

Received 29 July 2022, accepted 25 August 2022, date of publication 29 August 2022, date of current version 12 September 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3202896

TOPICAL REVIEW

Machine Learning and Marketing: A Systematic Literature Review

VANNESSA DUARTE^{ID}, SERGIO ZUNIGA-JARA^{ID}, AND SERGIO CONTRERAS^{ID}

Escuela de Ciencias Empresariales, Universidad Católica del Norte, Larrondo, Coquimbo 1281, Chile

Corresponding author: Vanessa Duarte (vannessa.duarte@ucn.cl)

ABSTRACT Even though machine learning (ML) applications are not novel, they have gained popularity partly due to the advance in computing processing. This study explores the adoption of ML methods in marketing applications through a bibliographic review of the period 2008–2022. In this period, the adoption of ML in marketing has grown significantly. This growth has been quite heterogeneous, varying from the use of classical methods such as artificial neural networks to hybrid methods that combine different techniques to improve results. Generally, maturity in the use of ML in marketing and increasing specialization in the type of problems that are solved were observed. Strikingly, the types of ML methods used to solve marketing problems vary wildly, including deep learning, supervised learning, reinforcement learning, unsupervised learning, and hybrid methods. Finally, we found that the main marketing problems solved with machine learning were related to consumer behavior, recommender systems, forecasting, marketing segmentation, and text analysis—content analysis.

INDEX TERMS Machine learning, marketing, scientific publications, deep learning, supervised learning, unsupervised learning.

I. INTRODUCTION

Due to improvements in information technology and the fast growth of the Internet, the revolution of data in the last decades has made businesses generate a substantial amount of useful data; however, we still don't know how to use it [1], [2]. The data must be transformed into information and knowledge that can be turned into tools to help organizations improve their decision-making [3]. In this regard, machine learning (ML) allows for generating useful results for companies with less effort and time [4], [5], and it is increasingly being used in marketing research. For example, ML is employed in market segmentation, tourism, customer lifetime value, loyalty and client segment, direct market, marketing campaigns, and other applications [6]. ML techniques provide computers with the ability to understand and use data and experiences like a human brain [7]. ML models are applied to data due to their ability to resolve different problems, from those that could be solved through conventional statistics and management of scientific techniques to complex problems

that require a bigger analysis; in this regard, ML allows solving problems faster and better than conventional techniques. Therefore, ML-based techniques are used to predict the results of new data, predictions, and classifications or to help people in the process of decision-making. Companies need to learn more and more about their consumers, their products, how to present them in the media, and how to plan future activities efficiently, making use of their historical data [8]. As we will see, ML has been widely used to discover the most relevant needs of consumers and the relationship they have with products and their attributes [9], [10], segment satisfaction, recognition or recommendation, the selection of a new product or reaction to advertising [11], [12], [13], [14].

Data can come from different sources both structured and unstructured [15], [16], [17]. Sources include websites, social media, and blogs (YouTube, Twitter Tweets, Google Trends, visits to Wikipedia, reviews on IMDB, restaurants, tourism, hotels, and Huffington Post news) to predict the consumers' demand, among others. Other sources include data from business transactions such as e-commerce [18], [19], retail scanners, as well as intentional sources of data creation through user and internet usage (e.g., web cookies),

The associate editor coordinating the review of this manuscript and approving it for publication was Michael Lyu.

location data (GSM, GPS, call center, among others), and personal data generated from searches [20]. The expectation is that ML would deliver a consistent and high-quality way to develop techniques that contribute to rapid innovation where organizations or entities can manage their boundaries [21]. Using ML, organizations can improve their market planning, position themselves in new markets, and analyze the changing market situation, consumer segmentation, retention marketing loyalty and their commitment to or renunciation of a brand or product [22], [23]. All this enables organizations to improve their services or products and influence decision-making. However, these techniques also represent a challenge as their use extends and evolves from memory-based algorithms models (user-oriented, item-oriented) to models of latent factors until reaching learning models such as Item2Vec, Product2Vec, or Doc2Vec and finally, deep-learning models [24], [25]. Accordingly, organizations must know what model to use, how to use it, and the advantages or disadvantages that it provides.

To obtain a clear idea of the most used techniques and methods of ML in marketing, we searched for scientific articles published between January 2000 and March 2022. We employed keywords related to ML in top journals of the marketing subject category within the Scopus and Journal Citation Reports (JCR) databases. Thus, after a thorough review, a total of 320 scientific articles were obtained, allowing us to observe what marketing problems are solved and the techniques used for this purpose. We did not only perform an overview of the methods and how ML influences this industry; instead, our study goes deeper and focuses on guiding the reader on how ML techniques could be applied to solve real marketing problems. In this article, we presented the advantages and disadvantages of the methods and which marketing problems are more feasible to solve with specific algorithms.

II. METHODOLOGY

ML techniques have gradually become a common election in marketing research [26]. To provide the reader with a guide to the techniques used in the marketing scientific literature and the marketing problems they can solve, we followed several steps. Figure 1 summarizes the methodology we followed. In step 1, we identified scientific journals whose main focus was marketing by searching the “Scimago Journal & Country Rank” (SJR) database for journals in the “marketing category”. Then, we filtered the search looking for journals of the Q1 quality quartile (SJR). To ensure that the journals were top-ranked, within the same SJR database, we additionally filtered the journals indexed in the Web of Science (WoS-JCR). JCR indexing is generally considered stricter than SJR, so this filter limits journals to being SJR Q1 and those belonging to JCR Q1, JCR Q2, JCR Q3, or JCR Q4. The final selection with this filter yielded 42 journals: J. of Marketing, J. of Marketing Research, Marketing Science, J. of Consumer Research, J. of Supply Chain Management, J. of Public Administration

Research and Theory, Public Administration Review, J. of the Academy of Marketing Science, J. of Retailing, International J. of Research in Marketing, Quantitative Marketing and Economics, Academy of Management Perspectives, J. of Consumer Psychology, J. of International Marketing, J. of Interactive Marketing, Industrial Marketing Management, Governance, J. of Advertising, American Review of Public Administration, Sport Management Review, Marketing Theory, J. of Travel and Tourism Marketing, J. of World Business, J. of Purchasing and Supply Management, International Business Review, International Marketing Review, International J. of Advertising, J. of Hospitality Marketing and Management, Psychology and Marketing, J. of Destination Marketing and Management, Business Horizons, J. of Public Policy and Marketing, J. of Retailing and Consumer Services, Electronic Commerce Research and Applications, Consumption Markets and Culture, J. of Services Marketing, Public Relations Review, J. of Marketing Management, Administration and Society, J. of Advertising Research, European J. of Marketing J. of Business Research, Marketing Letters.

In step 2, we searched for individual articles published by these journals in the Web of Science (WoS) database between January 2000 and March 2022, which is a range of almost 22 years. We tried using different keywords regarding real applications of ML techniques. Our first search yielded 689 published articles, of which only a small number of articles included what we were looking for. Finally, step 3, we decided to search for a list of specific ML methods. The final search is showed in the Figure 1. In the WoS database, we used “TS”, meaning search for topic terms in the following fields: Title; Abstract; Author Keywords; Keywords Plus. With this, we obtained 320 journal articles.

In step 4, we reviewed one by one each of the 320 articles and then performed a filter that would allow us to reach a final number of articles. These criteria were the following: the use of ML should be the main technique of the article, the ML techniques should have been declared by the authors (papers not showing a learning process were excluded), and the article must provide enough information concerning the technique used. Furthermore, the articles must define the technique as ML and show the application of a case with real data from verified sources (not experimental or simulated examples [27], [28]). Some articles that used semi-supervised learning but did not show a real application were rejected [29], [30], [31]. Our database ignores articles that are not in the area of marketing [32] (e.g., financial credit scores). Ordinary regression (OLS), hierarchical regression, and classic grouping (clustering) were not included if they did not exhibit any learning technique. Articles that only exhibited the use of software but did not provide intermediate results were not included either [33], [34]. Articles that presented software but did not exhibit the parameters employed and the reasoning behind its use were not included [35]. Finally, a total of 125 articles were included in this review. In step 5, we searched within these 125 articles for the main groups of

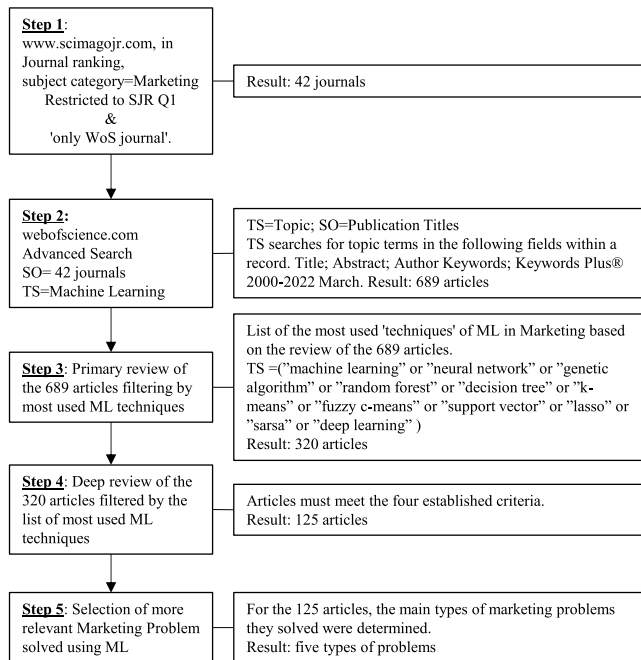


FIGURE 1. Methodology steps followed in this study.

marketing problems solved with ML, finally determining the following five: consumer behavior (CB), forecasting (FC), market segmentation (MS), recommender system (RS), and text and video or content analysis (TX).

III. BRIEF SUMMARY OF THE ARTICLES STUDIED

This section presents a brief descriptive summary of some characteristics of the reviewed articles, including the number of articles published per year, their citations, their quality quartile, the journals in which they were published, the type of learning they use, and the type of marketing problems they solve. Figure 2 demonstrates an increase in the number of published articles using ML in marketing recently (data for 2022 is until March). Furthermore, between 2000 and 2007, only six articles met our quality criteria (there were no publications that met the criteria in the years 2001, 2003, 2005, 2006 and 2007), and for this reason, some of the next figures report only information starting from the year 2008. On the other hand, as expected, older articles tended to have a higher number of citations on average, with some fluctuations.

Regarding the distribution of articles each year by JCR-quartile, Figure 3 shows that there are no articles classified as Q4 JCR that meet our criteria and that publications in high-impact Q1 JCR journals tend to exhibit a progressive increase over the years. Q2 JCR journals did not exhibit a significant change, except in 2019. Additionally, the presence of Q3 WoS-JCR journals is almost marginal in all the years, and this is primarily because we tried to maintain the quality of the articles published, discarding journals of lower quartiles.

Figure 4 shows the annual distribution of the top nine journals that published articles that met the search criteria. In total, 22 journals exist in our database. As illustrated in

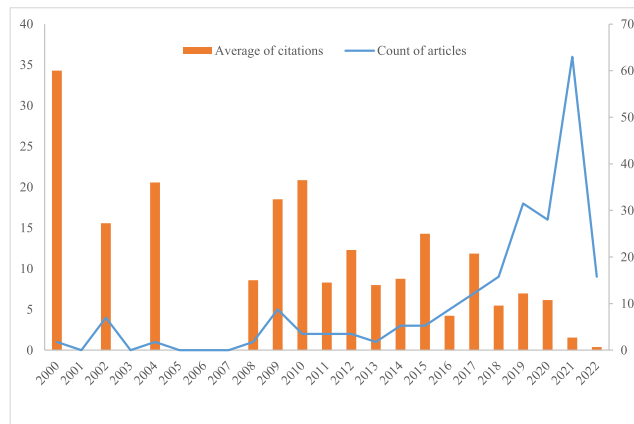


FIGURE 2. Number of articles published per year (line) and the average number of citations in each article (bars) (January 2000 to March 2022).

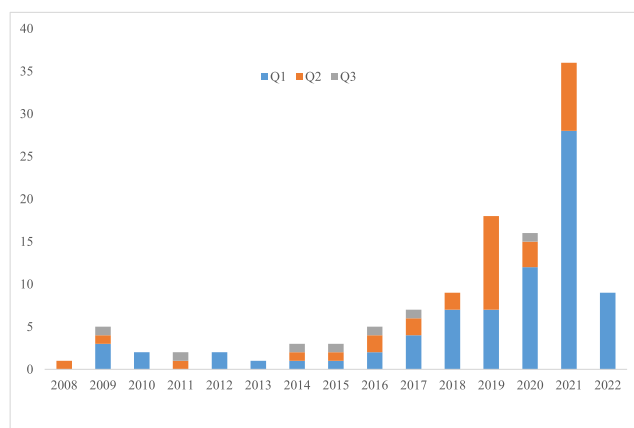


FIGURE 3. Number of articles applying ML in marketing published by JCR quartile every year (2008 to March 2022).

Figure 4, these journals have published at least four articles applying ML in marketing. The Electronic Commerce Research and Applications is the journal with the highest number of publications over the years with 24 articles published, followed by the Journal of Business Research and the Journal of Retailing and Consumer Services with 21. The Journal of Marketing Science exceeded 10 publications in all years, and the others on the list have between four and eight publications in that period. Other journals that do not appear in this list have published two articles in these years (three journals) and one article (11 journals).

IV. MACHINE-LEARNING TECHNIQUES USED IN MARKETING RESEARCH

Regarding the main ML techniques used in our review of literature on marketing, it is difficult to achieve a systematic and organized classification widely accepted. Figure 5 shows a simplified organization of ML types of learning and ML techniques, indicating that ML can be broadly categorized into two classes: supervised and unsupervised learning [36]. Supervised learning is used with labeled data in training and learning. Unsupervised learning is a technique to find

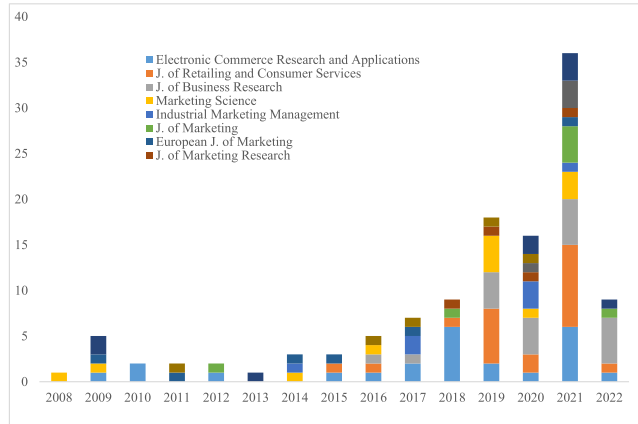


FIGURE 4. JCR journals with the highest number of published articles meeting the criteria (2008 to Mar 2022).

