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Two Decades of Research on Consumer Behaviour and Analytics:
Reviewing the Past to Prepare for the Future

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ABSTRACT

The present study is a systematic literature review that identifies the context of consumer behaviour and analytics in business to forecast the future of consumer behaviour with changing business trends through TCCM (theory, context, characteristics, method) guidelines. The authors identified that prior research used theories in different disciplines to explain the phenomenon in customer behaviour and analytics literature. When considering the theory, these phenomena often can be segregated based on the industry (e.g., marketing, advertising, sales, healthcare, human resource management, tourism), focusing on status-based mechanisms (e.g., cross-gaming predictive models), inertia-based mechanisms (e.g., theory of rational expectations and adaptive learning), or relationship-based mechanisms (e.g., theory of consumer engagement behaviour).

KEYWORDS

Behavioural Analytics, Consumer Behaviour, Systematic Review, TCCM Framework, Thematic Review

INTRODUCTION

Data is the brand new oil, and the ever-developing need and use of statistics has converted business operations into a new era. Entrepreneurs have additionally adopted the lens of information analytics to revisit client behaviors. Data opened a new methodological paradigm and gave a sparkling

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dimension to revisit theoretical arguments inside advertising and marketing. Several researchers offer a systematic evaluation of literature to deal with a gap in knowledge on the function of analytics in customer behaviors. This paper presents an efficient audit of studies distributed between 2001 to 2021 (twenty years of exploration) in consumer behaviors and analytics. It is critical to comprehend the consolidated ideas of purchaser conduct and examination, as organizations utilize big data and customer analytics tools to discover consumer behaviors (Cruz-Cárdenas et al., 2015; Balica et al., 2022; Kral et al., 2022).

Further, companies can settle on information-driven choices utilizing consumer behaviors analytics examination as they have an individual-level perspective on their customers (Cruz-Cárdenas et al., 2015; Erevelles et al., 2016). Data can be considered an important aspect, and the increasing demand for and application of data has changed how organizations work. Marketers have often re-examined customer/consumer actions through the prism of knowledge analytics. It created a brand new analytical framework and offered a replacement dimension for revisiting theoretical debates within the field of selling. Consumer marketing is becoming increasingly data-driven providing proper consumer-related predictions for business growth (Smith, 2019). Consumer behaviors and analytics can be considered a creative area that introduces new methods and ideas to suit the new reality of analytics-driven marketing (Maheshwari et al., 2020; Smith, 2019). When buying products and services for personal use, people's behaviors and decision-making processes are referred to as consumer behaviors (Maheshwari et al., 2020; Smith, 2019). When considering marketing aligned with consumer behaviors, it can be viewed as a subdivision of economics using scarce resources, consumer psychology, and covert behaviors. Marketing was traditionally described as an application area for its main disciplines (Foxall, 2015; Gambhir, et al., 2022; Gandhi & Kar, 2022).

Today's business theory is focused on how an organization can maximize sales by meeting current and potential customer needs (Kehinde et al., 2016). In marketing management, this involves the use of behavioral science. Consumer theories are most often taken from one of the fundamental disciplines (e.g., psychology and economy) and applied to a particular marketing subject (Alboukaey et al., 2020; Barnes et al., 2020). However, if the laws and principles of marketers' and consumers' behaviors were established, analyzed, and clearly stated, it would benefit marketing and its application (Larsen et al., 2017). The quest for economic and understandable definitions of behavioral classes in marketing is focused on comparing different theories, approaches, and implementations to describe, predict, and control behaviors (Guha & Kumar, 2018; Hofacker et al., 2016; Larsen et al., 2017). Marketing management has ideally shifted from production to market orientation where "information on all important buying influences permeate all business functions" (Zimmerman & Blythe, 2017).

Further, when considering consumer behaviors and analytics, it is evident that the researchers have studied consumer behaviors over many years. Unfortunately, much of the research conducted on consumer behaviors and analytics was based on the perspective of the sellers (Cialdini, 2016; East et al., 2016; Harris et al., 2016). However, consumer behaviors goes far beyond reciprocity. Analytics plays an essential role in building a competitive advantage for the firms, characterized by information overload. Some companies can succeed, while others remain behind to sort through data and generate actionable insights (Cialdini, 2016). The Coca-Cola Company provides the most recent example of data-driven real-world business applications. Coca-Cola is the world's largest beverage company. It has more than 500 brands, and is sold in more than 200 countries. Coca-Cola is one of the pioneer non-tech multinationals to use big data (Bernard, 2017). This company used ethnological tools, such as social media platforms, mobile apps, cloud-based computing, and digital commerce, to change and predict consumer behaviors in firms (Bernard, 2017).

Additionally, Coca-Cola has developed capabilities in areas such as artificial intelligence (AI) to maximize the value of the data collected. Throughout its businesses, the decision-making approach is data-driven (Bernard, 2017). In 2017, Coca-Cola launched a new flavor of Cherry Sprite. Coca-Cola recognized the need to come up with a unique flavor based on the data from its self-service beverage outlets. These outlets empower the customer to mix and prepare their beverages. Coca-Cola used the records of customers' preferred combinations in such self-serving outlets and converted the most popular aroma into a drink ready for a broader public (Bernard, 2017). Coca-Cola also extensively used data generated via its social media platforms. Its Twitter follower count is more than 35 million, and Facebook fans are more than 105 million, giving Coca-Cola access to a massive amount of data about its brand performance. In 2015, the brand chatter of Coca-Cola was calculated to be on average every two seconds (Bernard, 2017). Sofi et al. (2018) identified that Coca-Cola predicts consumer behaviors through the theoretical lens of exploratory, confirmatory, and grounded theory approaches.

Therefore, we contribute to the literature on consumer behaviors and analytics in multiple ways. First, this study can be considered the most recent and among the first reviews regarding consumer behaviors and analytics, considering two decades. In total, the authors reviewed more than 200 theoretical and empirical studies. Most of these studies are recently published and have not been incorporated in previously published reviews. Our research goes beyond the traditional citation count. We employ the TCCM approach to conduct a comprehensive review of the literature. TCCM is a widely known method due to its accuracy and comprehensive nature (Chen et al., 2020; Singh & Dhir, 2019).

Firstly, following TCCM, this study revealed that the existing studies were based primarily on several theories to expound consumption and analytics, mainly proposing and testing consumer conduct effects using relationship-based psychological mechanisms. Secondly, based on this study, the authors highlight the scope of future research through the TCCM structure. The TCCM analysis further supports future research by showing missing links in the current literature on consumer behaviors and analytics. Therefore, this study answers the following research question: "What are the future research trends in the field of consumer behaviors and analytics in business literature?" For the comprehensive identification of research gaps and for providing future research directions across theory, context, characteristics, and methodologies prevalent in the literature of consumer behaviors and analytics, we used the TCCM framework (Paul & Criado, 2020; Paul & Rosado-Serrano, 2019). This can be justified based on the precedent studies of (Bhattacharjee et al., 2022; Chen & Meyer-Waarden, 2022; Sharma et al., 2022).

This paper is arranged in the following order. In the next section, the authors introduce the current review approach used for this paper. Then, the authors provide an overview of consumer behaviors and analytics literature. Subsequently, the authors present the theoretical perspectives in previous papers that previous researchers used to explain consumer behaviors and analytics phenomena. Next, the authors presented the findings of the prior studies, highlighting the predictor and criterion variables (mediating and moderating variables) and methodology used in current consumer behaviors and analytics research. Finally, this paper presents the future research directions through the lens of the TCCM framework.

METHODOLOGY

The principal aim of this paper is to detect the possible future research gaps and to map the literature over two decades. Structured reviews are the most relevant review type for this study. Authors reviewed the studies published between the year 2001 to 2021, using the Publish or Perish software (Arbaugh & Hwang, 2015; Repanovici, 2010). This study accessed and reviewed research papers published in top management and marketing journals across well-known databases, such as Scopus and Web of Science. Authors searched the databases using keywords, such as "consumer behaviors and analytics" and "data analytics and consumer behaviors." The results were screened for publication in peer-reviewed journals in the English language. The initial findings are presented in Table 1.

Initially, a total of 504 articles were found by the authors. From 504 studies, authors identified 23 duplicated records after categorization using the software program Endnote. The authors selected the papers that focused on consumer behaviors and data analytics, explicitly using the initial abstract

Table 1. Initial findings

Database	Number of Articles
Scopus	209
Web of Science	295
Total	**504**

screening technique. The abstracts were first screened, and the papers that did not concentrate on consumer behaviors and data analytics were excluded. For example, due to out-of-scope problems, publications on consumer behaviors theoretical application excluding the data analytics and publications on human resource management on data analytics were identified as disqualified. Furthermore, papers written in computer science, human intelligence, tourism, journalism, education, and non-marketing contexts were excluded from the review. Therefore, from the remaining 481 articles, 278 were identified as unnecessary due to out-of-scope issues. The remaining 203 articles were assessed using inclusion and exclusion criteria through PRISMA guidelines (Frizzo-Barker et al., 2020; Sprong et al., 2021; Tueanrat et al., 2020) (see Table 2).

