic vary-

- ing systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(10), 2625-2626. <https://doi.org/10.1109/TSMC.2017.2741558>
52. Supak, S., Brothers, G., Bohnenstiehl, D., & Devine, H. (2015). Geospatial analytics for federally managed tourism destinations and their demand markets. *Journal of Destination Marketing and Management*, 4(3), 173-186. <https://doi.org/10.1016/j.jdmm.2015.05.002>
 53. Tang, J., & Li, J. (2016). Spatial network of urban tourist flow in Xi'an based on microblog Big Data. *Journal of China Tourism Research*, 12(1), 5-23. <https://doi.org/10.1080/19388160.2016.1165780>
 54. Tang, T. Y., Fang, E. E., & Feng, W. (2014). Is neutral really neutral? The effects of neutral user-generated content on product sales. *Journal of Marketing*, 78(4), 41-58. <https://doi.org/10.1509/jm.13.0301>
 55. Thackeray, R., Neiger, B. L., Hanson, C. L., & McKenzie, J. F. (2008). Enhancing promotional strategies within social marketing programs: use of Web 2.0 social media. *Health Promotion Practice*, 9(4), 338-343. <https://doi.org/10.1177/1524839908325335>
 56. Trabucchi, D., Buganza, T., & Pellizzoni, E. (2017). Give Away Your Digital Services: Leveraging Big Data to Capture Value. *Research Technology Management*, 60(2), 43-52. <https://doi.org/10.1080/08956308.2017.1276390>
 57. Trusov, M., Ma, L., & Jamal, Z. (2016). Crumbs of the cookie: User profiling in customer-base analysis and behavioral targeting. *Marketing Science*, 35(3), 405-426. <https://doi.org/10.1287/mksc.2015.0956>
 58. Verhoef, P. C., Stephen, A. T., Kannan, P. K., Luo, X., Abhishek, V., Andrews, M.,... & Hu, M. M. (2017). Consumer connectivity in a complex, technology-enabled, and mobile-oriented world with smart products. *Journal of Interactive Marketing*, 40, 1-8. <https://doi.org/10.1016/j.intmar.2017.06.001>
 59. Vieira, E. S., & Gomes, J. A. N. F. (2009). A comparison of Scopus and web of science for a typical university. *Scientometrics*, 81(2), 587-600. <https://doi.org/10.1007/s11192-009-2178-0>
 60. Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. *Digital Policy, Regulation and Governance*, 21(3), 264-279. <https://doi.org/10.1108/DPRG-09-2018-0050>
 61. Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing*, 80(6), 97-121. <http://dx.doi.org/10.1509/jm.15.0413>
 62. Wiencierz, C., & Röttger, U. (2017). The use of Big Data in corporate communication. *Corporate Communications: An International Journal*, 22(3), 258-272. <https://doi.org/10.1108/CCIJ-02-2016-0015>
 63. Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? *International Journal of Market Research*, 60(5), 435-438. <https://doi.org/10.1177/1470785318776841>
 64. Wu, C. H., Ho, G. T. S., Lam, C. H. Y., & Ip, W. H. (2015). Franchising decision support system for formulating a center positioning strategy. *Industrial Management and Data Systems*, 115(5), 853-882. <https://doi.org/10.1108/IMDS-10-2014-0291>
 65. Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of Big Data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research*, 69(5), 1562-1566. <https://doi.org/10.1016/j.jbusres.2015.10.017>
 66. Yang, Y., Pan, B., & Song, H. (2014). Predicting Hotel Demand Using Destination Marketing Organization's Web Traffic Data. *Journal of Travel Research*, 53(4), 433-447. <https://doi.org/10.1177/0047287513500391>