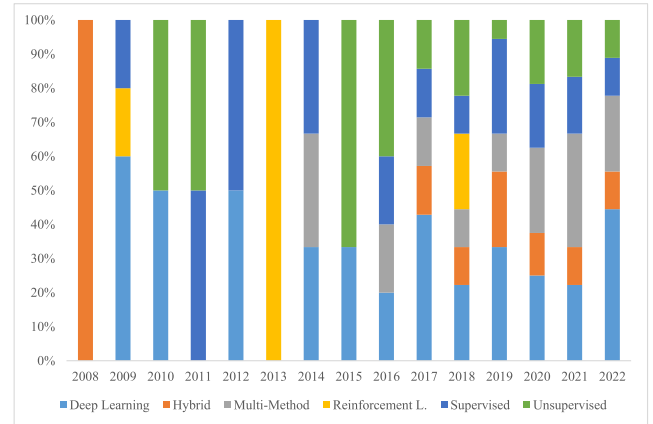


FIGURE 6. Distribution of the number of articles according to the type of ML (2008 to March 2022).

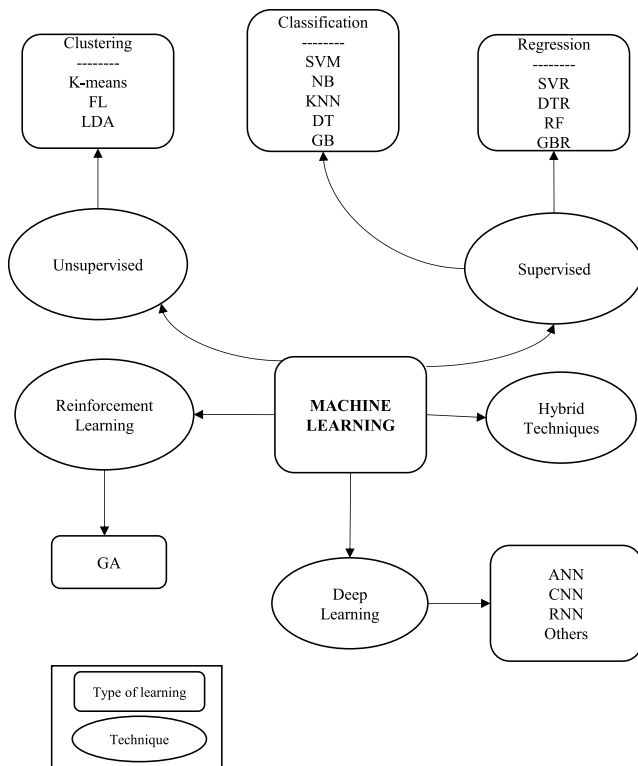


FIGURE 5. Classification of the most used types of learning and techniques in marketing research.

some pattern or structure of the data by itself where no labels are given. In the same way, some techniques do not belong to any of the categories due to their features that are not supervised or unsupervised, including deep learning, reinforcement learning, and hybrid methods.

Figure 6 shows the percentage distribution of articles published in the marketing area over time. Here, deep learning is present in almost all years. Similarly, in recent years, several techniques have been used simultaneously (multi-technique) for the purpose of comparison to select the one that provides the best results. Hybrid learning combining different techniques has been increasingly applied recently

due to the higher speed of computational capability. It is also noteworthy that supervised and unsupervised learning has been widely used in recent years, but not as other techniques.

Regarding the specific techniques used in the marketing articles, within deep learning, as mentioned earlier, Figure 7a shows that the most used technique is the artificial neural network (ANN), followed by the convolutional neural network (CNN) and other techniques that change the way neurons are interconnected or the adaptations of the original model. For classification techniques (Figure 7b), the decision tree (DT) is the most used technique, and this could be due to its simplicity in the implementation and compression of the results. Additionally, other variations of DT are used, including gradient boosting (GB) and random forest (RF).

Support vector machine (SVM) or naïve Bayes (NB) is almost equally used. Furthermore, this review ascertained that regression models (Figure 7c) were rarely used; however, eXtreme Gradient Boosting (XGB) is the most used. In the case of unsupervised learning techniques, the ones found are clustering (Figure 7d), in which K-means is frequently used for market segmentation and latent Dirichlet allocation (LDA) for text processing. In hybrid techniques (Figure 7e), the most used in combination with other ways to improve prediction are deep learning techniques such as ANN and CNN, followed by SVM. Some published articles sought to compare some techniques based on their performance (Figure 7f); in this case, the most compared technique is DT and RF, followed by SVM. Numerous techniques are used in ML; however, we merely provided a brief overview of the most common ones implemented in marketing applications, as detailed in this review and Figure 7. The algorithms used by the papers include individual algorithms or a combination of them [37].

In the following sections, we will comment on the most used ML techniques in marketing, organizing them by type of learning according to Figure 5. We will be referencing the articles that have used each technique as we go along.

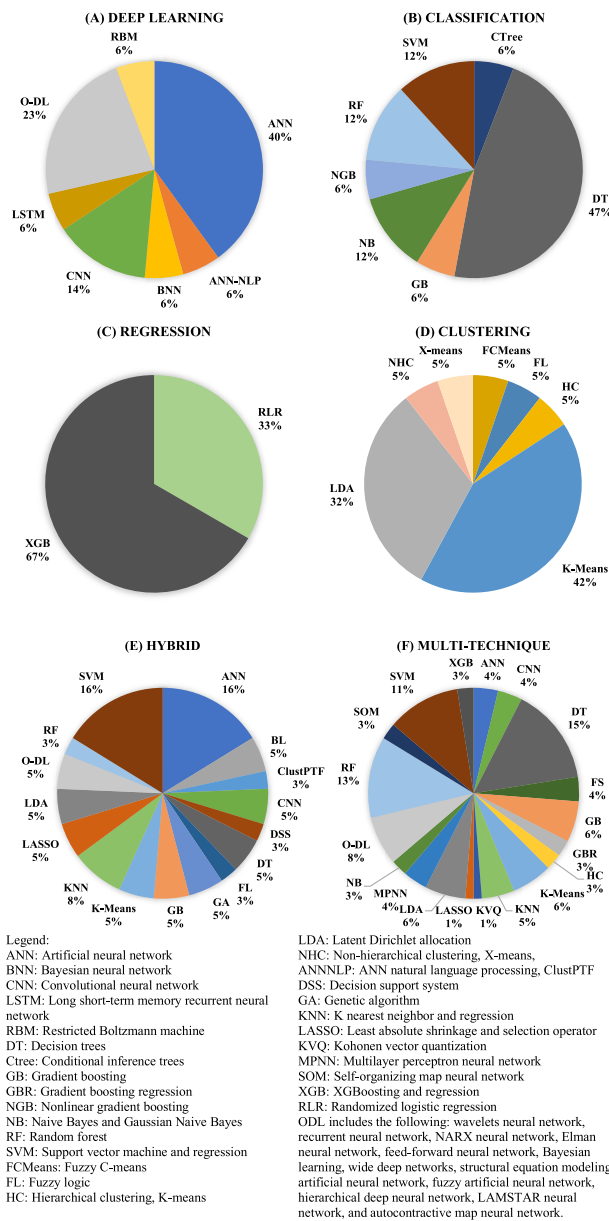


FIGURE 7. ML techniques percentage share use in solving marketing problems.

A. DEEP LEARNING

Deep learning algorithms are a group of powerful techniques that work through easily obtainable software; in particular, these models were developed as a generalization of mathematical models. It works with a biological brain that is composed of several interconnected neurons, governed by algorithms that allow them to learn from mistakes, recognize patterns, and operate with incomplete information [38]. Some authors use the restricted Boltzmann machine (RBM) to learn co-occurrence patterns of items to elaborate on the latent association of items, and then they use a backpropagation neural network (BPNN) to predict those items belonging to an interest search [39], [40]. Other applications are prominent in

content analysis to solve natural language processing (NLP) tasks and identify information from words in a review [41], [42], [43], [44], [45], news events [46], or hierarchical attention networks (HAN) [47]. CNN is also applied as a content generator [48], and it is also used for text and image detection in social networks, brands, and retail [49], [50], [51], [52]. Moreover, further applications of deep learning emerge in decision-making processes such as buying, which uses a multilayer perceptron neural network (MPL-NN) [53], or ranking products with hierarchical deep learning [47], [54]. Furthermore, the ANN is one of the most used deep learning algorithms. ANNs can be classified into two dimensions: supervised or unsupervised; and can be either recursive or non-recursive [11]. ANN results depend on its architecture. Usually, ANNs use a standard backpropagation algorithm to train the network. However, the recurrent neural network (RNN) is a kind of ANN that is adapted to model sequential tasks [44], [55]. Moreover, other models or techniques implement a different kind of backpropagation; for instance, the Elman neural network is a semi-recursive ANN that uses the back-propagation-through time learning algorithm to find patterns in value sequences [56], and the nonlinear auto-regressive with exogenous ANN (NARX-ANN) is an important class of discrete-time nonlinear systems. Additionally, large-scale memory storage and retrieval (LAMSTAR) combines a self-organization map (SOM) [57] and statistical decision tools [58], and long short-term memory (LSTM) is a variant of RNNs that aims to process long-term time series and solve the problem of the vanishing gradient in an RNN [25], [55], [59]. On another note, wavelet neural networks are feedforward ANNs with one hidden layer, radial wavelets as activation functions in the hidden nodes (HUs), and a linear output layer [60].

B. SUPERVISED LEARNING

Classification techniques are usually computer programs that learn from the input data given and use this training data to learn to classify by observing patterns in this data. On the other hand, supervised learning for regression is a set of algorithms used to predict continuous values; for example, randomized logistic regression (RLR) works by splitting the training data and running a regression on each [61], [62]. Some examples of supervised learning in marketing include strategies to communicate decisions, choices [63], satisfaction [64] and product development [65], churn models [66], [67], classification of online articles and reviews [68], [69], demand prediction, or measurement of influencer index. In ML there are some algorithms that can be used for marketing purposes, including the following:

1) SUPPORT VECTOR MACHINE (SVM)

SVM is a classification method that employs the mapping of the input vector onto a high-dimensional feature space and then, constructs a linear model that implements nonlinear class boundaries in the original space [70]. The data is classified through a special kind of linear model, namely,

the optimal hyperplane, that maximizes the distance between observations that belong to each category [71]. Support vector regression (SVR) is also a popular SVM where the hyperplane is the actual nonlinear function that should be estimated, and the sign of the residuals represents the two classes [72]. The capacity of the system is controlled by parameters that do not depend on the dimensionality of feature space [73], [74]. Mostly, this technique is used to forecast customer retention [75], online customer reviews [68], and prices in supply chains [76].

2) NAÏVE BAYES (NB)

Naïve Bayes is based on Bayes' theorem models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. It offers "a competitive classification performance for text categorization compared with other data-driven classification methods" [64]. This technique is used to measure customer satisfaction [64] or predict customer churn [66].

3) K-NEAREST NEIGHBOR (KNN)

KNN is a non-parametric method used for classification and regression. The algorithm requires the specification of a similarity function that produces a similar score between pairs, a response variable of interest, and the number of nearest neighbors (k' nearest neighbors) [73], [77]. The output for classification is to classify an object by a plurality vote of its neighbors; in other words, the object is assigned to the class of that single nearest neighbor. For regression, the output is the average of the values of the k' nearest neighbors of the object. KNN for regression is a popular algorithm that allows the prediction of the numerical target based on a similarity measure, which is often any distance function [73]. This technique is used in hybrid techniques or to compare performance, especially in predicting the influence on social networks [73], differences in the evaluation of products [77], and brand personality [78], among others.

4) DECISION TREE (DT)

DT is a method that generates rules for data classification using a representation of a tree-like structure [79], and regression trees respond to their predictors by recursive binary splits [80]. The output is made by a decision node with two or more branches and a leaf node. This technique is suitable for describing sequences of interrelated decisions or predicting future data trends, and it can classify specific entities into specific classes based on their features. Some variations of DT include the conditional inference tree (Ctree), which is a non-parametric class of regression trees embedding tree-structured regression models into rule-based procedures [81], and decision trees with cost-sensitive learning methods have been utilized by academics to solve the problem of class imbalance in data, especially in churn [79]. This technique has been used to predict the value of reviews [69], [82], the choice of a brand based on social networks [81], and sales [83], [84]. Notably, it is one of the most used supervised

techniques to be included in recommender systems [63], [85], [86], [87], [88].

5) LASSO

Lasso is a linear model that estimates sparse coefficients. It does both parameter shrinkage and variable selection automatically [73].

6) ENSEMBLE METHODS

Ensemble methods are algorithms that construct a set of classifiers and then classify new data points by taking a (weighted) vote of their predictions [89]. The fundamental principle of ensemble learning is to divide a large dataset into small data chunks [68] (bagging models) or combine multiple learning algorithms to obtain better performance (boosting models) [80]. Random forest is the most commonly used algorithm within bagging models, and it uses a multitude of decision trees or statistical data structures during training to best divide and average the labels to create a more balanced prediction [90]; additionally, it combines several base classifiers into a robust classifier by increasing the overall accuracy of the aggregated model [79].

The training set is randomly generated. RF is implemented to reduce the correlation between the random distributions of the input set and improve the bagging [91], [92]. Some techniques can improve the RF algorithm; for instance, non-parametric RF is more robust to outliers compared to other bagging or boosting algorithms [92]. Boosting models improve accuracy based on the idea that it is easier to find an average of many approximate rules of the thumb than to find a single highly accurate prediction rule [80]. Boosting models include gradient boosting (GB) that builds a set of weak learnings (commonly used DT) to produce suitable learning by correcting prior learning [74]. GB adjusts the predictor to the residual errors made by the previous learning, i.e., increases the gradient to allow optimization of an arbitrary loss function [92]. XGBoost (XGB) is a model used for regression or classification commonly based on decision trees. XGB is an efficient model for making decisions from a large dataset, and it is obtained by recursively partitioning the data space and fitting the prediction model at each partition. The individual decisions are entirely inaccurate but are better than those generated randomly [91]. RF combines several decision trees at the end of the process, whereas gradient boosting combines decision trees at the beginning of the process [93].

C. REINFORCEMENT LEARNING

Reinforcement learning corresponds to supervised algorithms in which an agent interacts with the environment and learns to increase the maximum reward [94]. These algorithms are commonly used as a recommender system for configuring campaigns, digital advertising, and revenue, promoting different product categories, and retailing, among others. The most used method is genetic algorithms (GA). This method is based on the mechanics of natural evolution and natural genetics with chromosomes whose values are the

outcome of Boolean functions as a data structure. They do not require a starting value. GA learns and tries to maximize the accumulated reward using a survival-of-the-fittest scheme with a random organized search to find the best solution to a problem [95].