Studies outside the scope of the review, such as computer science, human intelligence, tourism, journalism, and education, were further removed from the review process. To maintain the academic rigor, articles were screened, and only ABDC journal rankings of "B" or above, or Scimago journal rankings of "Q2" or above, were chosen. As a result of the screening, a total of 139 studies were removed, and only a total of 64 studies were identified as qualified for this review. Following PRISMA guidelines, Figure 1 demonstrates the inclusion and exclusion criteria used for this review.

Finally, the authors conducted a detailed content analysis for the final 72 studies based on the TCCM framework. As a result of this contextual thematic analysis, the authors discussed the results using time-based trend analysis to predict the future of consumer behaviors with changing course of analytics.

THEMATIC ANALYSIS BASED ON TCCM FRAMEWORK

The literature on consumer behaviors and analytics focused on various aspects that determine the importance of data on consumer behaviors. To summarize the existing knowledge, the authors developed a comprehensive map of consumer behaviors and analytics literature (see Figure 2). This map further illustrates the different theoretical applications and concepts relevant to the consumer behaviors and analytics literature.

Table 2. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Scope and contribution: - Consumer behaviors theoretical applications - Publications on human resource management on data analytics -Contribution for marketing and current business context -Published during the period of 1991 to 2021 - Higher impact factor and quality levels of the published source	**Scope and contribution:** -Focused on computer science, human intelligence, tourism, journalism, education, and non-marketing contexts -Not published from 1991 to 2021 - Lower impact factor and quality levels of the published source

Figure 1. Flow chart of the literature search process

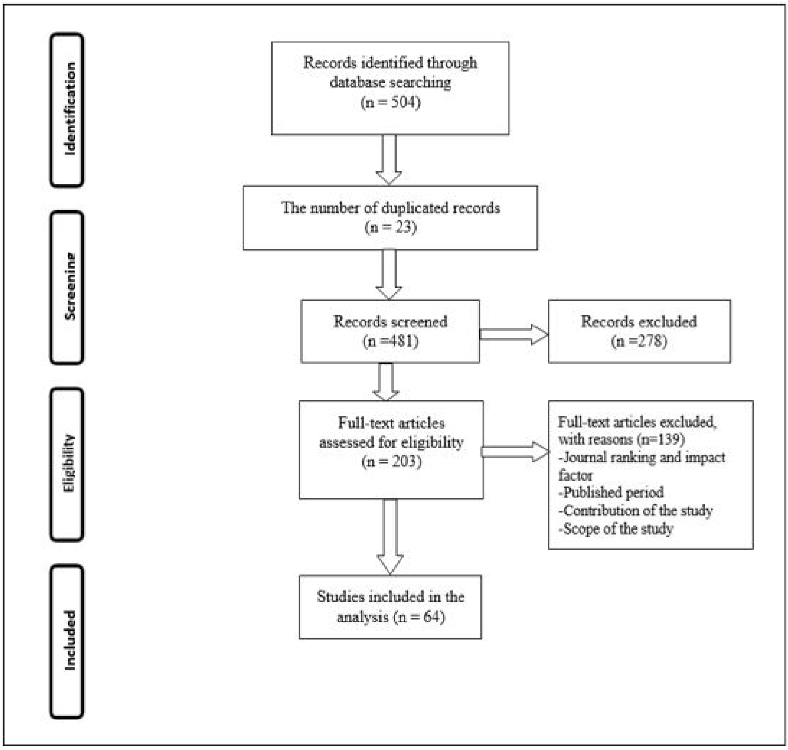
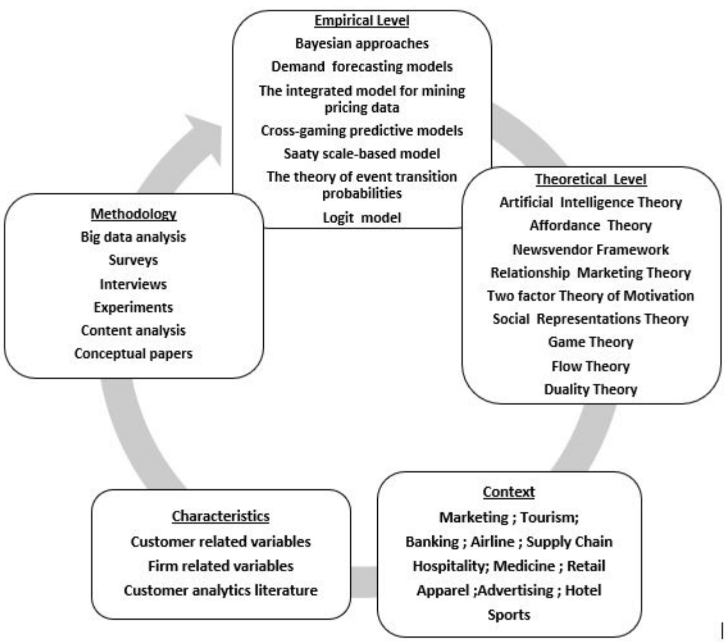


Figure 2. Overview of the school of thoughts in customer behaviors and analytics literature



In the following sections, the authors systematically review the literature on customer behaviors and analytics literature through the lens of the TCCM framework (Paul & Rosado-Serrano, 2019). Accordingly, the first section discusses the theoretical monarchy of customer behaviors and analytics literature. Authors reviewed the theoretical frameworks that have been frequently used in explaining customer behaviors through data analytics. These theories include artificial intelligence theory, affordance theory, newsvendor framework, relationship marketing theory, two-factor theory of motivation, social representation theory, game theory, flow theory, and duality theory. Then the authors reviewed the empirical realm of the customer behaviors and analytics literature through Bayesian approaches, demand forecasting models, the integrated model for mining pricing data, cross-gaming predictive models, the Saaty scale-based model, the theory of event transition probabilities, and the logit model. Next, this micro perspective is extended by reviewing the literature. Finally, the authors evaluated the key methodological aspects, including the research approach, data types, and analytics-based tools used to gain insights into customer behaviors and analytics. Using this systematic review, the authors outline a comprehensive scope for future research.

THEORY

The current literature on customer behaviors and analytics uses different theoretical frameworks and paradigms to describe the pertinent effects. The word theory implies several sentences that are coherent and empirically validated (Clark et al., 2002; Rudner, 1966). As a result, theories can be interpreted as reasoned interpretations of multiple vital structures (e.g., customer behaviors and analytics design) linked with each other with the aim of forecasting/elucidating empirical phenomena in their application. Pantano (2020) investigated "the extent to which it is possible to systematically evaluate retail service encounters through consumers' facial expressions through 'differential emotions theory."

Retailers face considerable pressure applying price optimization models to improve their income, margins, and market share. To estimate the difference in demand at different prices, mathematical models can combine cost and inventory information to recommend price improvements for profit and revenue. For example, Simchi-Levi and Wu (2018) identified three crucial changes through price theory, such as (1) Data: Access to in-house and out-of-home data, such as website traffic, consumer decision-making, and price strategies for the competing parties; (2) Analytics: Deciphering consumers' behaviors and generating estimates of demand and price by the use of advances in machine-learning algorithms and programming languages; and (3) Automation: Real-time dynamic pricing of a long list of products sold in the marketplace. Similarly, Pantano and Dennis (2019) applied Bayes' theorem to collect customer tweets for U.K.-based fashion retailers familiar between consumers and businesses.

In addition, Chiang and Yang (2018) tried to estimate the customer lifetime value using point-of-sale transaction records. By using the utilities theory regarding customers of beer brands, they tried to understand the relationship between consumer personality traits and how they relate to the country-of-origin effect. Tupikovskaja-Omovie and Tyler (2020) used flow theory and Google Analytics data to understand digital consumer behaviors. Similarly, Sturley et al. (2018) identified gaps in the retail sector to use spatial modelling to capture consumer behaviors via a state-of-the-art framework. For fashion retailing, Silva et al. (2019) suggested the application of big data analytics to predict trends for waste reduction and marketing. These findings were further justified by Ibrahim and Wang (2019), who offered a better understanding of customers' opinions toward online retailing by using Twitter data.

Papanagnou and Matthews-Amune (2018) used demand forecasting models through multivariate time series analysis techniques to identify the demand volatility in retail pharmacy settings when considering retail pharmacies. Prior studies on health plan decision-making used the expected utility (EU) model as the underlying theoretical framework. Abraham et al. (2006) extended the Hirshleifer and Riley (1979) theoretical framework to identify the factors that make employees search for information on the quality of health plans and how they used this information to switch health plans.

The semiotics, reader-response, and the theory of co-optation contributed to advertising by focusing on quality assessments to show how advertisements are "readed" by consumers (Belk, 2017). The three main theories—fuzzy set theory, customer loyalty theory, and complexity theory in consumer brand engagement (CBE)—described how replacing normative matrix algebra and symmetric analytics set by theoretical models and asymmetric analysis via Boolean algebra is more rigorous in validating major principles of complexity theory in CBE. Table 3 (below) further illustrates the theories employed in customer behaviors and analytics research.