D. UNSUPERVISED LEARNING

Unsupervised learning methods are algorithms that identify patterns in datasets containing data points that are neither classified nor labeled. Unsupervised learning involves analyzing data without trying to predict anything [96]. Clustering is a well-known technique for finding groups in data [97]. There are two kinds of clustering: hierarchical clustering techniques, and nonhierarchical techniques, more suitable for segmenting large databases [98]. Unsupervised learning is commonly used for market segmentation and text analysis (TA). In market segmentation, it is used for retail segmentation [98], market structuring [99], buyers of certain brands [100], e-commerce markets [101], and service opportunities [102]. On the other hand, in TA, it seeks to analyze news, reviews, and social networks to measure sentiment or veracity [97], [103], [104], [105], [106], [107].

1) K-MEANS

K-means is one of the most popular clustering algorithms achieves results using highly efficient approaches [101]. K-means requires a number of seeds that have the same dimension as the input vector and is equal to the number of clusters to be create. The learning process adapts the seeds to conform approximately to the actual distribution vector and stop when the difference between the new seeds and the old seeds is smaller than a threshold [102].

2) FUZZY FRAMEWORK (FL)

Fuzzy models involve inference blocks that apply relevant fuzzy rules for depicting the actual importance level of trust factors [108]. These rules are also introduced to fuzzy semantic DT-based methods to improve the learning and prediction performance [109]. Fuzzy c-means is another technique that is used to estimate the probability of each data point belonging to each cluster. This technique allows data points to be members of multiple clusters rather than forcing them to belong to one single cluster [97]. The nature of fuzzy models is similar to the meaning of “divide and conquer”. The backgrounds of rules (if condition else action) divide the input space into a number of local fuzzy regions, while the consequences describe the behavior within a region through its constituents. The components of the consequences result in different kinds of mathematical fuzzy models, but their backgrounds are essentially the same [60].

3) LATENT DIRICHLET ALLOCATION (LDA)

LDA is a simple and efficient learning model that is used to recover the parameters for high-dimensional data into a wide class of topics. K is the number of latent factors (topics) found

in a more dimensional observation. Typically, it is used to process natural language or text characteristics [103].

E. HYBRID METHODS

Several published articles used different models to improve the algorithm’s performance. They integrated neural networks with a new architectural design for feedforward ANNs used in multilevel output choice problems. The ANN is trained with a genetic algorithm [110], such as fuzzy logic or other techniques as opposed to the standard backpropagation training method. Other methods include ensemble learning models to measure different features in marketing segmentation and influencer index while others aimed to get better accuracy. Additionally, this study demonstrated that some articles optimized parameter procedures that play an important role in the predictive models [111].

V. MAIN MARKETING PROBLEMS SOLVED WITH MACHINE LEARNING

Figure 8 shows the types of learning used to solve different marketing problems. In this figure, we notice that deep learning is the most prevalent method across the published articles and is also most employed to solve marketing problems.

This may be because deep learning techniques are versatile and employ different ways of solving complex problems. Unsupervised techniques are primarily used to solve market segmentation problems and are not used for forecasting. Reinforcement learning is only used in recommender systems. Hybrid techniques can be seen with a greater preponderance in forecasting, requiring a more accurate prediction. Supervised techniques can be used to solve any marketing problem. Overall, the important thing to know is the nature of the data available.

In terms of the specific marketing problems solved in the published articles, Figure 9 shows that issue of recommender systems is the most prevalent. Consumer behavior, forecasting, and market segmentation are also important. Notably, text and video analysis has become more popular recently, and this is also related to improvements in speed and the simplicity in the use of ML techniques that allow this process to be carried out, including deep learning and unsupervised learning. The following sections will detail each one of these applications.

A. CONSUMER BEHAVIOR

Consumer behavior refers to the study of how clients, both individuals and organizations, meet their needs and desires to choose, purchase, use and get rid of goods, ideas, and services. In other words, it refers to the decision taken by clients during the purchasing process and the factors that can influence this decision [112], [113]. These factors can be cultural, social, and psychological, among others. Within the applications of consumer behavior, we can stress characterization of clients, customer retention, trend prediction, competition, etc.

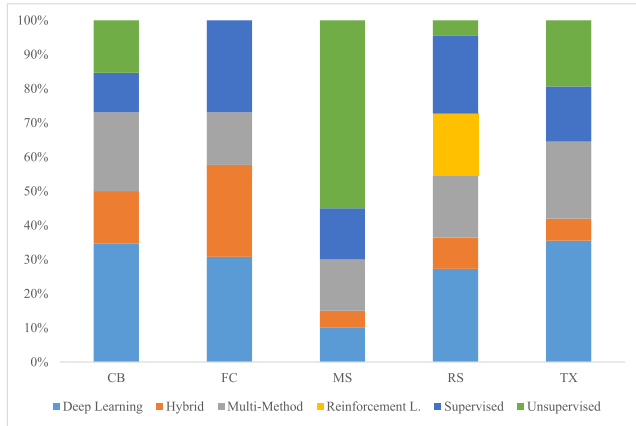


FIGURE 8. Percentage distribution of the number of articles published between 2008 and March 2022 by type of learning for each marketing problem (CB: consumer behavior, FC: forecasting, MS: market segmentation, RS: recommender system, TX: text and video analysis and context analysis).

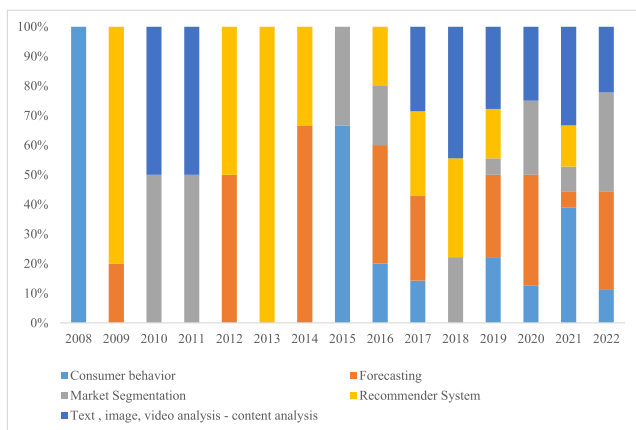


FIGURE 9. Distribution of the number of articles by the main marketing problem they solve (2008 to March 2022).

The articles correlated purchases in online shopping websites with the clients’ trust based on factors of security and design [108], number of navigation clicks for daily offers [114], or usefulness of reviews [82]. Additionally, the reviewed articles also correlated purchases with the stores’ facades featured on the Internet [115] and investigated competitive advantages by identifying dynamic problems of tourist destinations, including stakeholders (suppliers, customers, competitors) [116], personalities of individuals, and their travel intentions both during and after the pandemic [117]. In the same way, the articles also examined children’s classification (rating) behavior toward certain trademarks based on emotions and loyalty [118], the credibility in the classification of most popular users on consumer reviews platforms such as Yelp [119], the prediction of customer responses to campaigns [120], and the future behaviors of a panel of customers [55]. Furthermore, the price sensitivities and the importance of consumer behavior in supermarkets [121] or purchases of ecological buildings [122] have been studied. Studies also investigated the adoption

of payment according to the attributes of products coincidences in shopping baskets [123] and the use of peer-to-peer mobile payment systems and key backgrounds of clients’ intention [124]. It is possible to extract a hierarchy of product attributes based on contextual information of how attributes are expressed in consumer reviews [12]. In the healthcare/health-related products industry, consumer satisfaction was studied through posts on a review website [125]. Additionally, some studies analyzed the impact of film contracts in movie production and profitability of members of the channel [126], the consumer’s perception of the attributes of certain brands in online posts through visual listening [49], and the customers’ repurchasing behavior of same-brand smartphones [127]. Some studies estimated the possibility that a consumer performing some actions, such as use airline services again [128] or willingness to share personal information according to their interests or social interactions [84]. Some studies focused on limited player telemetry data to observe churn from a gamified app [67]. The influence of the increase in online movie searches and their revenues [129]. Other studies use other models such as the recency, frequency, and monetary (RFM) model to observe behavior patterns [130]. They even use data from unsolicited communications from consumers on Twitter related to shopping malls [131] or discover how emotional robots can influence the affective feelings of potential consumers on Instagram [93].

B. RECOMMENDER SYSTEMS

Recommender systems are software tools that can provide suggestions and/or recommendations regarding products and/or services to final clients [132], [133]. These systems seek to replace the old word-of-mouth method with an automatized process [134]. Their objective in marketing is to generate more sales, diversify the products sold, increase the satisfaction and loyalty of clients, and provide a better understanding of clients’ needs. In this regard, the applications include training, personalized content, e-commerce, and services [135]. The analysis performed in this review ascertained that recommender systems are employed in market selection [136] or orientation [137], in models aiming to overcome difficulties in processing information of potential providers during the early stages of the selection process [138], or in the process of diagnosing problems in independent clients [86]. Recommender systems are used in distribution systems of vehicles in auctions [139], the probability of making a purchase and the amount in different products [140], classification based on reviews [47], or the use of choice experiments [63].

In the same way, a study focused on customers, studying their loyalty and asset management in hotels [85], the inconsistencies in their opinions in a cognitive purchase decision-making process [53], the classification of their elements directly for predictive recommendation [39], and their experiences using chatbots [23]. Publicity and campaigns have also used ML techniques to combine means of publicity (television and online) [72], estimate when, what, and how much

to spend on publicity to increase profits [141], efficiently evaluate online publicity [88], and optimize micro-focalized techniques of campaigns [142]. Other applications of recommender systems are found in brand management, associated with personality, identification of associations and potential collaborations [143], or in the investigation of the moderating effects of consumer knowledge (expertise) in a beer recommendation [144]. Some authors focused on social media reviews for food recommendations in vegetarian restaurants [145] or recommendations based on sentiment analysis of data from TripAdvisor [146].

C. FORECASTING

Marketing forecasting is an analysis that projects the trends, features, and future numbers on its objective market. This allows having, in advance, these economic variables are investigated in market research using marketing forecasting [147]. The forecasting methods range from simple mobile averages to sophisticated models of supply-product [148], [149]. The most used methods for forecasting in marketing are the ones based on probabilistic techniques [92]. However, these techniques have evolved with the new availability of several data (Big Data), which has generated a new interest in these techniques [150].

Most of predictions presented in the articles are related to the prediction of market prices [76], forecasting of demand or purchase patterns in business segments [40], [60], [74], [151], classification or prices of products [65], [152], or difference in prices in auctions [58], [153]. Furthermore, forecasting models are also employed to identify the probabilities of abandonment, retention, or cancellation of clients and their attributes [66], [75], [79], [111] and the customer lifetime value for the banking sector [154]. Forecasting models are also used to draw predictions regarding the success of bank telemarketing sales of time deposits [83], the volume of call center arrivals' calls [56], [92] or sales volume [59]. Studies also carried out comparisons and predictions regarding the influence of social networks on social media promoted posts detection [73], [91], determinants of trust in s-commerce based on social presence and social support [155], the discrepancy between the evaluation of online and live products [77]. Other studies focused on predicting satisfaction and brand recommendation as well as purchase intention [156] and how natural-look campaigns are associated with the increase in artificial beauty practices [157].

D. MARKETING SEGMENTATION

Marketing segmentation is one of the main strategies in the field of marketing [158]. Its objective is to identify and delimit market segments or "groups of buyers" that will then transform into objects of the company's marketing plans [158], [159]. The advantage of marketing management is that this technique divides the total demand into relatively homogeneous segments, which are identified for some common characteristics. These features are relevant to explaining and predicting the consumers' responses—in a determined

segment—to the marketing stimulus [158], [159], [160]. The segmentation can be made according to geographic, behavioral, psychological, and demographic criteria [161].

In this field, the articles analyzed presented the market preferences according to reviews of hotels, tourism, and hospitality sectors [57], [162], stereotypes [109], number of sales of smartphones according to types of sellers [137], market structures or segments according to products or services and profits [99], [100], [102], [163], and how to carry out promotions and the effect on sales [80]. Other authors segmented customers according to retailer-brand and channel usage [164], brand equity and engagement in brand-related social media behavior [81], or consumer sentiments on social media [165]. Furthermore, some studies looked for patterns of interest in trade based on clicks [101], including segments that vary in their donation intentions, political attitudes, and preferred types of charities [166]. Other works predicted the characteristics and segments of companies that adopt the use of workforce-based robotics [167] or determined the differences in business model attributes of FinTech [168]. Additionally, some works segmented consumers based on their psychological profiles [169].

E. TEXT ANALYSIS – CONTENT ANALYSIS

TA, or content analysis, aims to extract legible information through non-structured text machines to allow approaches based on data for content management. To surpass the ambiguity of human language and achieve high precision for a specific domain, TA requires the development of mining channels of personalized texts [170], [171]. The analysis of content allows researchers to examine great volumes of data with relative ease in a systematic manner [172].

The analysis of text in marketing, according to the bibliographic review, is based on the identification of the influence of word-of-mouth reviewers [173], chain operation in the hospitality industry [42], or movie spoilers [106]; additionally, TA is also based on the usefulness and classification of the attributes of reviews, opinions, or comments of online consumers or Twitter users their consumption trends, satisfaction, or patterns [41], [43], [64], [68], [174], and YouTube review videos [175]. Furthermore, it also includes analysis of news [46], review of publicity [69], and generation, classification, and auto-tagging of content or published text [90], [103], [176]; additionally, it helps determine the clients' needs based on user-generated content (UGC) or Instagram messages [48], [51]. Recently, an analysis of feelings has been carried out with different purposes, capturing the feelings, attitudes, and emotions of Indian consumers towards electric vehicles [177]. It included messages from Twitter users, obtaining a deeper understanding of the role of language in consumer behavior [61], and creating positive emotions for upset customers [44]. Additionally, the analysis investigated how negative feelings influence the market for firms [105] and the use and adoption of digital technologies and platforms for teleworking in the post-pandemic era [107]. In other social networks, the social influence and facilitating

conditions directly impact the users' sentiments toward intelligent personal assistants (IPAs) [178], and studies also investigated estimates of love and loyalty for brands in Facebook photos [179] or prominent figures [78]. Moreover, other studies examined brand images on social networks (brand selfies) and user responses [52], how the media evaluates public agencies, particularly in low-trust contexts [104], and how narratives affect the effectiveness of influencers in sponsorship and likes and comments [180]. Components of effective communication in a digital interaction can be understood by asking the following: to what extent do what a salesperson says (auditory cues) and how he or she says it (visual cues) affect his or her effectiveness in digital sales interactions (DSIs) [181]. In this regard, some works provide recommendations for project creators and crowdfunding platforms [45].

VI. SUMMARY OF THE MARKETING PROBLEMS AND THE TECHNIQUES USED TO SOLVE

In this section, in Table 1, we highlight the marketing problems that are solved using ML and the most used techniques for each. Moreover, Table 1 provides a summary of the advantages and disadvantages of each technique. This table can serve as a basic guide for the use of ML techniques to solve certain marketing problems.

Regarding the evaluation of the performance of the techniques, the findings of this review study demonstrated that the statistical parameters differ between techniques. In the case of the regressions, the coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) [145] are used. Metrics such as precision, recall, F1-score, accuracy [42], [128], and confusion matrix are employed to evaluate classification performance.

In the articles that we reviewed, the input data came from social networks [78], [141], such as Twitter [107], [165], Instagram [51], [182], Facebook [73], [179], online reviews [47], [156], [173], and videos or comments on YouTube [90], [175]. To analyze review opinions, the following sources are considered: film classification data [106], [126], hotel websites [42], [57], [64], [85], [103], and Yelp [82], [119], [183]. Datasets or product databases such as telephone numbers [137], matching products in the shopping cart [123], daily sales [114], and online purchases [108], among other types of data entries, are also used. The results depended on the approach that the authors adopted in sentiment analysis, investigating the feelings and emotions found in the data [184]. In classification or regression, a rating of the best-selling products or those that would work best for the market, sales, and demands are obtained. In market segmentation, the segments of customers, consumers, suppliers, services, and others are usually obtained. The variety of output depends on the marketing problem to be solved. Now, based on the articles analyzed, it was observed that most of the articles published after 2018 presented the technique's accuracy, while other articles only discussed the output of the technique used.

TABLE 1. Marketing problems and the techniques used to solve them from the literature: summary of advantages and disadvantages.

Marketing					Technique	Advantages	Limitations
CB	RS	F	MS	TX			
		✓			Boosting	High precision, therefore, the technique is more likely to correctly classify observations that have higher weights.	The method is sensitive to noise when observations have interpretability and comprehensibility problems, especially with non-convex optimization problems.
				✓	Random Forest	It has the possibility of using a non-linear system and improved accuracy, compared to individual decision trees.	Very difficult to interpret and understand. It is difficult to generalize to data outside the range, and is sensitive to the presence of a linear relationship between variables.
		✓		✓	K-NN	It has good accuracy, is easy to implement, and does not need a training period.	The optimal value for 'k' is the most critical aspect. It is sensible to noisy and missing data. It does not work well with high dimensionality, it already complicates the calculation of the distances for each dimension.
	✓	✓	✓	✓	SVM, SVR	It is based on the theory of statistical learning. Minimize the upper limit efficiently by handling arbitrary nonlinearities. Excellent predictive power. It is easy to model nonlinear dependencies. It works well even with unstructured and semi-structured data.	It is a black box. It is difficult to interpret and inference from variable weights and individual impact. Choosing a "good" kernel function is not easy.
	✓	✓		✓	Decision Tree	It generates decision values of greater sensitivity. It is a simple interpretation technique for decision making, which is why it is popular in business.	It often requires more time to train the model. It is inadequate to predict continuous values, and is susceptible to small changes in the data.
✓	✓				Genetic algorithms	It provides multiple optimal solutions (parallelism). It requires little information. It can be optimized with discrete functions, multi-objective problems and continuous functions.	It can be difficult to design the object function and to obtain the correct representation and operators. The implementation of the algorithm is still an art. Genetic algorithms don't scale well with complexity.
		✓		✓	Naive Bayes	It allows you to cast options, change utility functions, compensate for class imbalance, and combine models. Optimal for a high degree of dependencies between variables.	Only linear discriminant functions can be learned. It provides a robust function to estimate probabilities.
			✓		K-means	It provides automatic detection of non-overlapping interactions. It is more robust than hierarchical methods.	Variables must be distributed normally, and all groups must have equal or similar variance-covariance.
✓			✓	✓	Fuzzy Logic	It has high ability to predict complicated problems, using a small simple number of rules.	Success depends on the complexity and number of fuzzy rules provided, and also on the type of membership functions, background variables, and regressors.
				✓	LDA	It is easy to implement. It is a probabilistic model that can be applied to different topics. It's pretty intuitive.	LDA is criticized for the assumption of interchangeability of documents. It is inappropriate when short text is available.
✓	✓	✓	✓	✓	Deep Learning	It has the ability to work with incomplete knowledge. It has high fault tolerance and high parallel processing capacity.	It requires a pre-processing of the data, and the determination of the appropriate structure of the network. The final network is not properly understood and interpreted. It requires a lot of data for acceptable training.

We identified the best algorithms used based on the articles that compared techniques (multi-technique). For classification, the use of DT, NB, RF, KNN, SVM, and XGB were compared in [128], and the findings demonstrated that XGB offered the best accuracy followed by RF in all the tests performed.

Another study compared the performance of ANN and RF [67] with input data from video games, and in the three tests carried out for both classification and regression, the results were similar with a similar time window, but when deciding

and adjusting the RF, the prediction improved. In the case of text analysis [125] with data from healthcare/health-product e-commerce firms, linear regression (LR), XGB, RF, and DT were used. The study concluded that in terms of the RMSE, XGB and RF displayed the best predictive power, although LR was almost the same. With input data from reviews to measure the help they provide [82], DT, RF, GB, bagging gradient-boosted trees (B-GB), and ANN were compared, and the regression results reported that B-GB had the best performance with an increasing volume of data. In the case of classification, the B-GB model performed classification the best with an accuracy of over 0.9, while DT displayed the worst performance is DT. One of the published articles conducted a comparison for sentimental analysis [177], and it concluded that CNN was the best model to find sentiment polarity in Electric Vehicles (EV) data compared to other deep learning algorithms such as ANN and RNN. The study compared SVM, Doc2Vec, RNN, and CNN. The accuracy of CNN reached over 81%. Furthermore, [145] combined various algorithms to segment and predict customer needs and preferences. In particular, the study joined LDA, SOM, and DT for regression and classification (CART), and the best results corresponded to the union of LDA+SOM+CART with an MAE of 0.3852, RMSE 0.46, and R2 0.93 as compared to the other unions such as LDA+CART, LDA+RF, LDA+ANN, and LDA+MLR. Moreover, [130] compared SVM, DT, and MLP, concluding that DT was the best with over 96% accuracy, followed by MLP. On the other hand, [169] compared the conventional psychological continuum model (PCM) segmentation algorithm, K-means clustering, and Bayesian LPA, and in this case, unsupervised algorithms were compared, showing that Bayesian LPA presented the best performance followed by K-means. To predict arrivals in a call center, [92] compared GB, GBR, SVR, KNN, and RF based on MAE and ascertained that RF performed the best, with GB, GBR, and SVR achieving similar results, while KNN exhibited a bad performance under that parameter MAE.

Finally, regarding the use of software, few published articles reported which software they use or apply. However, some works used Python with ML-specific libraries [61], [78], [107], [144], [183] or R® [75], [80], [81], [92]. Others used the free open-source software package called Stanford CoreNLP [105] or frameworks such as Rapidminer® [88].

VII. DISCUSSION AND CONCLUSION

This research aimed to analyze the degree of adoption of ML in the field of marketing research. For this purpose, we analyzed journals indexed in the WoS. Of the 42 marketing journals that we reviewed, only 13 of them published at least one article that meets our quality criteria. Overall, the most used ML tool was artificial neural networks, both in hybrid methods and isolated use. In the classification methods, the most used technique was decision trees. When comparing the techniques, the most efficient techniques were the gradient booster and the extreme gradient booster technique, as they

demonstrated the best results. Regarding the unsupervised techniques, KNN is widely used for market segmentation (40%), and LDA is widely used for TA (31%). According to the distribution of types of learning with respect to the marketing application, reinforced learning appears only in recommender systems.

In brief, our results highlight that a significant and diverse number of ML techniques are employed in extensive marketing-based applications. In the field of scientific production, the number of publications increased over time, but this growth was mostly observed in journals with a ranking Q1 and Q2. In the period of years studied, the most used technique was deep learning. We also realized that until 2008, certain techniques were used generically in all marketing applications; however, their use has expanded to a larger level by the year 2022. It is noteworthy that several techniques are widely used in a specific year, displaying a kind of boom in popularity, followed by a period of decline and stability in their use. For example, text mining analysis exhibited disproportional use during some periods (2009–2010), then no use for seven years, and finally being used again in 2016.

In the foregoing, we can see that in general, ML techniques have experienced a degree of maturity in the field of marketing. This is reflected in a larger diversity of applications and a larger diversity of ML techniques. This has also accompanied advances in ML applications, dispensing with the need of having advanced knowledge of programming. Accordingly, this allows researchers who are not specialized in computer science to use the aforementioned techniques in their areas of expertise (e.g., marketing). Last, digital marketing has promoted the need for better handling of more data with a more complex analysis, which is provided by ML applications.

Regarding the limitations of this study, we can highlight the lack of marketing categories in WoS and the use of JCR as a proxy for this category. However, articles excluded did not affect the main results of this research.

Regarding future works, research must focus on the applications of other recent ML techniques in areas of marketing that have not been presented before. Despite the incipient maturity, there is also a belief that some ML techniques—given their simplicity—are not being applied correctly due to the lack of knowledge surrounding them. Hence, a study must be conducted to know if these conditions could produce unexpected results using techniques that allow a larger simplicity or visualization of the results (DT and CA) against more complex techniques such as ANN or SVM.

REFERENCES

- [1] S. Erevelles, N. Fukawa, and L. Swayne, "Big data consumer analytics and the transformation of marketing," *J. Bus. Res.*, vol. 69, no. 2, pp. 897–904, Feb. 2016, doi: [10.1016/j.jbusres.2015.07.001](https://doi.org/10.1016/j.jbusres.2015.07.001).
- [2] J.-L. Seng and T. C. Chen, "An analytic approach to select data mining for business decision," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8042–8057, Dec. 2010, doi: [10.1016/j.eswa.2010.05.083](https://doi.org/10.1016/j.eswa.2010.05.083).
- [3] A. Miklosik and N. Evans, "Impact of big data and machine learning on digital transformation in marketing: A literature review," *IEEE Access*, vol. 8, pp. 101284–101292, 2020, doi: [10.1109/ACCESS.2020.2998754](https://doi.org/10.1109/ACCESS.2020.2998754).