CONTEXT

By considering industry and country, the authors were able to sum up the results of customer behaviors, and analytics. Throughout the course of the study, the industry is referred to as the contribution sector. Besides the affiliation of the authors and the focus of the study, countries are also concerned about the affiliation of the authors.

Industry

Among the industry sectors, retailing and marketing were most commonly studied. This is primarily due to the easy availability of data in the retail industry. In the retail sector, big data technology applications can enable effective decision management and achieve further improvements (Ahmed et al., 2015). For instance, Pantano (2020) tested whether the facial expressions of customers can provide insight into the quality of retail service encounters. It was shown by Simchi-Levi and Wu (2018) that price optimization models could be used to calculate revenue, margins, and market shares. Among the factors that influence consumer behavior in the retail industry, personality traits have also been identified (Chiang & Yang, 2018). Consumer behavior to switch plans provided by health care service providers has been analyzed in depth by the healthcare industry (Abraham et al., 2006). Moreover, the hotel and tourism industry also predicted consumer perceptions (Buzova et al., 2020; Giglio et al., 2020; Pantano & Dennis, 2019; Tupikovskaja-Omovie & Tyler, 2020; Xiang et al., 2015). For example, Mosander et al. (2010) studied consumption patterns of consumers to improve marketing (Pantano, Giglio, & Dennis, 2019). By analyzing big data, the automobile sector focused on consumer consumption behaviors (Zhou et al., 2019). Additionally, similar trends were identified in the banking, food, and airline sectors, where the data was mainly used to predict consumer behavior.

Several aspects of marketing have been promoted by the use of social media data, including sports, sales, and advertising (Gene et al., 2020; Goyal & Kumar, 2021; Oh et al., 2017; Ozturkcan et al., 2019; Zhang et al., 2020). Ting and Kauffman (2012) proposed that service operations could be significantly improved by using adaptive learning techniques. Reutterer et al. (2020) proposed an

Table 3. Major theories employed in customer behaviors and analytics research

Theory	No. of articles	Exemplary studies
Artificial intelligence theory	4	Ahmed et al. (2015); Oztekin (2018); Shirazi & Mohammadi (2019); Fuchs et al., (2014)
Price theory	2	Simchi-Levi & Wu (2018); Zhang et al., (2020)
Customer loyalty theory	2	de Villiers (2015); Sturley et al. (2018)
Cross-gaming predictive models	5	Suh & Alhaery (2014); Martens et al., (2016); Fiore et al., (2017); Routh et al., (2020); Shirazi & Mohammadi (2019)
Relationship marketing theory	2	Wong & Wei (2018); Kitchens et al., (2018)

individual-level buyer behaviors prediction technique for purchase regularities via stochastic modelling. In conclusion, introduction of advanced analytics tools to predict consumer buying behaviors is also seen as moderately reported in the existing literature (Huang & Mieghem, 2013; Kitchens et al., 2018; Marinelli et al., 2020; Martínez et al., 2020; Miles, 2014; Radha & Babu, 2020).

Country

In relation to geographical coverage, we considered studies based on the institutional location of the principal authors and on the contribution from the study for the country. Figure 3 depicts the distribution of papers in geographical areas.

Most of the studies have been conducted in developed countries, such as the United States and the United Kingdom. It is notable that a smaller number of studies have been conducted in the other geographic areas, as shown in Figure 3. Therefore, the studies that concentrated on the U.S.A. mainly focused on the consumer buying behaviors prediction through various price optimization (Simchi-Levi & Wu, 2018), logistic regression analysis (Suh & Alhaery, 2014), big data analysis (Aluri et al., 2019; Hofacker et al., 2016; Xiang et al., 2015), and through various data analytic models (Miles, 2014; Oh et al., 2017; Oztekin, 2018). For the U.K., the main focus is on diversified areas, such as consumer response to the automatic systems (Pantano, 2020); consumer perception identification (Giglio et al., 2020); using big data analytics for making marketing and management strategies (Birkin, 2019; Pantano & Dennis, 2019; Tupikovskaja-Omovie & Tyler, 2020); consumer behaviors (Duffy & Ney, 2015; Ibrahim & Wang, 2019; Ma et al., 2019); and brand familiarity (Huang & Mieghem, 2013).

CHARACTERISTICS

Prior researchers investigated different variables related to the organization, customer, and customer analytics literature. Table 4 summarizes different variables that have been studied in customer behaviors and analytics literature.

According to Table 4, the findings of the existing literature can be summarized in a detailed manner as follows.

Figure 3. Distribution of papers in terms of geographical areas over 2001 to 2021

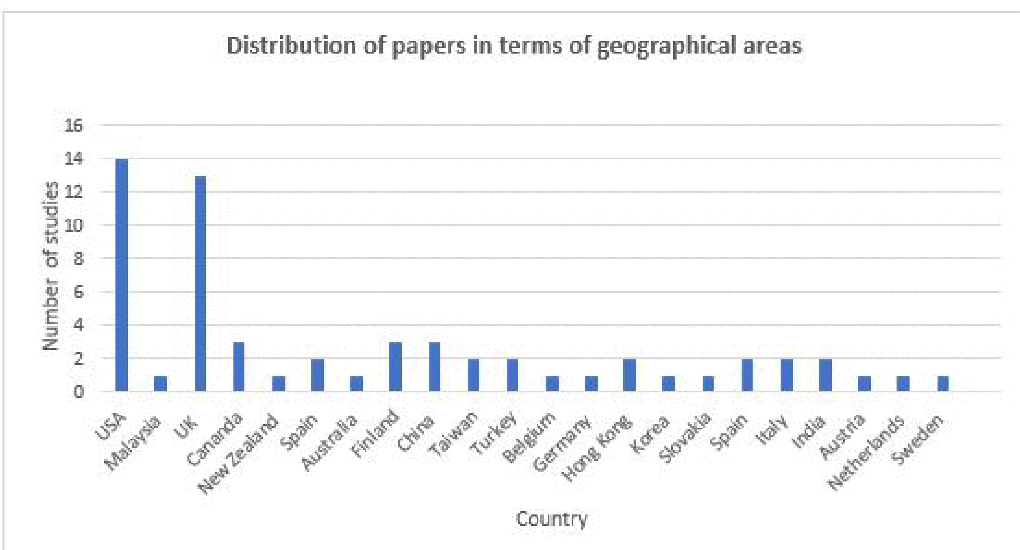


Table 4. Variables investigated in current customer behaviors and analytics literature

Identified variables	No. of articles
Predictor variables	
Organization-related variables	
Data characteristics	7
Management of scarce resource	2
Leadership attributes	1
Product/brand/service characteristics	7
Quality of the database	7
Advances in machine learning	2
Consumer culture	1
Consumer-related variables	
Consumer perception	2
Competitor pricing strategies	4
Customer relationship management	6
Customer behaviors and analytics related variables	
Techniques and practices by the government	2
Perceived values and benefits	2
Mediating variables	
Firm-related variables	
Risk factors	1
Retailers' marketing intelligence	1
Consumer-related variables	
Relationship characteristics	3
Consumer brand engagement	2
Consumer privacy concerns	2
Customer behaviors and analytics related variables	
Updated technology	9
Criterion variables	
Firm-related variables	
Big data analytics into marketing	6
Social media engagement	5
Brand personality	1
Marketing decision making	1
Consumer-related variables	
Buying decision making	5
Consumer experience	2
Customer behaviors and analytics-related variables	
Database marketing	2

INDEPENDENT VARIABLES (IVS)

The literature indicates various clusters of variables and their subgroups concerning predictor/independent variables (IVs). Organization (firm)-related variables captured multiple characteristics linked to separate intra-organization units that cover data attributes of the organization, such as the application of big data technology applications for enabling efficient decision handling and achieving improvements within the retailing domain (Abraham et al., 2006). Further, the characteristics of the datasets within the organization ultimately affect the decision-making process (Abraham et al., 2006; Pantano & Dennis, 2019; Pantano et al., 2019; Suh & Alhaery, 2014). Scarcity management is another important independent variable related to the company. The evidence from past research shows that more attention is needed on forecasting data or time series models, as the scarcity of resources could lead to an ultimate loss for the firms (Boone et al., 2019; Christensen & Bower, 1996). Leadership attributes are another firm-related independent variable. Future researchers could further explore the leadership attributes to establish their own identity in managerial marketing, consumer behaviors, or marketing analytics (Sheth, 2019).