- [4] T. F. Bahari and M. S. Elayidom, "An efficient CRM-data mining framework for the prediction of customer behaviour," *Proc. Comput. Sci.*, vol. 46, no. 1, pp. 725–731, 2015, doi: [10.1016/j.procs.2015.02.136](https://doi.org/10.1016/j.procs.2015.02.136).
- [5] H. C. Jessen and G. Paliouras, "Data mining in economics, finance, and marketing," in *Machine Learning and its Applications*, vol. 2049, G. Paliouras, V. Karkaletsis and C. D. Spyropoulos, Eds. Berlin, Germany: Springer, 2001, pp. 295–299, doi: [10.1007/3-540-44673-7_18](https://doi.org/10.1007/3-540-44673-7_18).
- [6] M. Tkáč and R. Verner, "Artificial neural networks in business: Two decades of research," *Appl. Soft Comput.*, vol. 38, pp. 788–804, Jan. 2016, doi: [10.1016/j.asoc.2015.09.040](https://doi.org/10.1016/j.asoc.2015.09.040).
- [7] Ö. Çelik, "A research on machine learning methods and its applications," *J. Educ. Technol. Online Learn.*, vol. 1, no. 3, pp. 25–40, Sep. 2018, doi: [10.31681/jetol.457046](https://doi.org/10.31681/jetol.457046).
- [8] A. Miklosik, M. Kuchta, N. Evans, and S. Zak, "Towards the adoption of machine learning-based analytical tools in digital marketing," *IEEE Access*, vol. 7, pp. 85705–85718, 2019, doi: [10.1109/ACCESS.2019.2924425](https://doi.org/10.1109/ACCESS.2019.2924425).
- [9] J. R. Hauser, "Consideration-set heuristics," *J. Bus. Res.*, vol. 67, no. 8, pp. 1688–1699, Aug. 2014, doi: [10.1016/j.jbusres.2014.02.015](https://doi.org/10.1016/j.jbusres.2014.02.015).
- [10] D. Dzyabura and J. R. Hauser, "Active machine learning for consideration heuristics active machine learning for consideration heuristics," *Marketing Sci.*, vol. 30, no. 5, pp. 801–819, Sep. 2011. [Online]. Available: <https://www.jstor.org/stable/23011979>
- [11] R. Briesch and P. Rajagopal, "Neural network applications in consumer behavior," *J. Consum. Psychol.*, vol. 20, no. 3, pp. 381–389, Jul. 2010, doi: [10.1016/j.jcps.2010.06.001](https://doi.org/10.1016/j.jcps.2010.06.001).
- [12] X. Wang, J. He, D. J. Curry, and J. H. Ryoo, "Attribute embedding: Learning hierarchical representations of product attributes from consumer reviews," *J. Marketing*, vol. 1, no. 21, pp. 1–21, Nov. 2021, doi: [10.1177/002224292111047822](https://doi.org/10.1177/002224292111047822).
- [13] M.-H. Huang and R. T. Rust, "A strategic framework for artificial intelligence in marketing," *J. Acad. Marketing Sci.*, vol. 49, no. 1, pp. 30–50, Jan. 2021, doi: [10.1007/s11747-020-00749-9](https://doi.org/10.1007/s11747-020-00749-9).
- [14] S.-H. Chen, "The gamma CUSUM chart method for online customer churn prediction," *Electron. Commerce Res. Appl.*, vol. 17, pp. 99–111, May 2016, doi: [10.1016/j.elerap.2016.04.003](https://doi.org/10.1016/j.elerap.2016.04.003).
- [15] B. Balducci and D. Marinova, "Unstructured data in marketing," *J. Acad. Marketing Sci.*, vol. 46, no. 4, pp. 557–590, Jul. 2018, doi: [10.1007/s11747-018-0581-x](https://doi.org/10.1007/s11747-018-0581-x).
- [16] X. Liu, P. V. Singh, and K. Srinivasan, "A structured analysis of unstructured big data by leveraging cloud computing," *Marketing Sci.*, vol. 35, no. 3, pp. 363–388, May 2016, doi: [10.1287/mksc.2015.0972](https://doi.org/10.1287/mksc.2015.0972).
- [17] S. C. Buraga, D. Amariei, and O. Dospinescu, "An OWL-based specification of database management systems," *Comput., Mater. Continua*, vol. 70, no. 3, pp. 5537–5550, 2022, doi: [10.32604/cmc.2022.021714](https://doi.org/10.32604/cmc.2022.021714).
- [18] A. A. Salamai, A. A. Ageeli, and E.-S. M. El-kenawy, "Forecasting E-commerce adoption based on bidirectional recurrent neural networks," *Comput., Mater. Continua*, vol. 70, no. 3, pp. 5091–5106, 2022, doi: [10.32604/cmc.2022.021268](https://doi.org/10.32604/cmc.2022.021268).
- [19] B. Anastasiu, N. Dospinescu, and O. Dospinescu, "Understanding the adoption of incentivized Word-of-Mouth in the online environment," *J. Theor. Appl. Electron. Commerce Res.*, vol. 16, no. 4, pp. 992–1007, Mar. 2021, doi: [10.3390/jtaer16040056](https://doi.org/10.3390/jtaer16040056).
- [20] M. M. Mariani and S. F. Wamba, "Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies," *J. Bus. Res.*, vol. 121, pp. 338–352, Dec. 2020, doi: [10.1016/j.jbusres.2020.09.012](https://doi.org/10.1016/j.jbusres.2020.09.012).
- [21] M. Krafft, L. Sajtos, and M. Haenlein, "Challenges and opportunities for marketing scholars in times of the fourth industrial revolution," *J. Interact. Marketing*, vol. 51, pp. 1–8, Aug. 2020, doi: [10.1016/j.intmar.2020.06.001](https://doi.org/10.1016/j.intmar.2020.06.001).
- [22] A. Galletta, L. Carnevale, A. Celesti, M. Fazio, and M. Villari, "A cloud-based system for improving retention marketing loyalty programs in industry 4.0: A study on big data storage implications," *IEEE Access*, vol. 6, pp. 5485–5492, 2017, doi: [10.1109/ACCESS.2017.2776400](https://doi.org/10.1109/ACCESS.2017.2776400).
- [23] A. K. Kushwaha, P. Kumar, and A. K. Kar, "What impacts customer experience for B2B enterprises on using AI-enabled chatbots? Insights from big data analytics," *Ind. Marketing Manage.*, vol. 98, pp. 207–221, Oct. 2021, doi: [10.1016/j.indmarman.2021.08.011](https://doi.org/10.1016/j.indmarman.2021.08.011).
- [24] Z. Sun, Q. Guo, J. Yang, H. Fang, G. Guo, J. Zhang, and R. Burke, "Research commentary on recommendations with side information: A survey and research directions," *Electron. Commerce Res. Appl.*, vol. 37, Sep. 2019, Art. no. 100879, doi: [10.1016/j.elerap.2019.100879](https://doi.org/10.1016/j.elerap.2019.100879).
- [25] K. M. Fouad, S. F. Sabbeh, and W. Medhat, "Arabic fake news detection using deep learning," *Comput., Mater. Continua*, vol. 71, no. 2, pp. 3647–3665, 2022, doi: [10.32604/cmc.2022.021449](https://doi.org/10.32604/cmc.2022.021449).
- [26] L. Ma and B. Sun, "Machine learning and AI in marketing—Connecting computing power to human insights," *Int. J. Res. Marketing*, vol. 37, no. 3, pp. 481–504, Sep. 2020, doi: [10.1016/j.ijresmar.2020.04.005](https://doi.org/10.1016/j.ijresmar.2020.04.005).
- [27] K. Misra, E. M. Schwartz, and J. Abernethy, "Dynamic online pricing with incomplete information using multiarmed bandit experiments," *Marketing Sci.*, vol. 38, no. 2, pp. 226–252, Mar. 2019, doi: [10.1287/mksc.2018.1129](https://doi.org/10.1287/mksc.2018.1129).
- [28] E. M. Schwartz, E. T. Bradlow, and P. S. Fader, "Customer acquisition via display advertising using multi-armed bandit experiments," *Marketing Sci.*, vol. 36, no. 4, pp. 500–522, Jul. 2017, doi: [10.1287/mksc.2016.1023](https://doi.org/10.1287/mksc.2016.1023).
- [29] H.-J. Lee, H. Shin, S.-S. Hwang, S. Cho, and D. MacLachlan, "Semi-supervised response modeling," *J. Interact. Marketing*, vol. 24, no. 1, pp. 42–54, Feb. 2010, doi: [10.1016/j.intmar.2009.10.004](https://doi.org/10.1016/j.intmar.2009.10.004).
- [30] S. Lee and W. Kim, "Sentiment labeling for extending initial labeled data to improve semi-supervised sentiment classification," *Electron. Commerce Res. Appl.*, vol. 26, pp. 35–49, Nov. 2017, doi: [10.1016/j.elerap.2017.09.006](https://doi.org/10.1016/j.elerap.2017.09.006).
- [31] K. Xia, L. Gao, L. Wang, W. Li, X. Li, and W. Ijomah, "Service-oriented disassembly sequence planning for electrical and electronic equipment waste," *Electron. Commerce Res. Appl.*, vol. 20, pp. 59–68, Nov. 2016, doi: [10.1016/j.elerap.2016.09.007](https://doi.org/10.1016/j.elerap.2016.09.007).
- [32] F. N. Koutanaei, H. Sajedi, and M. Khanbabaei, "A hybrid data mining model of feature selection algorithms and ensemble learning classifiers for credit scoring," *J. Retailing Consum. Services*, vol. 27, pp. 11–23, Nov. 2015, doi: [10.1016/j.jretconser.2015.07.003](https://doi.org/10.1016/j.jretconser.2015.07.003).
- [33] J. R. Hauser, O. Toubia, T. Evgeniou, R. Befurt, and D. Dzyabura, "Disjunctions of conjunctions, cognitive simplicity, and consideration sets," *J. Marketing Res.*, vol. 47, no. 3, pp. 485–496, Jun. 2010, doi: [10.1509/jmkr.47.3.485](https://doi.org/10.1509/jmkr.47.3.485).
- [34] F. J. Martínez-López and J. Casillas, "Marketing intelligent systems for consumer behaviour modelling by a descriptive induction approach based on genetic fuzzy systems," *Ind. Marketing Manage.*, vol. 38, no. 7, pp. 714–731, Oct. 2009, doi: [10.1016/j.indmarman.2008.02.003](https://doi.org/10.1016/j.indmarman.2008.02.003).
- [35] V. Srivastava and A. D. Kalro, "Enhancing the helpfulness of online consumer reviews: The role of latent (content) factors," *J. Interact. Marketing*, vol. 48, pp. 33–50, Nov. 2019, doi: [10.1016/j.intmar.2018.12.003](https://doi.org/10.1016/j.intmar.2018.12.003).
- [36] N. Syam and A. Sharma, "Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice," *Ind. Marketing Manage.*, vol. 69, pp. 135–146, Feb. 2018, doi: [10.1016/j.indmarman.2017.12.019](https://doi.org/10.1016/j.indmarman.2017.12.019).
- [37] H. Ghoddsui, G. G. Creamer, and N. Rafizadeh, "Machine learning in energy economics and finance: A review," *Energy Econ.*, vol. 81, pp. 709–727, Jun. 2019.
- [38] K. B. DeTienne and D. H. DeTienne, "Neural networks in strategic marketing: Exploring the possibilities," *J. Strategic Marketing*, vol. 25, no. 4, pp. 289–300, Jun. 2017, doi: [10.1080/0965254X.2015.1076881](https://doi.org/10.1080/0965254X.2015.1076881).
- [39] Z. Wen, D. Yuhang, Y. Ye, and Y. Taketoshi, "DeRec: A data-driven approach to accurate recommendation with deep learning and weighted loss function," *Electron. Commerce Res. Appl.*, vol. 31, pp. 12–23, Sep. 2018, doi: [10.1016/j.elerap.2018.08.001](https://doi.org/10.1016/j.elerap.2018.08.001).
- [40] F. Xia, R. Chatterjee, and J. H. May, "Using conditional restricted Boltzmann machines to model complex consumer shopping patterns," *Marketing Sci.*, vol. 38, no. 4, pp. 711–727, Jul. 2019, doi: [10.1287/mksc.2019.1162](https://doi.org/10.1287/mksc.2019.1162).
- [41] W. Ou, V.-N. Huynh, and S. Sriboonchitta, "Training attractive attribute classifiers based on opinion features extracted from review data," *Electron. Commerce Res. Appl.*, vol. 32, pp. 13–22, Nov. 2018, doi: [10.1016/j.elerap.2018.10.003](https://doi.org/10.1016/j.elerap.2018.10.003).
- [42] J. J. Zhu, Y.-C. Chang, C.-H. Ku, S. Y. Li, and C.-J. Chen, "Online critical review classification in response strategy and service provider rating: Algorithms from heuristic processing, sentiment analysis to deep learning," *J. Bus. Res.*, vol. 129, pp. 860–877, May 2021, doi: [10.1016/j.jbusres.2020.11.007](https://doi.org/10.1016/j.jbusres.2020.11.007).
- [43] P. S. Dhillon and S. Aral, "Modeling dynamic user interests: A neural matrix factorization approach," *Marketing Sci.*, vol. 40, pp. 1059–1080, Sep. 2021, doi: [10.1287/mksc.2021.1293](https://doi.org/10.1287/mksc.2021.1293).
- [44] Y. A. Argyris, K. Monu, Y. Kim, Y. Zhou, Z. Wang, and Z. Yin, "Using speech acts to elicit positive emotions for complainants on social media," *J. Interact. Marketing*, vol. 55, pp. 67–80, Aug. 2021, doi: [10.1016/j.intmar.2021.02.001](https://doi.org/10.1016/j.intmar.2021.02.001).

- [45] Y. Wei, J. Hong, and G. J. Tellis, "Machine learning for creativity: Using similarity networks to design better crowdfunding projects," *J. Marketing*, vol. 86, no. 2, pp. 87–104, Mar. 2022, doi: [10.1177/00222429211005481](https://doi.org/10.1177/00222429211005481).
- [46] S. Han, X. Hao, and H. Huang, "An event-extraction approach for business analysis from online Chinese news," *Electron. Commerce Res. Appl.*, vol. 28, pp. 244–260, Mar./Apr. 2018, doi: [10.1016/j.elerap.2018.02.006](https://doi.org/10.1016/j.elerap.2018.02.006).
- [47] H.-C. Lee, H.-C. Rim, and D.-G. Lee, "Learning to rank products based on online product reviews using a hierarchical deep neural network," *Electron. Commerce Res. Appl.*, vol. 36, Jul. 2019, Art. no. 100874, doi: [10.1016/j.elerap.2019.100874](https://doi.org/10.1016/j.elerap.2019.100874).
- [48] A. Timoshenko and J. R. Hauser, "Identifying customer needs from user-generated content," *Marketing Sci.*, vol. 38, no. 1, pp. 1–20, Jan. 2019, doi: [10.1287/mksc.2018.1123](https://doi.org/10.1287/mksc.2018.1123).
- [49] L. Liu, D. Dzyabura, and N. Mizik, "Visual listening in: Extracting brand image portrayed on social media," *Marketing Sci.*, vol. 39, no. 4, pp. 669–686, Jul. 2020, doi: [10.1287/mksc.2020.1226](https://doi.org/10.1287/mksc.2020.1226).
- [50] N. Bharadwaj, M. Ballings, P. A. Naik, M. Moore, and M. M. Arat, "A new livestream retail analytics framework to assess the sales impact of emotional displays," *J. Marketing*, vol. 86, no. 1, pp. 27–47, Jan. 2022, doi: [10.1177/00222429211013042](https://doi.org/10.1177/00222429211013042).
- [51] Y. Ha, K. Park, S. J. Kim, J. Joo, and M. Cha, "Automatically detecting image–text mismatch on Instagram with deep learning," *J. Advertising*, vol. 50, no. 1, pp. 52–62, Jan. 2021, doi: [10.1080/00913367.2020.1843091](https://doi.org/10.1080/00913367.2020.1843091).
- [52] J. Hartmann, M. Heitmann, C. Schamp, and O. Netzer, "The power of brand selfies," *J. Marketing Res.*, vol. 58, no. 6, pp. 1159–1177, Dec. 2021, doi: [10.1177/00222437211037258](https://doi.org/10.1177/00222437211037258).
- [53] O. R. Vincent, A. S. Makinde, and A. T. Akinwale, "A cognitive buying decision-making process in B2B e-commerce using analytic-MLP," *Electron. Commerce Res. Appl.*, vol. 25, pp. 59–69, Sep. 2017, doi: [10.1016/j.elerap.2017.08.002](https://doi.org/10.1016/j.elerap.2017.08.002).
- [54] A. Chaudhuri and S. K. Ghosh, "Reducing hierarchical deep learning networks as game playing artefact using regret matching," in *Handbook of Deep Learning Applications*, V. E. Balas, S. S. Roy, D. Sharma, and P. Samui, Eds. Cham, Switzerland: Springer, 2019, pp. 345–362, doi: [10.1007/978-3-030-11479-4_16](https://doi.org/10.1007/978-3-030-11479-4_16).
- [55] M. Sarkar and A. D. Bruyn, "LSTM response models for direct marketing analytics: Replacing feature engineering with deep learning," *J. Interact. Marketing*, vol. 53, pp. 80–95, Feb. 2021, doi: [10.1016/j.intmar.2020.07.002](https://doi.org/10.1016/j.intmar.2020.07.002).
- [56] M. Ebadi Jalal, M. Hosseini, and S. Karlsson, "Forecasting incoming call volumes in call centers with recurrent neural networks," *J. Bus. Res.*, vol. 69, no. 11, pp. 4811–4814, Nov. 2016, doi: [10.1016/j.jbusres.2016.04.035](https://doi.org/10.1016/j.jbusres.2016.04.035).
- [57] A. Ahani, M. Nilashi, E. Yadegaridehkordi, L. Sanzogni, A. R. Tarik, K. Knox, S. Samad, and O. Ibrahim, "Revealing customers' satisfaction and preferences through online review analysis: The case of Canary islands hotels," *J. Retailing Consum. Services*, vol. 51, pp. 331–343, Nov. 2019, doi: [10.1016/j.jretconser.2019.06.014](https://doi.org/10.1016/j.jretconser.2019.06.014).
- [58] F. Dong, S. M. Shatz, H. Xu, and D. Majumdar, "Price comparison: A reliable approach to identifying shill bidding in online auctions?" *Electron. Commerce Res. Appl.*, vol. 11, no. 2, pp. 171–179, Mar. 2012, doi: [10.1016/j.elerap.2011.12.003](https://doi.org/10.1016/j.elerap.2011.12.003).
- [59] Q.-Q. He, C. Wu, and Y.-W. Si, "LSTM with particle swarm optimization for sales forecasting," *Electron. Commerce Res. Appl.*, vol. 51, Jan. 2022, Art. no. 101118, doi: [10.1016/j.elerap.2022.101118](https://doi.org/10.1016/j.elerap.2022.101118).
- [60] C. P. D. Veiga, C. R. P. D. Veiga, W. Puchalski, L. D. S. Coelho, and U. Tortato, "Demand forecasting based on natural computing approaches applied to the foodstuff retail segment," *J. Retailing Consum. Services*, vol. 31, pp. 174–181, Jul. 2016, doi: [10.1016/j.jretconser.2016.03.008](https://doi.org/10.1016/j.jretconser.2016.03.008).
- [61] D. Hovy, S. Melumad, and J. J. Inman, "Wordify: A tool for discovering and differentiating consumer vocabularies," *J. Consum. Res.*, vol. 48, no. 3, pp. 394–414, Oct. 2021, doi: [10.1093/jcr/tucab018](https://doi.org/10.1093/jcr/tucab018).
- [62] F. Pedregosa, "Scikit-learn: Machine learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, Oct. 2011.
- [63] T. Hennig-Thurau, A. Marchand, and P. Marx, "Can automated group recommender systems help consumers make better choices?" *J. Marketing*, vol. 76, no. 5, pp. 89–109, Sep. 2012, doi: [10.1509/jm.10.0537](https://doi.org/10.1509/jm.10.0537).
- [64] M. J. Sánchez-Franco, A. Navarro-García, and F. J. Rondán-Cataluña, "A naive Bayes strategy for classifying customer satisfaction: A study based on online reviews of hospitality services," *J. Bus. Res.*, vol. 101, pp. 499–506, Aug. 2019, doi: [10.1016/j.jbusres.2018.12.051](https://doi.org/10.1016/j.jbusres.2018.12.051).
- [65] A. Greenstein-Messica and L. Rokach, "Machine learning and operation research based method for promotion optimization of products with no price elasticity history," *Electron. Commerce Res. Appl.*, vol. 40, Mar. 2020, Art. no. 100914, doi: [10.1016/j.elerap.2019.100914](https://doi.org/10.1016/j.elerap.2019.100914).
- [66] A. Amin, F. Al-Obeidat, B. Shah, A. Adnan, J. Loo, and S. Anwar, "Customer churn prediction in telecommunication industry using data certainty," *J. Bus. Res.*, vol. 94, pp. 290–301, Jan. 2019, doi: [10.1016/j.jbusres.2018.03.003](https://doi.org/10.1016/j.jbusres.2018.03.003).
- [67] E. Loria and A. Marconi, "Exploiting limited players' behavioral data to predict churn in gamification," *Electron. Commerce Res. Appl.*, vol. 47, May 2021, Art. no. 101057, doi: [10.1016/j.elerap.2021.101057](https://doi.org/10.1016/j.elerap.2021.101057).
- [68] J. P. Singh, S. Irani, N. P. Rana, Y. K. Dwivedi, S. Saumya, and P. K. Roy, "Predicting the 'helpfulness' of online consumer reviews," *J. Bus. Res.*, vol. 70, pp. 346–355, Jan. 2017, doi: [10.1016/j.jbusres.2016.08.008](https://doi.org/10.1016/j.jbusres.2016.08.008).
- [69] A. Costa, J. Guerreiro, S. Moro, and R. Henriques, "Unfolding the characteristics of incentivized online reviews," *J. Retailing Consum. Services*, vol. 47, pp. 272–281, Mar. 2019, doi: [10.1016/j.jretconser.2018.12.006](https://doi.org/10.1016/j.jretconser.2018.12.006).
- [70] R. Gholami and N. Fakhari, "Support vector machine: Principles, parameters, and applications," in *Handbook of Neural Computation*, P. Samui, S. Sekhar, and V. E. Balas, Eds. New York, NY, USA: Academic, 2017, pp. 515–535, doi: [10.1016/B978-0-12-811318-9.00027-2](https://doi.org/10.1016/B978-0-12-811318-9.00027-2).
- [71] K.-J. Kim and H. Ahn, "A corporate credit rating model using multi-class support vector machines with an ordinal pairwise partitioning approach," *Comput. Oper. Res.*, vol. 39, no. 8, pp. 1800–1811, Aug. 2012, doi: [10.1016/j.cor.2011.06.023](https://doi.org/10.1016/j.cor.2011.06.023).
- [72] G. M. Goerg, C. Best, S. Shobowale, N. Remy, and J. Koehler, "When to combine television with online campaigns: Cost savings versus extended reach," *J. Advertising Res.*, vol. 57, no. 3, pp. 283–304, Sep. 2017, doi: [10.2501/JAR-2017-037](https://doi.org/10.2501/JAR-2017-037).
- [73] A. Arora, S. Bansal, C. Kandpal, R. Aswani, and Y. Dwivedi, "Measuring social media influencer index- insights from Facebook, Twitter and Instagram," *J. Retailing Consum. Services*, vol. 49, pp. 86–101, Jul. 2019, doi: [10.1016/j.jretconser.2019.03.012](https://doi.org/10.1016/j.jretconser.2019.03.012).
- [74] G. Verstraete, E.-H. Aghezzaf, and B. Desmet, "A data-driven framework for predicting weather impact on high-volume low-margin retail products," *J. Retailing Consum. Services*, vol. 48, pp. 169–177, May 2019, doi: [10.1016/j.jretconser.2019.02.019](https://doi.org/10.1016/j.jretconser.2019.02.019).
- [75] S. E. Schaeffer and S. V. R. Sanchez, "Forecasting client retention—A machine-learning approach," *J. Retailing Consum. Services*, vol. 52, Jan. 2020, Art. no. 101918, doi: [10.1016/j.jretconser.2019.101918](https://doi.org/10.1016/j.jretconser.2019.101918).
- [76] C. Kiekintveld, J. Miller, P. R. Jordan, L. F. Callender, and M. P. Wellman, "Forecasting market prices in a supply chain game," *Electron. Commerce Res. Appl.*, vol. 8, no. 2, pp. 63–77, Mar. 2009, doi: [10.1016/j.elerap.2008.11.005](https://doi.org/10.1016/j.elerap.2008.11.005).
- [77] D. Dzyabura, S. Jagabathula, and E. Müller, "Accounting for discrepancies between online and offline product evaluations," *Marketing Sci.*, vol. 38, no. 1, pp. 88–106, Jan. 2019, doi: [10.1287/mksc.2018.1124](https://doi.org/10.1287/mksc.2018.1124).
- [78] U. Pamuksuz, J. T. Yun, and A. Humphreys, "A brand-new look at you: Predicting brand personality in social media networks with machine learning," *J. Interact. Marketing*, vol. 56, pp. 55–69, Nov. 2021, doi: [10.1016/j.intmar.2021.05.001](https://doi.org/10.1016/j.intmar.2021.05.001).
- [79] A. T. Jahromi, S. Stakhovych, and M. Ewing, "Managing B2B customer churn, retention and profitability," *Ind. Marketing Manage.*, vol. 43, no. 7, pp. 1258–1268, Oct. 2014, doi: [10.1016/j.indmarman.2014.06.016](https://doi.org/10.1016/j.indmarman.2014.06.016).
- [80] L. Peng, G. Cui, and Y. Chung, "Do the pieces fit? Assessing the configuration effects of promotion attributes," *J. Bus. Res.*, vol. 109, pp. 337–349, Mar. 2020, doi: [10.1016/j.jbusres.2019.11.081](https://doi.org/10.1016/j.jbusres.2019.11.081).
- [81] B. Schivinski, "Eliciting brand-related social media engagement: A conditional inference tree framework," *J. Bus. Res.*, vol. 130, pp. 594–602, Jun. 2021, doi: [10.1016/j.jbusres.2019.08.045](https://doi.org/10.1016/j.jbusres.2019.08.045).
- [82] M. Bilal, M. Marjani, I. A. T. Hashem, N. Malik, M. I. U. Lali, and A. Gani, "Profiling reviewers' social network strength and predicting the 'helpfulness' of online customer reviews," *Electron. Commerce Res. Appl.*, vol. 45, Jan. 2021, Art. no. 101026, doi: [10.1016/j.elerap.2020.101026](https://doi.org/10.1016/j.elerap.2020.101026).
- [83] Y. Feng, Y. Yin, D. Wang, and L. Dhamotharan, "A dynamic ensemble selection method for bank telemarketing sales prediction," *J. Bus. Res.*, vol. 139, pp. 368–382, Feb. 2022, doi: [10.1016/j.jbusres.2021.09.067](https://doi.org/10.1016/j.jbusres.2021.09.067).
- [84] C. S. Song and Y.-K. Kim, "Predictors of consumers' willingness to share personal information with fashion sales robots," *J. Retailing Consum. Services*, vol. 63, Nov. 2021, Art. no. 102727, doi: [10.1016/j.jretconser.2021.102727](https://doi.org/10.1016/j.jretconser.2021.102727).