Similarly, Guajardo (2019) highlighted the importance for firms to jointly track and analyze customer payment and usage behaviors, particularly in the initial stages of the adoption process. Several scholars identified the importance of maintaining a quality database in their organizations (Ibrahim & Wang, 2019; Kakatkar & Spann, 2019; Li et al., 2020; Maheshwari et al., 2020; Silva et al., 2019). Further, it was identified that the quality datasets helped forecast the firms' future with more accurate predictions (Huang & Mieghem, 2013; Martínez et al., 2020; Radha & Babu, 2020; Reutterer et al., 2020). It was identified that advances in machine learning and consumer culture could affect the revenue, margins, and market share of a firm (Pantano, 2020; Pantano & Dennis, 2019; Pantano et al., 2019; Simchi-Levi & Wu, 2018).

Consumer-related predictor variables (IVs) include consumer perception, competitor pricing strategies, and customer relationship management. It was proved that big data analytics and machine learning algorithms using visual data could help the luxury hotel industry monitor social media and understand consumers perception (Giglio et al., 2020) and the tourism sector (Buzova et al., 2020). Competitor pricing strategies are often observed in the retailing industry to optimize the prices of hundreds of competing products sold by the same retailers (Simchi-Levi & Wu, 2018). Further customer relationship management is vital for several industries, such as table games, to identify the customer-casino relationship (Suh & Alhaery, 2014) and determine consumers' tendency to purchase and co-purchase brands with traits similar to their own personality traits (Chiang & Yang, 2018). Further, it is also helpful for industries including sports (Naraine, Wear, & Whitburn, 2019); retail (Wang, Fan, & Zhang, 2020); digital services (Luca et al., 2020); and the marketing sector (Kitchens et al., 2018; Wong & Wei, 2018) due to the help in predicting future consumption patterns and retainment of existing customers. Customer behaviors and analytics-related IVs are less utilized in the current literature. The literature include techniques and practices by the government and perceived values and benefits of the customers (Marinelli et al., 2020; Sturley et al., 2018).

MEDIATING VARIABLES

When considering the mediating variables, only 28% of articles include mediating characteristics. Risk factors and retailers' marketing intelligence were identified as firm-related variables, and relationship characteristics, consumer brand engagement, and consumer privacy concerns as consumer-related variables. Updated technology was identified as customer behaviors and analytics-related variables. Risk factors can be identified through the computational characteristics of the proposed methods in computing risk (Lin et al., 2020; Routh et al., 2020). The big data analytics tool and SAS business intelligence systems were used to study the client retirement path and create churn prediction models in the banking sector (Shirazi & Mohammadi, 2019). By applying a Business Intelligence approach, it was identified how tourism managers use destination management information systems (DMIS) for gaining new knowledge about customer-based destination processes that focus on pre-and post-travel phases, like "Web-Navigation," "Booking" and "Feedback" (Fuchs et al., 2014).

Furthermore, consumer-related mediating variables, such as relationship characteristics, consumer brand engagement, and consumer privacy concerns, mediated the consumer analytics and behaviors through retaining customers in the sports sector (Naraine et al., 2019; Wang et al., 2020) by developing personality traits (Chiang & Yang, 2018). Studies have shown the impact of big data investments on service innovation and performance (Luca et al., 2020) and by improving the marketing practices (Kitchens et al., 2018; Wong & Wei, 2018). Similar to IVs, customer behaviors and analytics-related moderating variables are less utilized in the current literature with one variable of updated technology.

DEPENDENT VARIABLES (DVS)

Our review shows very few firm-related, consumer-related and customer behaviors and analytics-related variables. From these variables, the firm-related variable of big data analytics into marketing plays a vital role. The studies on big data analytics into marketing focused on the performance of the firm. These studies contributed to the current literature by identifying strategic value of employing big data analytics for firms (Kitchens et al., 2018), as well as by identifying proper supply chain practices, such as reducing waste, ensuring better quality control, using less fake materials, and reducing the supply chains (Shirazi & Mohammadi, 2019; Silva et al., 2019). Social media engagement is another identified dependent variable, as it helps to change the perceptions of the consumers (Giglio et al., 2020; Kumar et al., 2016; Naraine et al., 2019; Oh et al., 2017; Ozturkcan et al., 2019; Shirazi & Mohammadi, 2019; Tranfield et al., 2003). Brand personality and marketing decision-making was identified as less representative.

When considering the consumer-related variables, buyer decision-making and consumer experience plays a major role. It is essential to note that buying decision-making is more representative than the dependent variable of consumer experience. For the customer-related criterion variables, prior studies focus on reasons behind buying decision-making, such as competitor pricing strategies (Simchi-Levi & Wu, 2018), brand awareness (Kakalejčík et al., 2020), cross-buying behaviors (Kumar et al., 2016; Gupta et al., 2021; Jayawardena et al., 2021; Almomani et al., 2021). Consumer experience heavily depended on the brand reputation (Pantano & Dennis, 2019; Silva et al., 2019) and the quality of the product (Wang et al., 2020) or service (Papanagnou & Matthews-Amune, 2018).

METHODOLOGY

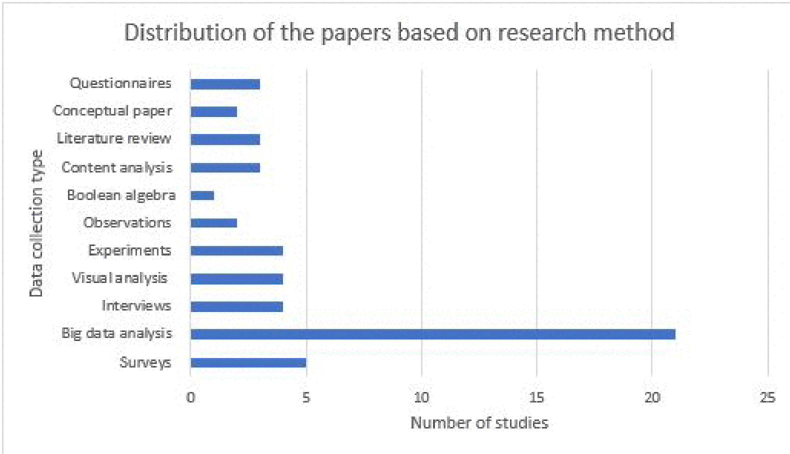
This section presents an overview of the studies based on the data collection method. The authors identified eight unique research methodologies used in the selected articles that studied the field of customer behaviors and analytics (see Figure 4).

As depicted in Figure 4, 40.4% studies used big data analytics as the primary research method. Surveys (9.6%) are the second-most popular data collection method, while interviews, experiments, and visual analysis were used as the third best option (7.7%). The other research methods of observations, Boolean algebra, content analysis, literature review, conceptual papers, and questionnaires are less represented in the current literature.

Future Research Agenda

In the past two decades, consumer behaviors and analytics have produced a wide variety of research, which has improved understanding of why and how consumer behaviors and analytics function.

Figure 4. Distribution of the papers based on the data collection methods



Future Directions – Theory

The authors identified that prior research used theories in different disciplines to explain the phenomenon in customer behaviors and analytics literature when considering the theory. These phenomena often can be segregated based on the industry (e.g., marketing, advertising, sales, healthcare, human resource management, tourism), focusing on status-based mechanisms (e.g., cross-gaming predictive models), inertia-based mechanisms (e.g., theory of rational expectations and adaptive learning), or relationship-based mechanisms (e.g., theory of consumer engagement behaviors). Most of the articles incorporated in this study used a single theory to investigate the current phenomenon. It is critical to note that using one conceptual framework or theoretical perspective is unlikely to account for the complexity of consumer behaviors and analytics grounded in multiple factors and features, such as customer, organization, employees, and competitors. Several studies were grounded based on the affecting factors, such as social media engagement, rewarding, point of sales data, and even cross-gaming behaviors. Therefore, current literature findings should be expanded through future researchers via adopting a multi-theoretical perspective.

Our study revealed a deficit of solid theoretical underpinnings in the current literature as existing empirical literature mostly applied fewer theories and models, such as artificial intelligence theory (Ahmed et al., 2015); cross-gaming predictive models (Suh & Alhaery, 2014); Saaty scale-based model (Zhou et al., 2019); Bayes' theorem (Pantano et al., 2019); social media analytics framework (Ozturkcan et al., 2019); utility Theory (Chiang & Yang, 2018); the social theory (Martens et al., 2016); parallel computing models (Guha & Kumar, 2018); duality theory (Gene et al., 2020); social representations theory (Pindado & Barrena, 2021); relationship marketing theory (Kitchens et al., 2018) and Bayesian approaches (Lin et al., 2020). When considering the social media data analysis, it was identified that data gathering from different social media networks, including Facebook, Pinterest, or even Instagram, is needed for future research (Ozturkcan et al., 2019; Pantano et al., 2019). Also, there is a need to combine the Twitter data analysis with different research designs such as surveys (descriptive) and interviews (exploratory; Ibrahim & Wang, 2019; Naraine et al., 2019; Pindado & Barrena, 2021) to get a more comprehensive picture of the phenomenon.

Future Directions – Context

Concerning the context, authors identified that a large number of studies focused on retailing and marketing sector, with fewer studies focusing on other industries, such as healthcare (Abraham et al., 2006); apparel sector (Moisander et al., 2010); information technology (Lau, Li, & Liao, 2014); higher education (Duffy & Ney, 2015); the food industry (Fiore et al., 2017); finance (Lin et al., 2020); banking (Shirazi & Mohammadi, 2019) and the airline industry (Ma et al., 2019). Other than the studies mentioned above, studies focusing on other domains were scarce—for example, at present, only one paper focuses on the airline industry through big data analysis (Ma et al., 2019). In the airline industry, domains like revenue and yield management have long been a source of concern (Belobaba, 1987; Chiang et al., 2007) and have been heavily studied by many researchers (Alderighi et al., 2015; Ma et al., 2019).

There are significantly fewer studies in the banking sector as well (Shirazi & Mohammadi, 2019). Without a doubt, the financial industry is changing at a growing magnitude and pace in response to discernible shifts in consumers' preferences and expectations, resulting in new technology and the widespread availability of various goods and services (Shirazi & Mohammadi, 2019). Furthermore, according to Chen et al. (2012), despite big data analytics being applied heavily in technology-driven ventures, scope exists for its application in different service industries, such as financial services.

When considering the food industry, food safety and health are increasingly becoming the focus of conscientious consumers' buying decisions (Fiore et al., 2017). Fiore et al. (2017) investigated the qualities commonly referred to as the characteristics of wheat flour known to customers to introduce a predictive buying model that allows for accurate decisions without the need for a real human expert's expertise. It was found that conscious consumers seem to be willing to pay a premium in line with recent safe and dynamic food market patterns (Fiore et al., 2017). Authors categorized the articles based on the country of contribution. Most studies centered on developed countries, such as the United Kingdom and the United States. The research focusing on the United States primarily focused on predicting consumer purchasing behaviors using various price optimization models (Simchi-Levi & Wu, 2018), logistic regression analysis (Suh & Alhaery, 2014), big data analysis (Aluri et al., 2019; Hofacker et al., 2016; Xiang et al., 2015), and data analytic models (Miles, 2014; Oh et al., 2017; Oztekin, 2018). As seen in Figure 3, fewer studies have been performed in other geographic regions specifically focusing on emerging economies, which is a plausible future research area found through this review.

Future Directions – Characteristics

In general, empirical research into the antecedents and implications of customer behaviors and analytics adoption and execution can be found in the customer behaviors and analytics literature. Table 3 summarizes the variables that have been studied in the literature on consumer behaviors and analytics. The variables were also classified as independent, moderating, and dependent based on their position in each sample. Leadership qualities develop firm-related branding in managerial marketing, customer behaviors, and marketing analytics (Sheth, 2019). On the other hand, consumer culture can affect a firm's revenue, margins, and market share (Pantano, 2020; Pantano & Dennis, 2019; Pantano et al., 2019; Simchi-Levi & Wu, 2018).

When considering the firm-related mediating variables, risk factors and retailers' marketing intelligence is identified as less focused areas. Risk factors can be identified through computational characteristics of the proposed methods in computing risk (Lin et al., 2020; Routh et al., 2020), and retailers' marketing intelligence is helpful as it provides new knowledge about customer-based processes (Fuchs et al., 2014). Furthermore, when considering the dependent variables, firm-related variables of brand personality and marketing decision-making are less represented. Therefore, future studies are necessary focusing on these variables, in order of priority: leadership attributes, consumer culture, risk factors, retailers' marketing intelligence, brand personality, and marketing decision-making.

Future Directions – Methodology

According to the authors, there were two significant gaps in the consumer behaviors and analytics literature related to the methodology of the study. First, the majority of the studies (see Figure 4) were empirical in nature, using big data analytics and surveys as methods for collecting data. In the majority of the studies, a descriptive research design was used, which raises real-world application questions but may not be able to fully investigate the practical scenario through the consumer's experience and perception of the situation (Cresswell, 2006). Secondly, the other research methods, such as observation, Boolean algebra, content analysis, literature review, conceptual papers, and questionnaires, were considered to be less representative by the authors. The future researcher can therefore expand their findings through the use of mixed methods with qualitative data collection techniques (Delphi, focus groups, semi-structured interviews, focus group discussions), which are less prevalent in the current research. While social media applications for understanding sports activities are still in their infancy in the European context, its importance has already been appreciated in the United States for some years (Ozturkcan et al., 2019). There is a need for more field experiment-based longitudinal studies, especially in the field of sports marketing (Argan et al., 2013). To enhance their findings, the authors suggest that future researchers should adopt more qualitative techniques with more longitudinal associations in order to enhance their findings in the future. A further illustration of the research approach and methods used in the studies on consumer behavior and analytics can be found in Table 5.

CONCLUSION

Finally, this study aims to systematically classify the consumer behaviors and analytics literature through the TCCM framework. To this end, the authors reviewed the literature published between 2001 to 2021 (two decades of research) in consumer behaviors and analytics. The primary purpose of this study is to perform a systematic literature review using the TCCM framework and to extend the review with contextual thematic analysis to discuss a time-based trend analysis to predict the future of consumer behaviors with changing course of analytics. As a result of this review, the authors categorized the findings based on the TCCM framework to provide a

Table 5. Research approach and methods used in consumer behaviors and analytics literature

Research methodology	No. of studies	Exemplary studies
Quantitative method	35	Abraham et al. (2006); Ahmed et al. (2015); de Villiers (2015); Suh & Alhaery (2014); Moisander et al. (2010); Pantano et al. (2019); Boone et al. (2019); Boone et al. (2019); Chiang & Yang (2018); Birkin (2019); Martens et al. (2016); Guajardo (2019); Kakatkar & Spann (2019); Guha & Kumar (2018); Hu & Winer (2017); Oh et al. (2017); Lee et al. (2020); Sturley et al. (2018); Naraine et al. (2019); Pindado & Barrena (2021); Fiore et al. (2017); Ting & Kauffman (2012); Lin et al. (2020); Ibrahim & Wang (2019); Li et al. (2020); Aluri et al. (2019); Luca et al. (2020); Reutterer et al. (2020); Huang & Mieghem (2013); Shirazi & Mohammadi (2019); Kitchens et al. (2018); Ma et al. (2019); Radha & Babu (2020); Wong & Wei (2018); Fuchs et al. (2014)
Experimental	7	Simchi-Levi & Wu (2018); Hofacker et al. (2016); Arda et al. (2017); Lau et al. (2014); Kakalejčík et al. (2020); Marinelli et al. (2020)
Qualitative method	12	Pantano (2020); Giglio et al. (2020); Belk (2017); Buzova et al. (2020); Pantano & Dennis (2019); Tupikovskaja-Omovie & Tyler (2020); Arda et al. (2017); Xiang et al. (2015); Duffy & Ney (2015); Sheth (2019); Kumar et al. (2016); Miles (2014)
Mixed method	5	Belk (2017); de Villiers (2015); Lin et al. (2020); Ibrahim & Wang (2019); Li et al. (2020)
Literature Review	7	Moisander et al. (2010); Santiago & Robert (2020); Ozturkcan et al. (2019); Zhang et al. (2020); Pomirleanu et al. (2013); Silva et al. (2019); Maheshwari et al. (2020)

more comprehensive analysis. The authors established two limitations of this study. Firstly, the scope of the review is limited to consumer behaviors and analytics literature only. The scope may be extended further to other areas, such as consumer culture, cross-cultural differences, and perceptions. Secondly, the scope of this analysis is limited to a twenty-year duration. Future researchers can replicate this study by considering a timeframe of more than twenty years. Finally, we expect this literature review to attract scholars to conduct innovative research and encourage similar studies in the future.

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APPENDIX

Key Highlights

- It is critical to note that using one conceptual framework or theoretical perspective is unlikely to account for the complexity of consumer behaviors and analytics grounded in multiple factors and features, such as customer, organization, employees, and competitors. Several studies were grounded based on the affecting factors, such as social media engagement, rewarding, point of sales data, and even cross-gaming behaviors.
- Our study revealed a deficit of solid theoretical underpinnings in the current literature, as existing empirical literature mostly applied fewer theories and models, such as artificial intelligence theory (Ahmed et al., 2015); cross-gaming predictive models (Suh & Alhaery, 2014); Saaty scale-based model (Zhou et al., 2019); Bayes' theorem (Pantano et al., 2019); social media analytics framework (Ozturkcan et al., 2019); utility theory (Chiang & Yang, 2018); the social theory (Martens et al., 2016); parallel computing models (Guha & Kumar, 2018); duality theory (Gene et al., 2020); social representations theory (Pindado & Barrena, 2021); relationship marketing theory (Kitchens et al., 2018) and Bayesian approaches (Lin et al., 2020).
- Concerning the context, authors identified that a large number of studies focused on the retailing and marketing sector, with fewer studies focusing on other industries, such as healthcare (Abraham et al., 2006); the apparel sector (Moisander et al., 2010); information technology (Lau, Li, & Liao, 2014); higher education (Duffy & Ney, 2015); the food industry (Fiore et al., 2017); finance (Lin et al., 2020); banking (Shirazi & Mohammadi, 2019) and the airline industry (Ma et al., 2019).
- When considering the firm-related mediating variables, risk factors and retailers' marketing intelligence is identified as less focused areas. Risk factors can be identified through computational characteristics of the proposed methods in computing risk (Lin et al., 2020; Routh et al., 2020), and retailers' marketing intelligence is helpful as it provides new knowledge about customer-based processes (Fuchs et al., 2014).
- The authors identified two significant gaps in consumer behaviors and analytics literature regarding the methodology. Firstly, most of the studies were empirical (see Figure 4) with the data collection methods of big data analytics and surveys. The majority of the studies used a descriptive research design that raises real-world application questions and may not explore the practical scenario through the consumer experience and perceptions (Cresswell, 2006). Authors identified other research methods of observations, Boolean algebra, content analysis, literature review, conceptual papers, and questionnaires as less representative.