- [85] A. Carr, J. Drennan, and L. Andrews, "Measuring customer equity and managing the customer asset: An explanatory study in the Australian hotels," *J. Marketing Manage.*, vol. 32, nos. 17–18, pp. 1670–1700, Nov. 2016, doi: [10.1080/0267257X.2016.1260043](https://doi.org/10.1080/0267257X.2016.1260043).
- [86] D. Hullova, P. Laczko, and J. Frishammar, "Independent distributors in servitization: An assessment of key internal and ecosystem-related problems," *J. Bus. Res.*, vol. 104, pp. 422–437, Nov. 2019, doi: [10.1016/j.jbusres.2019.01.012](https://doi.org/10.1016/j.jbusres.2019.01.012).
- [87] E. M. Schwartz, E. T. Bradlow, and P. S. Fader, "Model selection using database characteristics: Developing a classification tree for longitudinal incidence data," *Marketing Sci.*, vol. 33, no. 2, pp. 188–205, Mar. 2014, doi: [10.1287/mksc.2013.0825](https://doi.org/10.1287/mksc.2013.0825).
- [88] H. Wang and M. Hong, "Online ad effectiveness evaluation with a two-stage method using a Gaussian filter and decision tree approach," *Electron. Commerce Res. Appl.*, vol. 35, May 2019, Art. no. 100852, doi: [10.1016/j.elerap.2019.100852](https://doi.org/10.1016/j.elerap.2019.100852).
- [89] T. G. Dietterich, "Ensemble methods in machine learning," in *Proc. Int. Workshop Multiple Classifier Syst.*, Berlin, Germany, 2000, pp. 1–15, doi: [10.1007/3-540-45014-9_1](https://doi.org/10.1007/3-540-45014-9_1).
- [90] J. Salminen, V. Yoganathan, J. Corporan, B. J. Jansen, and S.-G. Jung, "Machine learning approach to auto-tagging online content for content marketing efficiency: A comparative analysis between methods and content type," *J. Bus. Res.*, vol. 101, pp. 203–217, Aug. 2019, doi: [10.1016/j.jbusres.2019.04.018](https://doi.org/10.1016/j.jbusres.2019.04.018).
- [91] A. Arora, A. Srivastava, and S. Bansal, "Business competitive analysis using promoted post detection on social media," *J. Retailing Consum. Services*, vol. 54, May 2020, Art. no. 101941, doi: [10.1016/j.jretconser.2019.101941](https://doi.org/10.1016/j.jretconser.2019.101941).
- [92] T. Albrecht, T. M. Rausch, and N. D. Derra, "Call me maybe: Methods and practical implementation of artificial intelligence in call center arrivals' forecasting," *J. Bus. Res.*, vol. 123, pp. 267–278, Feb. 2021, doi: [10.1016/j.jbusres.2020.09.033](https://doi.org/10.1016/j.jbusres.2020.09.033).
- [93] S. H.-W. Chuah and J. Yu, "The future of service: The power of emotion in human-robot interaction," *J. Retailing Consum. Services*, vol. 61, Jul. 2021, Art. no. 102551, doi: [10.1016/j.jretconser.2021.102551](https://doi.org/10.1016/j.jretconser.2021.102551).
- [94] Y. Li, W. Jiang, L. Yang, and T. Wu, "On neural networks and learning systems for business computing," *Neurocomputing*, vol. 275, pp. 1150–1159, Jan. 2018, doi: [10.1016/j.neucom.2017.09.054](https://doi.org/10.1016/j.neucom.2017.09.054).
- [95] M. Outanoute, M. Baslam, and B. Bouikhalene, "Genetic algorithm learning of Nash equilibrium: Application on price-QoS competition in telecommunications market," *J. Electron. Commerce Organizations*, vol. 13, no. 3, pp. 1–14, Jul. 2015.
- [96] C. Campbell, S. Sands, C. Ferraro, H.-Y. Tsao, and A. Mavrommatis, "From data to action: How marketers can leverage AI," *Bus. Horizons*, vol. 63, no. 2, pp. 227–243, Mar. 2020, doi: [10.1016/j.bushor.2019.12.002](https://doi.org/10.1016/j.bushor.2019.12.002).
- [97] A. Rogers, K. L. Daunt, P. Morgan, and M. Beynon, "Examining the existence of double jeopardy and negative double jeopardy within Twitter," *Eur. J. Marketing*, vol. 51, no. 7/8, pp. 1224–1247, Jul. 2017, doi: [10.1108/EJM-03-2015-0126](https://doi.org/10.1108/EJM-03-2015-0126).
- [98] D. S. Boone and M. Roehm, "Retail segmentation using artificial neural networks," *Int. J. Res. Mark.*, vol. 19, no. 3, pp. 287–301, 2002, doi: [10.1016/S0167-8116\(02\)00080-0](https://doi.org/10.1016/S0167-8116(02)00080-0).
- [99] S. L. France and S. Ghose, "An analysis and visualization methodology for identifying and testing market structure," *Marketing Sci.*, vol. 35, no. 1, pp. 182–197, Jan. 2016, doi: [10.1287/mksc.2015.0958](https://doi.org/10.1287/mksc.2015.0958).
- [100] T. Kim and H. Lee, "External validity of market segmentation methods: A study of buyers of prestige cosmetic brands," *Eur. J. Marketing*, vol. 45, no. 1/2, pp. 153–169, Feb. 2011, doi: [10.1108/03090561111095630](https://doi.org/10.1108/03090561111095630).
- [101] Q. Su and L. Chen, "A method for discovering clusters of e-commerce interest patterns using click-stream data," *Electron. Commerce Res. Appl.*, vol. 14, no. 1, pp. 1–13, 2015, doi: [10.1016/j.elerap.2014.10.002](https://doi.org/10.1016/j.elerap.2014.10.002).
- [102] I. Bose and X. Chen, "Exploring business opportunities from mobile services data of customers: An inter-cluster analysis approach," *Electron. Commerce Res. Appl.*, vol. 9, no. 3, pp. 197–208, May 2010, doi: [10.1016/j.elerap.2009.07.006](https://doi.org/10.1016/j.elerap.2009.07.006).
- [103] B. Hollenbeck, "Online reputation mechanisms and the decreasing value of chain affiliation," *J. Marketing Res.*, vol. 55, no. 5, pp. 636–654, Oct. 2018, doi: [10.1177/0022243718802844](https://doi.org/10.1177/0022243718802844).
- [104] A. Peci, "Agencies in the news? Public agencies' media evaluations in a low-trust context," *Governance*, vol. 34, no. 4, pp. 1075–1095, Oct. 2021, doi: [10.1111/gove.12579](https://doi.org/10.1111/gove.12579).
- [105] X. Liu, "Analyzing the impact of user-generated content on B2B Firms' stock performance: Big data analysis with machine learning methods," *Ind. Marketing Manage.*, vol. 86, pp. 30–39, Apr. 2020, doi: [10.1016/j.indmarman.2019.02.021](https://doi.org/10.1016/j.indmarman.2019.02.021).
- [106] J. H. Ryoo, X. Wang, and S. Lu, "Do spoilers really spoil? Using topic modeling to measure the effect of spoiler reviews on box office revenue," *J. Marketing*, vol. 85, no. 2, pp. 70–88, Mar. 2021, doi: [10.1177/0022242920937703](https://doi.org/10.1177/0022242920937703).
- [107] J. R. Saura, D. Ribeiro-Soriano, and P. Z. Saldaña, "Exploring the challenges of remote work on Twitter users' sentiments: From digital technology development to a post-pandemic era," *J. Bus. Res.*, vol. 142, pp. 242–254, Mar. 2022, doi: [10.1016/j.jbusres.2021.12.052](https://doi.org/10.1016/j.jbusres.2021.12.052).
- [108] M. Nilashi, O. Ibrahim, V. R. Mirabi, L. Ebrahimi, and M. Zare, "The role of security, design and content factors on customer trust in mobile commerce," *J. Retailing Consum. Services*, vol. 26, pp. 57–69, Sep. 2015, doi: [10.1016/j.jretconser.2015.05.002](https://doi.org/10.1016/j.jretconser.2015.05.002).
- [109] H. Fang, J. Zhang, and M. Sensoy, "A generalized stereotype learning approach and its instantiation in trust modeling," *Electron. Commerce Res. Appl.*, vol. 30, pp. 149–158, Jul. 2018, doi: [10.1016/j.elerap.2018.06.004](https://doi.org/10.1016/j.elerap.2018.06.004).
- [110] K. E. Fish, J. D. Johnson, R. E. Dorsey, and Y. J. G. Blodgett, "Using an artificial neural network trained with a genetic algorithm to model brand share," *J. Bus. Res.*, vol. 57, no. 1, pp. 79–85, 2004, doi: [10.1016/S0148-2963\(02\)00287-4](https://doi.org/10.1016/S0148-2963(02)00287-4).
- [111] N. Gordini and V. Veglio, "Customers churn prediction and marketing retention strategies. An application of support vector machines based on the AUC parameter-selection technique in B2B e-commerce industry," *Ind. Marketing Manage.*, vol. 62, pp. 100–107, Apr. 2017, doi: [10.1016/j.indmarman.2016.08.003](https://doi.org/10.1016/j.indmarman.2016.08.003).
- [112] J. F. Engel, R. D. Blackwell, and Y. P. W. Miniard, *Comportamiento del Consumidor*. Boston, MA, USA: Thomson Learning, 2002.
- [113] R. D. Blackwell et al., *Comportamiento del Consumidor*, 9th ed. Thomson Learning, 2002.
- [114] M. Hu, C. Dang, and P. K. Chintagunta, "Search and learning at a daily deals website," *Marketing Sci.*, vol. 38, no. 4, pp. 609–642, Jul. 2019, doi: [10.1287/mksc.2019.1156](https://doi.org/10.1287/mksc.2019.1156).
- [115] E. Pantano and C. Dennis, "Store buildings as tourist attractions: Mining retail meaning of store building pictures through a machine learning approach," *J. Retailing Consum. Services*, vol. 51, pp. 304–310, Nov. 2019, doi: [10.1016/j.jretconser.2019.06.018](https://doi.org/10.1016/j.jretconser.2019.06.018).
- [116] M. De Carlo, G. Ferilli, F. d'Angella, and M. Buscema, "Artificial intelligence to design collaborative strategy: An application to urban destinations," *J. Bus. Res.*, vol. 129, pp. 936–948, May 2021, doi: [10.1016/j.jbusres.2020.09.013](https://doi.org/10.1016/j.jbusres.2020.09.013).
- [117] S. Talwar, S. Srivastava, M. Sakashita, N. Islam, and A. Dhir, "Personality and travel intentions during and after the COVID-19 pandemic: An artificial neural network (ANN) approach," *J. Bus. Res.*, vol. 142, pp. 400–411, Mar. 2022, doi: [10.1016/j.jbusres.2021.12.002](https://doi.org/10.1016/j.jbusres.2021.12.002).
- [118] J. O. Haryanto, M. Silva, and L. Moutinho, "Neural network approach to understanding the children's market," *Eur. J. Marketing*, vol. 49, nos. 3–4, pp. 372–397, Apr. 2015.
- [119] I. Pranata and W. Susilo, "Are the most popular users always trustworthy? The case of yelp," *Electron. Commerce Res. Appl.*, vol. 20, pp. 30–41, Nov. 2016, doi: [10.1016/j.elerap.2016.09.005](https://doi.org/10.1016/j.elerap.2016.09.005).
- [120] D. Ayvaz, R. Aydoğan, M. T. Akçura, and M. Şensoy, "Campaign participation prediction with deep learning," *Electron. Commerce Res. Appl.*, vol. 48, Jul. 2021, Art. no. 101058, doi: [10.1016/j.elerap.2021.101058](https://doi.org/10.1016/j.elerap.2021.101058).
- [121] S.-S. Chen, B. Choubey, and V. Singh, "A neural network based price sensitive recommender model to predict customer choices based on price effect," *J. Retailing Consum. Services*, vol. 61, Jul. 2021, Art. no. 102573, doi: [10.1016/j.jretconser.2021.102573](https://doi.org/10.1016/j.jretconser.2021.102573).
- [122] Y.-K. Juan, Y.-H. Hsu, and X. Xie, "Identifying customer behavioral factors and price premiums of green building purchasing," *Ind. Marketing Manage.*, vol. 64, pp. 36–43, Jul. 2017, doi: [10.1016/j.indmarman.2017.03.004](https://doi.org/10.1016/j.indmarman.2017.03.004).
- [123] S. Gabel, D. Guhl, and D. Klapper, "P2 V-MAP: Mapping market structures for large retail assortments," *J. Marketing Res.*, vol. 56, no. 4, pp. 557–580, Aug. 2019, doi: [10.1177/0022243719833631](https://doi.org/10.1177/0022243719833631).
- [124] Z. Kalinic, V. Marinkovic, S. Molinillo, and F. Liébana-Cabanillas, "A multi-analytical approach to peer-to-peer mobile payment acceptance prediction," *J. Retailing Consum. Services*, vol. 49, pp. 143–153, Jul. 2019, doi: [10.1016/j.jretconser.2019.03.016](https://doi.org/10.1016/j.jretconser.2019.03.016).

- [125] S. Chatterjee, D. Goyal, A. Prakash, and J. Sharma, "Exploring healthcare/health-product ecommerce satisfaction: A text mining and machine learning application," *J. Bus. Res.*, vol. 131, pp. 815–825, Jul. 2021, doi: [10.1016/j.jbusres.2020.10.043](https://doi.org/10.1016/j.jbusres.2020.10.043).
- [126] S. Raut, S. Swami, E. Lee, and C. B. Weinberg, "How complex do movie channel contracts need to be?" *Marketing Sci.*, vol. 27, no. 4, pp. 627–641, Jul. 2008, doi: [10.1287/mksc.1070.0315](https://doi.org/10.1287/mksc.1070.0315).
- [127] J. Kim, H. Ji, S. Oh, S. Hwang, E. Park, and A. P. del Pobil, "A deep hybrid learning model for customer repurchase behavior," *J. Retailing Consum. Services*, vol. 59, Mar. 2021, Art. no. 102381, doi: [10.1016/j.jretconser.2020.102381](https://doi.org/10.1016/j.jretconser.2020.102381).
- [128] S. Hwang, J. Kim, E. Park, and S. J. Kwon, "Who will be your next customer: A machine learning approach to customer return visits in airline services," *J. Bus. Res.*, vol. 121, pp. 121–126, Dec. 2020, doi: [10.1016/j.jbusres.2020.08.025](https://doi.org/10.1016/j.jbusres.2020.08.025).
- [129] H. Kim, "Do online searches influence sales or merely predict them? The case of motion pictures," *Eur. J. Marketing*, vol. 55, no. 2, pp. 337–362, Jan. 2021, doi: [10.1108/EJM-08-2019-0655](https://doi.org/10.1108/EJM-08-2019-0655).
- [130] M. A. Rahim, M. Mushafiq, S. Khan, and Z. A. Arain, "RFM-based repurchase behavior for customer classification and segmentation," *J. Retailing Consum. Services*, vol. 61, Jul. 2021, Art. no. 102566, doi: [10.1016/j.jretconser.2021.102566](https://doi.org/10.1016/j.jretconser.2021.102566).
- [131] E. Pantano, C. Dennis, and M. D. Pietro, "Shopping centers revisited: The interplay between consumers' spontaneous online communications and retail planning," *J. Retailing Consum. Services*, vol. 61, Jul. 2021, Art. no. 102576, doi: [10.1016/j.jretconser.2021.102576](https://doi.org/10.1016/j.jretconser.2021.102576).
- [132] P. Resnick and H. R. Varian, "Recommender systems," *Commun. ACM*, vol. 40, no. 3, pp. 56–58, 1997.
- [133] T. Mahmood and F. Ricci, "Improving recommender systems with adaptive conversational strategies," in *Proc. 20th ACM Conf. Hypertext Hypermedia (HT)*, 2009, pp. 73–82.
- [134] G. Chartron and G. Kembellec, "General introduction to recommender systems," in *Recommender Systems*. Hoboken, NJ, USA: Wiley, 2014, pp. 1–23, doi: [10.1002/9781119054252](https://doi.org/10.1002/9781119054252).
- [135] F. Ricci, L. Rokach, and Y. B. Shapira, "Introduction to recommender systems handbook," in *Recommender Systems Handbook*. Cham, Switzerland: Springer, 2011, pp. 1–35.
- [136] L. E. Brouthers, S. Mukhopadhyay, T. J. Wilkinson, and K. D. Brouthers, "International market selection and subsidiary performance: A neural network approach," *J. World Bus.*, vol. 44, no. 3, pp. 262–273, Jul. 2009, doi: [10.1016/j.jwb.2008.08.004](https://doi.org/10.1016/j.jwb.2008.08.004).
- [137] M. Silva, L. Moutinho, A. Coelho, and A. Marques, "Market orientation and performance: Modelling a neural network," *Eur. J. Marketing*, vol. 43, no. 3/4, pp. 421–437, Apr. 2009, doi: [10.1108/03090560910935505](https://doi.org/10.1108/03090560910935505).
- [138] X. Luo, C. Wu, D. Rosenberg, and D. Barnes, "Supplier selection in agile supply chains: An information-processing model and an illustration," *J. Purchasing Supply Manage.*, vol. 15, no. 4, pp. 249–262, Dec. 2009, doi: [10.1016/j.pursup.2009.05.004](https://doi.org/10.1016/j.pursup.2009.05.004).
- [139] J. Du, L. Xie, and S. Schroeder, "PIN optimal distribution of auction vehicles system: Applying price forecasting, elasticity estimation, and genetic algorithms to used-vehicle distribution," *Marketing Sci.*, vol. 28, no. 4, pp. 637–644, Jul. 2009, doi: [10.1287/mksc.1080.0470](https://doi.org/10.1287/mksc.1080.0470).
- [140] M. George, V. Kumar, and D. Grewal, "Maximizing profits for a multi-category catalog retailer," *J. Retailing*, vol. 89, no. 4, pp. 374–396, Dec. 2013, doi: [10.1016/j.jretai.2013.05.001](https://doi.org/10.1016/j.jretai.2013.05.001).
- [141] V. K. Kanuri, Y. Chen, and S. Sridhar, "Scheduling content on social media: Theory, evidence, and application," *J. Marketing*, vol. 82, no. 6, pp. 89–108, Nov. 2018, doi: [10.1177/0022242918805411](https://doi.org/10.1177/0022242918805411).
- [142] L. Miralles-Pechuán, H. Ponce, and L. Martínez-Villaseñor, "A novel methodology for optimizing display advertising campaigns using genetic algorithms," *Electron. Commerce Res. Appl.*, vol. 27, pp. 39–51, Jan. 2018, doi: [10.1016/j.elerap.2017.11.004](https://doi.org/10.1016/j.elerap.2017.11.004).
- [143] D. Dzyabura and R. Peres, "Visual elicitation of brand perception," *J. Marketing*, vol. 85, no. 4, pp. 44–66, Jul. 2021, doi: [10.1177/0022242921996661](https://doi.org/10.1177/0022242921996661).
- [144] S. Chinchanchokchai, P. Thontirawong, and P. Chinchanchokchai, "A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations," *J. Retailing Consum. Services*, vol. 61, Jul. 2021, Art. no. 102528, doi: [10.1016/j.jretconser.2021.102528](https://doi.org/10.1016/j.jretconser.2021.102528).
- [145] M. Nilashi, H. Ahmadi, G. Arji, K. O. Alsalem, S. Samad, F. Ghabban, A. O. Alzahrani, A. Ahani, and A. A. Alarood, "Big social data and customer decision making in vegetarian restaurants: A combined machine learning method," *J. Retailing Consum. Services*, vol. 62, Sep. 2021, Art. no. 102630, doi: [10.1016/j.jretconser.2021.102630](https://doi.org/10.1016/j.jretconser.2021.102630).
- [146] M. Hong and J. J. Jung, "ClustPTF: Clustering-based parallel tensor factorization for the diverse multi-criteria recommendation," *Electron. Commerce Res. Appl.*, vol. 47, May 2021, Art. no. 101041, doi: [10.1016/j.elerap.2021.101041](https://doi.org/10.1016/j.elerap.2021.101041).
- [147] J. S. Armstrong, R. J. Brodie, and Y. S. H. McIntyre, "Forecasting methods for marketing: Review of empirical research," *Int. J. Forecast.*, vol. 3, nos. 3–4, pp. 355–376, 1987.
- [148] T. Frontitis and P. Apostolidis, "Forecasting applications in marketing and small business," *Marketing Intell. Planning*, vol. 5, no. 2, pp. 24–29, Feb. 1987.
- [149] J. Anema and F. Fraga, "Decision making framework for managers: Profit by forecasting, costs and price management," M.S. thesis, KTH Roy. Inst. Technol., Stockholm, Sweden, 2009. [Online]. Available: <https://api.semanticscholar.org/CorpusID:9778693>
- [150] M. Seyedan and F. Mafakheri, "Predictive big data analytics for supply chain demand forecasting: Methods, applications, and research opportunities," *J. Big Data*, vol. 7, no. 1, pp. 1–22, Dec. 2020.
- [151] A. Kumar, R. Shankar, and N. R. Aljohani, "A big data driven framework for demand-driven forecasting with effects of marketing-mix variables," *Ind. Marketing Manage.*, vol. 90, pp. 493–507, Oct. 2020, doi: [10.1016/j.indmarman.2019.05.003](https://doi.org/10.1016/j.indmarman.2019.05.003).
- [152] S. S. Khopkar and A. G. Nikolaev, "Predicting long-term product ratings based on few early ratings and user base analysis," *Electron. Commerce Res. Appl.*, vol. 21, pp. 38–49, Jan. 2017, doi: [10.1016/j.elerap.2016.12.002](https://doi.org/10.1016/j.elerap.2016.12.002).
- [153] O. Rafieian and H. Yoganarasimhan, "Targeting and privacy in mobile advertising," *Marketing Sci.*, vol. 40, no. 2, pp. 193–218, Mar. 2021, doi: [10.1287/mksc.2020.1235](https://doi.org/10.1287/mksc.2020.1235).
- [154] Y. Ekinci, N. Uray, and F. Ülengin, "A customer lifetime value model for the banking industry: A guide to marketing actions," *Eur. J. Marketing*, vol. 48, no. 3/4, pp. 761–784, Apr. 2014, doi: [10.1108/ejm-12-2011-0714](https://doi.org/10.1108/ejm-12-2011-0714).
- [155] L.-Y. Leong, T.-S. Hew, K.-B. Ooi, and A. Y.-L. Chong, "Predicting the antecedents of trust in social commerce—A hybrid structural equation modeling with neural network approach," *J. Bus. Res.*, vol. 110, pp. 24–40, Mar. 2020, doi: [10.1016/j.jbusres.2019.11.056](https://doi.org/10.1016/j.jbusres.2019.11.056).
- [156] R. V. Kübler, A. Colicev, and K. H. Pauwels, "Social Media's impact on the consumer mindset: When to use which sentiment extraction tool?" *J. Interact. Marketing*, vol. 50, no. 1, pp. 136–155, May 2020, doi: [10.1016/j.intmar.2019.08.001](https://doi.org/10.1016/j.intmar.2019.08.001).
- [157] R. K. Smith, E. Yazdani, P. Wang, S. Soleymani, and L. A. N. Ton, "The cost of looking natural: Why the no-makeup movement may fail to discourage cosmetic use," *J. Acad. Marketing Sci.*, vol. 50, no. 2, pp. 324–337, Mar. 2022, doi: [10.1007/s11747-021-00801-2](https://doi.org/10.1007/s11747-021-00801-2).
- [158] A. C. Tynan and J. Drayton, "Market segmentation," *J. Marketing Manage.*, vol. 2, no. 3, pp. 301–335, Jan. 1987, doi: [10.1080/0267257X.1987.9964020](https://doi.org/10.1080/0267257X.1987.9964020).
- [159] M. McDonald, M. Christopher, and Y. M. Bass, "Market segmentation," in *Marketing*. Cham, Switzerland: Springer, 2003, pp. 41–65.
- [160] E. Parry and P. Urwin, "Generational differences in work values: A review of theory and evidence," *Int. J. Manage. Rev.*, vol. 13, no. 1, pp. 79–96, Mar. 2011.
- [161] K. Kubacki, T. Dietrich, and Y. S. Rundle-Thiele, "Segmentation in social marketing: Why we should do it more often than we currently do," in *Segmentation Social Marketing*. Cham, Switzerland: Springer, 2017, pp. 1–6.
- [162] M. Nilashi, R. A. Abumalloh, B. Minaei-Bidgoli, W. A. Zogaan, A. Alhargan, S. Mohd, S. N. F. S. Azhar, S. Asadi, and S. Samad, "Revealing travellers' satisfaction during COVID-19 outbreak: Moderating role of service quality," *J. Retailing Consum. Services*, vol. 64, Jan. 2022, Art. no. 102783, doi: [10.1016/j.jretconser.2021.102783](https://doi.org/10.1016/j.jretconser.2021.102783).
- [163] B. Jacobs, D. Fok, and Y. B. Donkers, "Understanding large-scale dynamic purchase behavior," *Mark. Sci.*, vol. 40, pp. 844–870, Oct. 2021, doi: [10.1287/mksc.2020.1279](https://doi.org/10.1287/mksc.2020.1279).
- [164] P. J. Danaher, T. S. Danaher, M. S. Smith, and R. Loaiza-Maya, "Advertising effectiveness for multiple retailer-brands in a multimedia and multichannel environment," *J. Marketing Res.*, vol. 57, no. 3, pp. 445–467, Jun. 2020, doi: [10.1177/0022243720910104](https://doi.org/10.1177/0022243720910104).