Table 6. Summary of the analysis based on the TCCM framework

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Abraham et al. (2006)	Journal of health economics	-Health plan quality information	Hirshleifer and Riley (1979)	Firm-related variables: higher quality information	Health care /U.S.A.	Surveys	Consumer switching is influenced by changes in premiums and whether an individual has an existing relationship with a health care provider

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Ahmed et al. (2015)	International Conference on Software Engineering and Computer Systems	-An agent-based paradigm to facilitate the use of big data analytics	Artificial intelligence theory	Firm-related variables: The characteristics of data source	Retailing/ Malaysia	Big data analysis	In addition to the efficient decision making, large data technology applications in the retail domain are needed to achieve further improvements in this field
Pantano	Computers in Human Behavior	-Systematic evaluation of retail service encounters through consumers' facial expressions	Differential Emotions Theory	Consumer related variables: Consumer response to the automatic systems	Retailing/ U.K.	Interviews	A system of recognition of facial expression would open up consumer assessment of retail service meetings and allow consumers to automatically evaluate retail service meeting using facial expression identification systems
Giglio et al. (2020)	Journal of Business Research	- Consumers' perception on luxury hotel brands	Not discussed	Consumer related variables: Consumers' perception of luxury hotel brands	Hotel industry/ U.K.	Visual analysis	This survey shows how big data and machine learning algorithms could help to monitor social media and understand the perception of consumers in luxury hotels through new visual analyses. Also, to become more effective brand management strategies for luxury hotel operators
Simchi-Levi and Wu (2018)	International Journal of Production Research	- Price optimization models to calculate revenue, margins, and market share	Price theory	Consumer related variables: Buying decision making Firm-related variables: competitor pricing strategies, advances in machine learning	Retailing/ U.S.A.	Experiments	Advances in machine learning and easy access have led to the development of systems that are fully aware of consumption behaviors and preferences, and generate efficient estimates for demand-price relationships
Belk (2017)	Journal of Advertising	- Qualitative analyses in revealing how ads are "read" by consumers	Semiotics, reader response, and co-optation theory	Consumer related variables: consumer culture surrounded by advertising and brands	Advertising/ Canada	Observations, interviews, projective methods, focus groups, ethnography, and videos	This study concludes by evaluating how qualitative research into promotion and data analytics can be combined to produce a wealthier and more comprehensive understanding of consumer behaviors in response to advertising

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
de Villiers (2015)	Journal of Business Research	- New perspective in the consumer brand engagement (CBE) literature	Fuzzy set theory, customer loyalty theory, complexity theory in CBE	Consumer related variables: Consumer brand engagement	Marketing/ New Zealand	Boolean algebra	The article describes how to test major principles of CBE complexity theory using set theoretical models and asymmetrical analysis with the use of the Boolean algebra, rather than normative algebra and symmetric analytics
Suh and Alhaery (2014)	International Journal of Contemporary Hospitality Management	-Logistic regression analysis on the player data of a casino	Cross-gaming predictive models	Consumer related variables: customer-relationship management Consumer analytics related variables: database marketing	Table games/ U.S.A.	Daily data from local casinos in Las Vegas	-The results of a logistic regression analysis show that game-related behavioral data can predict a player's cross-game propensity -Cross-game advantages were linked to the frequency and the recurrence of casino travel, money won or lost in gaming, player values to the casino, play length, and the length of a relationship between a customer and a casino
Buzova et al. (2020)	Psychology Marketing	- Tourists' multisensory place perceptions by analyzing cruise travel blogs	Not discussed	Consumer related variables: visitors' onshore experience	Tourism/ Spain	Content analysis through Leximancer	-Empirical evidence of the relevance of multi-sensory perceptions to the tourists' assessment of the local experience -The analysis of freely written online narratives employs a novel methodological approach to evaluate sensory impressions
Prentice et al. (2020)	Journal of Retailing Consumer Services	- Timing effect between government measures and panic buying	Not discussed	Consumer related variables: consumer buying behaviors	Marketing/ Australia	Semantic and big data analysis	-The findings reveal a connection between timing of government measures and panic buying
Pantano and Dennis (2019)	International Journal of Retail and Distribution Management	-Tourism attraction through store buildings	Not discussed	Firm-related variables: Big data analytics into marketing and management strategies as a new data source	Tourism/ U.K.	Picture analysis using machine learning approach	- Findings show that a luxury shop building is the central object for many photos near the main entrance of the store, showing how attractive shop-building plays an important role in tourism

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Moisander et al. (2010)	International Journal of Consumer Studies International Journal of Consumer Studies	The paper contributes to the literature on green consumerism by systematic-cally interrogating and elaborating on the modes and practices of marketing thought and expertise through which consumers and consumption are rendered intelligible and action-able in the market. drawing from the literature on the analytics of government, the paper discusses marketing as a form of government, elaborating and illustrating the many ways in which consumer choice is shaped, modiðed and directed in the market through practices and techniques of consumer marketing. The aim is to critically reñect upon and render problematic the individualistic ideas of the green consumer as a powerful market force and to provoke discussion on the conceptualization – and construction – of consumer subjectivity and social problems in marketing. -Marketing data for consumer marketing	Microeconomics and the theory of rational choice	Consumer analytics related variables: Techniques and practices by government	Apparel/ Finland	Literature review	-In addition to literature on green consumption, the document systematically questions and explores the methods and practices by which marketing thought and expertise is made intelligible and operable by consumers and consumption on the market
Zhou et al. (2019)	Industrial Management Data Systems	-A big data analytic approach to discover vehicle consumer consumption behaviors	Saaty scale-based model	Firm-related variables: Product/ brand/ service characteristics	Automobile marketing / China	Big data analysis	-The "cost-effectiveness" trait is the most important aspect that vehicle consumers care about, according to big data analytics, and the data mining findings help automakers better understand consumer behaviors

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Pantano et al. (2019)	International Journal of Retail and Distribution Management	-Usage of Twitter data for fashion retailing	Bayes' theorem	Firm-related variables: consumer experience based rich datasets, retailers' marketing intelligence	Apparel/ U.K.	Big data analysis	-The findings include a compare and contrast of consumers' reactions to various retailers, as well as useful tips for systematically deciphering consumers' tweets and improving marketing intelligence
Hofacker et al. (2016)	Journal of consumer marketing	-Benefits of consumer behaviors on big data	Priori theory followed by experimentation	Consumer related variables: consumer privacy concerns, Firm-related variables: consumer decision-making process	Marketing/ U.S.A.	Experiments	- Big data appears to be changing the essence of the feedback loop between theory and outcomes
Santiago and Robert (2020)	California Management Review	- New product development (NPD) process of omnichannel environment	New product development (NPD) Framework	Firm-related variables: Updated technology	Marketing/ U.S.A.	Literature review	Described how the omnichannel environment, as well as the technologies that allow it, influence the pace and execution of each stage of the NPD process
Boone et al. (2019)	International Journal of Forecasting	- Forecasting of sales in the supply chain through customer analytics based on big data and associated technologies	Not discussed	Consumer related variables: customer expectations such as shortening lead times Firm-related variables: Management of scarce resource	Sales/ U.S.A.	Big data analysis	The authors concentrated on three aspects of the purchasing decision: the testing process, the store experience, and the final sales transaction. From this standpoint, we've looked at the various ways that big data can improve aggregate forecasts
Oztekin (2018)	Annals of Operations Research	- Host peer-to-peer educational events for healthcare professionals	Not discussed	Consumer related variables: individualized marketing plan	Marketing/ U.S.A.	Big data analysis	The results of the data analytic models show that support vector machines were the most accurate classifier, followed by artificial neural networks and decision trees
Chiang and Yang (2018)	Technological Forecasting Social Change	- The role of point-of-sale transaction records of customers to understand consumer personality traits relate to the country-of-origin (COO) traits	Utility Theory	Firm-related variables: Brand personality Consumer related variables: Relationship characteristics	Retail/ Taiwan	Big data analysis	The findings revealed that consumers tend to purchase and co-purchase brands with traits linked with their own personality

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Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Birkin (2019)	Journal of Transport Geography	-The augmentation of research in transport geography	Not discussed	Firm-related variables: Consumer data characteristics	Marketing/ U.K.	Big data analysis	-Careful ethical controls and well-designed security protocols are required to realize the potential of consumer data -Though modern data science approaches are useful, opportunities to restore and reinvigorate traditional techniques in new data should not be overlooked
Ozturkcan et al. (2019)	Behavior Information Technology	-Explored Twitter data related with football	Social media analytics framework	Consumer related variables: social media engagement	Sports Marketing/ Turkey	Big data analysis	-The study's results are useful for sports administrators and advertisers with recommendations such as: including specific contexts of winning or losing in their post-match marketing strategies, valuing weekdays as much as weekends, and using the after-work peak time of social media activity
Martens et al. (2016)	MIS quarterly	- Examined the use of massive, fine-grained data on consumer behaviors	The social theory	Firm-related variables: Quality of the dataset	Marketing/ Belgium	Big data analysis	- The results show that there is no appreciable improvement from moving to big data when using traditional structured data
Guajardo (2019)	Production Operations Management	-Empirical analysis of consumer usage and payment behaviors	Not discussed	Firm-related variables: Quality of the dataset	Marketing/ Developing economies	PAYG company reports	The analysis highlights the importance for firms of jointly tracking and analyzing payment and usage behaviors by customers, particularly in initial stages of the adoption process

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Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Kakatkar and Spann (2019)	International Journal of Research in Marketing	- Marketing analytics in retailing using anonymized and fragmented event-based (AFE) tracking data	The theory of event transition probabilities	Firm-related variables: Quality of the dataset	Marketing/ Germany	Big data analysis	-Author contrasted the importance of anonymized and fragmented event-based data in the future of retailing with other types of aggregate and individual-level data. -A technique for analyzing AFE data was proposed that allows for the approximate recovery of individual-level heterogeneity and the extraction of meaningful variables from raw data
Guha and Kumar (2018)	Production Operations Management	-Use of big data analytics in the domains of information systems, operations management, and healthcare	Parallel computing models	Firm-related variables: big data characteristics and applications	Information systems, operations management and healthcare	Big data analysis	-Presented a framework for applications of big data in the domains of information systems, operations management, and healthcare
Hu and Winer (2017)	International Journal of Research in Marketing	-Utilizing a large proprietary dataset of Groupon users	Logit model	Firm-related variables: Product/ brand/ service characteristics	Marketing / Hong Kong	Large proprietary dataset of Groupon user	-The tipping point does not stimulate consumers to refer the deal to others - By eliminating customers' confusion about whether the offer will ultimately tip, information about the tipping point increases deal purchase likelihood and accelerates deal purchase pace after adjusting for detailed deal characteristics
Oh et al. (2017)	Information & Management	- Examined the effects of social media, from the perspective of consumer engagement behaviors	Theory of consumer engagement behaviors	Consumer related variables: social media engagement	Marketing/ U.S.A.	Downloaded data via Web Application Programming Interface	-This research proposed and tested a set of CEB metrics on social media, as well as providing empirical support for the connection between CEB and economic performance. The findings highlight the value of putting money into social media communication through various platforms

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Tupikovskaja-Omovie and Tyler (2020)	International Journal of Information Management	- Google Analytics data to develop customer journey maps to understand digital consumer behaviors	Flow theory	Firm-related variables: Marketing decision-making	Fashion retailing/ U.K.	Google Analytics data	-The conclusion reached is that eye tracking can be used to audit the Google Analytics database for potential gaps in data and to inform and improve marketing decision-making
Lee et al. (2020)	Information Systems Research	-Development of a model source app for user behaviors in cross-promotion campaigns	Duality theory	Firm-related variables: Technology adoption Consumer related variables: Purchasing behaviors	Advertising/ Korea	Big data analysis	-The empirical findings suggest that when it comes to download decisions, users prefer more diverse apps than when it comes to consumption decisions, which is reinforced by the psychology literature on people's variety-seeking behaviors
Zhang et al. (2020)	European Journal of Operational Research	- Analytical model of the joint optimization of coupon face value and duration together with the product price, and determines the impact of coupon design on consumers' redemption behaviors	Regret theory, Resource slack theory	Consumer related variables: Purchasing behaviors	Advertising/ China	Content analysis	- The most important results concern (1) the best face value and length, (2) coupons as a price discrimination tool, and (3) coupon redemption trends
Arda et al. (2017)	Decision Support Systems	- Examined the organizational citizenship behaviors (OCB) of employees by designing and developing an analytic network process (ANP) methodology	Organizational citizenship behaviors theory	Firm-related variables: Product, brand and service characterizes	Business/ Turkey	in-depth interviews and focus groups	-The study's main contribution is the design and development of a prescriptive analytics approach for assessing organizational citizenship behaviors, which is uncommon in the field of organizational behaviors
Xiang et al. (2015)	International Journal of Hospitality Management	-Explored the utility of big data analytics to understand hospitality issues	Two factor theory of motivation	Firm-related variables: Product, brand and service characterizes	Hotel/ U.S.A.	Text analysis	-The results show that there are many aspects of the guest experience that have different weights and, more significantly, novel, substantive semantic compositions -The connection between guest satisfaction and experience appears to be solid, implying that these two aspects of customer behaviors are inextricably linked

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Lau et al. (2014)	Decision Support Systems	-Designed of a novel social analytics methodology that can leverage the sheer volume of consumer reviews archived at social media sites	Not discussed	Firm-related variables: Updated technology	Information Technology/ Hong Kong	Experiments	-The proposed system substantially outperforms the Opinion Finder baseline system in the polarity prediction task performed at the document stage
Duffy and Ney (2015)	Journal of Marketing Education	-The role of digital technology to be integrated into the marketing classroom	Not discussed	Firm-related variables: Updated technology	Higher Education/ U.K.	In-depth interviews	-This article aims to address the evolving pedagogical challenges of reflecting these tripartite views in marketing module creation through exploratory depth interviews with undergraduate students, educators, and industry practitioners, and to provide guidance for higher education institutions
Kakalejčík et al. (2020)	Journal of Research in Interactive Marketing	- Impact of newly created brand awareness on customer's buying behaviors in online environment	Theory of Barreda et al. (2015)	Firm-related variables: Updated technology	Business/ Slovakia	Data collected from Web analytics tools	-The authors determined three parameters based on the degree of theoretical brand recognition based on the findings of the interaction study of individual consumer journeys
Sheth (2019)	Journal of Historical Research in Marketing	-Author's journey of more than 50 years	Theory of Buyer Behavior with John Howard	Firm -related variables: Leadership attributes	Marketing/ U.S.A.	An autobiographical evaluation	-Marketing has changed and adapted to the external world over the last 50 years, this presents a huge opportunity for the next generation of academics to carve out a niche in managerial marketing, customer behaviors, or marketing analytics
Sturley et al. (2018)	International Review of Retail Distribution and Consumer Research	-Assessed the feasibility of modelling consumer store choice behaviors	The spatial interaction model	Customer analytics literature: Perceived values and benefits	Retail/U.K.	Retailers' loyalty card database	-The findings may open new possibilities for spatial modelling in the retail industry, allowing the complexity of customer behaviors to be captured and simulated within a novel modelling framework

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Pomirleanu et al. (2013)	Journal of Research in Interactive Marketing	-The 20-year review of marketing and business journals examines the internet marketing literature	Not discussed	Firm-related variables: Updated technology	Internet Marketing / U.S.A.	Literature Review	-The results show that the number of internet marketing articles published in top marketing journals has increased, and that the number of journals publishing internet marketing articles has expanded
Naraine et al.	Managing Sport Leisure	-Analyzed user engagement from within the Twitter community of professional sport organizations	Grönroos' relationship marketing model	Firm-related variables: Social media engagement	Sports/ Canada	Twitter network data	-Results confirm that these communities are mostly comprised of Millennial users interested in the other Toronto sports teams, rival- or competing- teams, but who engage in social media during non-games time periods
Pindado and Barrena (2021)	British Food Journal	- Investigated the use of Twitter for studying the social representations of different regions across the world	Social representations theory	Firm-related variables: Social media engagement	Marketing / Spain	Big data analysis	-Twitter users have a weak, positive attitude towards food trends, and significant differences were found across regions identified, which suggests that factors at the regional level, such as cultural context determine users' attitude towards food innovations
Silva et al. (2019)	Journal of Business Strategy	- Applications of big data in fashion retailing	Not discussed	Firm-related variables: Quality of the data set	Fashion retail industry/ Not discussed	Conceptual paper	-The authors find that the main reasons underlying the application of big data analytics in fashion are trend prediction, waste reduction, consumer experience, consumer engagement and marketing, better quality control, less counterfeits and shortening of supply chains
Fiore et al. (2017)	British Food Journal	-Investigated the attributes of wheat flour	Not discussed	Firm-related variables: Product, brand and service characterizes	Food industry / Italy	Questionnaire -based survey	-In line with recent nutritious and dynamic food market trends, aware consumers seem to be able to pay four times the price for "type 1" wheat flour compared to the basic forms of wheat flour