- [165] R. Airani and K. Karande, "How social media effects shape sentiments along the Twitter journey? A Bayesian network approach," *J. Bus. Res.*, vol. 142, pp. 988–997, Mar. 2022, doi: [10.1016/j.jbusres.2021.12.071](https://doi.org/10.1016/j.jbusres.2021.12.071).
- [166] A. Robson and D. J. Hart, "Feed the world or help the heroes? Exploring how political attitudes influence charitable choice," *J. Marketing Manage.*, vol. 36, nos. 17–18, pp. 1680–1706, Nov. 2020, doi: [10.1080/0267257X.2020.1819380](https://doi.org/10.1080/0267257X.2020.1819380).
- [167] M. T. Ballestar, A. García-Lazaro, J. Sainz, and I. Sanz, "Why is your company not robotic? The technology and human capital needed by firms to become robotic," *J. Bus. Res.*, vol. 142, pp. 328–343, Mar. 2022, doi: [10.1016/j.jbusres.2021.12.061](https://doi.org/10.1016/j.jbusres.2021.12.061).
- [168] L. Laidroo, E. Koroleva, A. Kliber, R. Rupeika-Apoga, and Z. Grigaliuniene, "Business models of FinTechs—Difference in similarity?" *Electron. Commerce Res. Appl.*, vol. 46, Mar. 2021, Art. no. 101034, doi: [10.1016/j.elerap.2021.101034](https://doi.org/10.1016/j.elerap.2021.101034).
- [169] B. J. Baker, J. Du, M. Sato, and D. C. Funk, "Rethinking segmentation within the psychological continuum model using Bayesian analysis," *Sport Manage. Rev.*, vol. 23, no. 4, pp. 764–775, Oct. 2020, doi: [10.1016/j.smr.2019.09.003](https://doi.org/10.1016/j.smr.2019.09.003).
- [170] C. W. Roberts, *Text Analysis for the Social Sciences: Methods for Drawing Statistical Inferences From Texts and Transcripts*. Evanston, IL, USA: Routledge, 2020.
- [171] S. Saeed, S. Naz, and Y. M. I. Razzak, "An application of deep learning in character recognition: An overview," in *Handbook of Deep Learning Applications*, V. E. Balas, S. S. Roy, D. Sharma, and P. Samui, Eds. Cham, Switzerland: Springer, 2019, pp. 53–81, doi: [10.1007/978-3-030-11479-4_3](https://doi.org/10.1007/978-3-030-11479-4_3).
- [172] S. Stemler, "An overview of content analysis," *Pract. Assess. Res. Eval.*, vol. 7, no. 1, p. 17, 2000.
- [173] Y.-M. Li, C.-H. Lin, and C.-Y. Lai, "Identifying influential reviewers for word-of-mouth marketing," *Electron. Commerce Res. Appl.*, vol. 9, no. 4, pp. 294–304, Jul. 2010, doi: [10.1016/j.elerap.2010.02.004](https://doi.org/10.1016/j.elerap.2010.02.004).
- [174] S. Saumya, J. P. Singh, A. M. Baabdullah, N. P. Rana, and Y. K. Dwivedi, "Ranking online consumer reviews," *Electron. Commerce Res. Appl.*, vol. 29, pp. 78–89, May 2018, doi: [10.1016/j.elerap.2018.03.008](https://doi.org/10.1016/j.elerap.2018.03.008).
- [175] C. Campbell, L. F. Pitt, M. Parent, and P. Berthon, "Tracking back-talk in consumer-generated advertising: An analysis of two interpretative approaches," *J. Advertising Res.*, vol. 51, no. 1, pp. 224–238, Mar. 2011, doi: [10.2501/JAR-51-1-224-238](https://doi.org/10.2501/JAR-51-1-224-238).
- [176] J. Hartmann, J. Huppertz, C. Schamp, and M. Heitmann, "Comparing automated text classification methods," *Int. J. Res. Marketing*, vol. 36, no. 1, pp. 20–38, 2019, doi: [10.1016/j.ijresmar.2018.09.009](https://doi.org/10.1016/j.ijresmar.2018.09.009).
- [177] R. Jena, "An empirical case study on Indian consumers' sentiment towards electric vehicles: A big data analytics approach," *Ind. Marketing Manage.*, vol. 90, pp. 605–616, Oct. 2020, doi: [10.1016/j.indmarman.2019.12.012](https://doi.org/10.1016/j.indmarman.2019.12.012).
- [178] M. J. Sánchez-Franco, F. J. Arenas-Márquez, and M. Alonso-Dos-Santos, "Using structural topic modelling to predict users' sentiment towards intelligent personal agents. An application for Amazon's echo and Google home," *J. Retailing Consum. Services*, vol. 63, Nov. 2021, Art. no. 102658, doi: [10.1016/j.jretconser.2021.102658](https://doi.org/10.1016/j.jretconser.2021.102658).
- [179] C. Kaiser, A. Ahuvia, P. A. Rauschnabel, and M. Wimble, "Social media monitoring: What can marketers learn from Facebook brand photos?" *J. Bus. Res.*, vol. 117, pp. 707–717, Sep. 2020, doi: [10.1016/j.jbusres.2019.09.017](https://doi.org/10.1016/j.jbusres.2019.09.017).
- [180] Y. Feng, H. Chen, and Q. Kong, "An expert with whom i can identify: The role of narratives in influencer marketing," *Int. J. Advertising*, vol. 40, no. 7, pp. 972–993, Oct. 2021, doi: [10.1080/02650487.2020.1824751](https://doi.org/10.1080/02650487.2020.1824751).
- [181] N. Bharadwaj and G. M. Shipley, "Salesperson communication effectiveness in a digital sales interaction," *Ind. Marketing Manage.*, vol. 90, pp. 106–112, Oct. 2020, doi: [10.1016/j.indmarman.2020.07.002](https://doi.org/10.1016/j.indmarman.2020.07.002).
- [182] R. Rietveld, W. Van Dolen, M. Mazloom, and M. Worrying, "What you feel, is what you like influence of message appeals on customer engagement on Instagram," *J. Interact. Marketing*, vol. 49, no. 1, pp. 20–53, Feb. 2020, doi: [10.1016/j.intmar.2019.06.003](https://doi.org/10.1016/j.intmar.2019.06.003).
- [183] G. S. Budhi, R. Chiong, Z. Wang, and S. Dhakal, "Using a hybrid content-based and behaviour-based featuring approach in a parallel environment to detect fake reviews," *Electron. Commerce Res. Appl.*, vol. 47, May 2021, Art. no. 101048, doi: [10.1016/j.elerap.2021.101048](https://doi.org/10.1016/j.elerap.2021.101048).
- [184] M. A. Khan, S. Abbas, A. Raza, F. Khan, and T. Whangbo, "Emotion based signal enhancement through multisensory integration using machine learning," *Comput., Mater. Continua*, vol. 71, no. 3, pp. 5911–5931, 2022, doi: [10.32604/cmc.2022.023557](https://doi.org/10.32604/cmc.2022.023557).



VANNESSA DUARTE was born in San Cristobal, Tachira, Venezuela, in 1982. She received the B.S. degree in computer science engineering from the Universidad Nacional Experimental del Táchira, Venezuela, in 2005, and the Ph.D. degree in engineering science from the Universidad Central de Venezuela, Caracas, Venezuela, in 2018. From 2008 to 2009, she was an Associate Professor and a Researcher with the National Institute of Bioengineering, Universidad Central de Venezuela. Since 2019, she has been an Assistant Professor with the School of Business Sciences, Universidad Católica del Norte, Coquimbo. She has ten years of experience in university education. Her research interests include bioengineering, mainly in the development of biological models of bone remodeling with mechanical and piezoelectric loads, data science. Her particular attention to the implementation of machine learning applied to different areas, such as health, business, robotics, and decision making.



SERGIO ZUNIGA-JARA received the B.S. degree in business administration from The Universidad Austral, Valdivia, Chile, in 1985, the M.S. degree in managerial finance from the Universidad de Chile, Santiago, Chile, in 1992, and the Ph.D. degree in managerial finance from the Universidad de Barcelona, Barcelona, España, in 2000. He is currently a Full Professor in finance and management with the School of Business Administration. He has published articles on business, finance, and natural resources economics. His research interests include the field of entrepreneurship motivations and intention, financial economics, and e-learning. He meets the highest standard in research by the Chilean Government Accrediting Agency.



SERGIO CONTRERAS received the B.S. degree in business administration from the Universidad Católica del Norte, Coquimbo, Chile, in 2003, the master's degree in business administration from the Loyola University of Chicago, IL, USA, in 2004, and the Ph.D. degree in regional planning from the University of Illinois, IL, USA, in 2020. From 2005 to 2007, he was the Management Performance Manager of the SEREMI de Salud, Chile. From 2007 to 2009, he was the Regional Advisor of the Ministry of Finance in Chile. From 2010 to 2014, he was formulating and executing investment projects in the mining industry. He was part of the NCSA at the University of Illinois, a supercomputing facility. Since 2019, he has been an Assistant Professor with the School of Business Sciences, Universidad Católica del Norte, Chile. His research interests include public policies that promote production and entrepreneurship, regional economics, and big data. He has participated in national and international research projects, publishing in high-impact journals. He received the Certificate in Data Warehousing from the Loyola University of Chicago, in 2004.

• • •