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Ting and Kauffman (2012)	Decision Support Systems	-Proposed an analytics approach that leverages adaptive learning	The theory of rational expectations and adaptive learning	Firm-related variables: Product, brand and service characterizes	Marketing/ Not discussed	Model evaluation	-According to the findings, understanding the effects of customer responses in business operations is critical for developing cost-effective and value-adding service designs
Lin et al. (2020)	International Journal of Production Economics	-Proposed a Bayesian approach to estimate the multivariate risk measures	A Bayesian approach	Firm-related variables: risk factors	Finance / Taiwan	A Bayesian approach	-After using the Cornish–Fisher (CF) approximation with Markov Chain Monte Carlo (MCMC) sampling, the proposed approach will bring prior knowledge into the Bayesian analysis and completely explain the risk measures' actions
Maheshwari et al. (2020)	International Journal of Production Research	-A recent review on big data Analytics, Supply Chain Management, Logistics Management, and Inventory Management	Not discussed	Firm-related variables: Quality of the data set	Supply chain management/ India	Content analysis	-The results and observations provide scientists and business experts with up-to-date information by providing an exhaustive list of achievements and problems in the fields of big data Analytics, Supply Chain Management, Logistics Management, and Inventory Management
Ibrahim and Wang (2019)	Computers in Human Behavior	- Brand-related tweets associated with five leading U.K. online retailers	Not discussed	Firm-related variables: Quality of the data set	Retail/ U.K.	Twitter data	-This study offers a better understanding of customers' opinions towards online retailing and provides insight into what customers are really thinking about by analyzing their opinions as expressed on Twitter

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Li et al. (2020)	Journal of Enterprise Information Management	- Analyzed the influencing factors of customer online shopping	Feature selection theory, Game theory	Firm-related variables: Quality of the data set, Updated technology	Supply chain/ China	Big data analysis	-The feature selection algorithm, for starters, will boost the efficiency of optimization in large data samples - The consumer buying behaviors is influenced by the level of visualization and the quality of information (page value) -The Stackelberg game method is used to determine the relationship between optimal pricing and the degree of visualization
Aluri et al. (2019)	Journal of Hospitality Tourism Research	-This study demonstrated how machine learning can be used to increase understanding of what customers value in the engagement-to-loyalty value chain	Not discussed	Firm-related variables: Updated technology	Hospitality / U.S.A.	Big data analysis	-The results show that machine learning processes are superior in identifying customers who find value in specific promotions
Routh et al. (2020)	Journal of the Operational Research Society	-Demonstrated a competing risk random survival forest model	Not discussed	Customer-related variables: Purchasing behaviors	Hospitality/U.S.A.	customer churn data	-Developed a new framework for evaluating customer churn under competing risk
Wang et al. (2020)	Journal of the Operational Research Society	-Built a two-period game-theoretic model to capture dynamics of customers behaviors	Game Theory	Customer-related variables: Relationship characteristics	Supply chain / China	customers' purchase history data	-Results show that manufacturers always prefer long-term wholesale contracts
Papanagnou and Matthews-Amune (2018)	Computers Operations Research	-Explored how sales structured data improve inventory management	Demand forecasting models	Firm-related variables: Customer service quality	Retail pharmacies/ U.K.	Google index and Newspaper Keyword Index (NKI), weekly sales of OTC medicine	-Results support the assumption that using multivariate time series analysis technique, customer generated content from a variety of internet sources has the potential of reducing demand forecasting errors in the short term and improving response to demand volatility in retail pharmacy settings

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Luca et al. (2020)	Journal of the Academy of Marketing Science	- Practice-oriented framework of the impact of big data investments	Affordance theory	Customer-related variables: Relationship characteristics Firm-related variables: Product, brand and service characterizes	Digital services / U.K.	Big data analysis	-Construct validity is established, and a preliminary nomological test of direct, indirect, and conditional effects of big data marketing affordances on perceived big data output is provided
Kumar et al. (2016)	Journal of Marketing Education	-Examined the effect of firm-generated content (FGC) in social media on three key customer metrics: spending, cross-buying, and customer profitability	Not discussed	Firm-related variables: Social media engagement	Marketing / Finland	Surveys	-The results indicate that after the authors account for the effects of television advertising and e-mail marketing, FGC has a positive and significant effect on customers' behaviors
Reutterer et al. (2020)	International Journal of Research in Marketing	- Stochastic modelling approach for predicting individual-level buyer behaviors	Not discussed	Firm-related variables: Quality of the data set	Marketing / Austria	Dietary supplements, donation, office supplies and grocery datasets	-The authors show significant improvements in predictive precision against baseline models and efficiency increases comparable to or on par with a more complex model alternative using detailed simulation studies and six data sets covering a broad variety of empirical settings
Huang and Mieghem (2013)	Production Operations Management	-Used a newsvendor framework to examine how product availability induces strategic customers to voluntarily provide advance demand information	Newsvendor framework	Firm-related variables: Quality of the data set	Marketing / U.K.	Company sales data reports	-In comparison to other techniques, such as advance selling, quantity commitment, availability of assurances, and rapid response, click monitoring is normally beneficial to both the firm and its customers
Shirazi and Mohammadi (2019)	International Journal of Information Management	-Constructed a predictive churn model	The Datameer big data analytics tool and SAS business intelligence system	Customer-related variables: Decision-making	Banking/ Canada	Big data analysis	-The Datameer big data analytics tool on the Hadoop platform and predictive techniques using the SAS business intelligence system were applied to study the client retirement journey path

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Martínez et al. (2020)	European Journal of Operational Research	-Developed an advanced analytics tools that predict future customer behaviors	Not discussed	Customer-related variables: Decision-making Firm-related variables: Quality of the data set	Marketing / Netherlands	Transactional data provided by a large manufacturer located in central Europe	-In this study, the gradient tree boosting method turns out to be the best performing method
Kitchens et al. (2018)	Journal of Management Information Systems	-Presented a framework for designing advanced customer analytics solutions based on relationship-oriented constructs	Relationship marketing theory	Firm-related variables: Updated technology	Marketing / Not discussed	Big data analysis	-Contributes to the design science literature in the creation of a synergistic ecosystem of novel IT artifacts for performing advanced customer analytics in the era of big data -Contributes to managerial practice for firms attempting to employ big data analytics to drive strategic value -Contributes to the nascent literature regarding predictive analytics using big data
Ma et al. (2019)	Transportation Research Part E: Logistics Transportation Review	-This study outlined the connections between yield management, crises, and crisis communication	Situational Crisis Communication theory, image repair theory	Firm-related variables: Product, brand and service characterizes	Airline industry/ U.K.	Big data analysis	-Using big data captured on a social media platform, this study combined traditional yield management with emerging social big data analytics
Miles (2014)	Academy of Marketing Studies Journal	-Examined use of marketing analytics to measure customer behaviors in small business enterprises	Theoretical concepts in accounting, finance, and marketing	Customer-related variables: Decision-making	Marketing / U.S.A.	Survey questionnaire	This study looked at three important marketing analytics, such as consumer behaviors analytics; marketing behaviors analytics and economic behaviors analytics
Radha and Babu (2020)	International Journal of Enterprise Network Management	-A new method for sentiment clustering and classification of cloud customer's behaviors feedback	Not discussed	Customer-related variables: Decision-making Firm-related variables: Quality of the data set	Marketing / India	Big data analysis	Unstructured data has been converted into structured data by clustering the feedback of customers
Marinelli et al. (2020)	British Food Journal	-Investigated the food and beverage automatic retail environment	Model suggested by Blackwell et al. (2006)	Customer analytics literature: Perceived value and benefits	Marketing / Italy	Experiments	-The experimental results demonstrated that planograms positively impact food purchases -A planogram acts as a mediator in the relationship between shopping time and purchase, resulting in shorter shopping times and more purchases

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Table 6. Continued

Source	Journal Name	Key Constructs	Theory	Characteristics	Context	Method	Key Findings
Wong and Wei (2018)	International Journal of Retail Distribution Management	-Developed a customer online behaviors analysis tool	The integrated model for mining pricing data	Customer-related variables: Relationship characteristics	Marketing/ Hong Kong	Big data analysis	-The flight duration time and the purchase lead time have a substantial relationship. With regard to their travel habits and the significance of the relationships between destination pairs, the next travel destinations of segmented high-value customers are expected
Fuchs et al. (2014)	Journal of Destination Marketing	- Developed a theoretical fundament for technical architecture of a Business Intelligence application	Knowledge Destination Framework	Customer-related variables: Customer decision-making	Tourism/ Sweden	Big data analysis	-This paper discussed how tourism managers can use Destination Management Information Systems to learn more about customer-based destination processes

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