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Machine learning in marketing: A literature review, conceptual framework, and research agenda

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ABSTRACT

In recent years, machine learning (ML) and artificial intelligence (AI) have attracted considerable attention in different industry sectors, including marketing. ML and AI hold great promise for making marketing intelligent and efficient. In this study, we conduct a literature review of academic journal studies on ML in marketing applications and propose a conceptual framework highlighting the main ML tools and technologies that serve as the foundation of ML applications in marketing. We use the 7Ps marketing mix, that is, product, price, promotion, place, people, process, and physical evidence, to analyze these applications from 140 selected articles. The applications are supported by various ML tools (text, voice, image, and video analytics) and techniques such as supervised, unsupervised, and reinforcement learning algorithms. We propose a two-layer conceptual framework for ML applications in marketing development. This framework can serve future research and provide an illustration of the development of ML applications in marketing.

1. Introduction

In recent years, the extensive development of information and communication technologies in the private and public sectors has initiated the emergence of a new digital marketing environment (Miklosik et al., 2019; Shah & Murthi, 2021). With the rapid advancement of information technology, a huge amount of marketing data is captured and used to generate meaningful insights. To make effective marketing decisions, corporations need to apply new data-oriented methods to process and analyze these data. Machine learning (ML) can be applied to predict consumer behavior and support marketing decision making by mining useful information from large amounts of generated data. As a result, the applications of ML and artificial intelligence (AI) have attracted considerable attention in the marketing field.

Mitchell (1997, p. 2) describes ML as "a computer program [that] is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." ML is considered a subset of AI (Kumar et al., 2021). Its ability to look for patterns in data and enable better decision-making have attracted researchers and practitioners, such that it has been widely applied in different business functions, including marketing (Chen et al., 2017), accounting (Ding et al., 2020), finance (Yazdani et al., 2018), and customer service (Jain & Kumar, 2020).

ML is a powerful tool used for data analysis; it automates analytical model building and can be used for mining large sets of data, providing marketers opportunities to gain new insights into consumer behavior and improve the performance of marketing operations (Cui et al., 2006). Research has presented how ML and AI are used in marketing (e.g., (Ascarza, 2018; Chatterjee et al., 2021; Huang & Rust, 2021)). Several studies have focused on understanding various ML technologies that support the use of ML in marketing (e.g., (Homburg et al., 2020; Alabdulrahman & Viktor, 2021)). Additionally, marketing theories that serve as the basis of applications have been discussed in a few studies (e.g., (Evgeniou et al., 2007; Fang & Hu, 2018)).

ML in business and industry marketing is on the rise. Using examples centered on behavioral research, Hagen et al. (2020) present strategies on how ML methods can be of value to behavioral scientists. Davenport et al. (2020) propose a multidimensional framework to understand the impact of AI, which involves intelligence levels, task types, and embedding of AI in robots. They also propose a research agenda that addresses how marketing strategies and customer behaviors will change in the future. Rust (2020) examines the future of marketing by considering advanced and impactful technologies (e.g., AI, big data, the Internet) that are revolutionizing marketing, resulting in the deepening

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of customer relationships and the service economy.

Systematic literature reviews of ML-based applications in marketing is limited. It remains unclear how well different types of ML tools and algorithms are applied in different marketing contexts. In the present study, we address this gap in the literature to guide future research. We investigate how different ML tools and technologies support the development of ML applications in marketing. A two-layer conceptual ML-based marketing application framework is proposed based on the findings of the literature review.

The reminder of this paper is organized as follows. Section 2 introduces the research method. Section 3 presents the literature review and analysis. Section 4 concludes the paper by discussing its limitations and contributions. Section 5 provides an outlook for future research.

2. Research method

2.1. Literature search

This study involved a literature review of the applications of ML in marketing and use of tools and technologies to develop ML applications. We followed the approach developed by (Ngai et al., 2009) in searching for relevant articles in the extant literature.

We searched for relevant articles in the databases of Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI), which are the two most popular datasets in the Web of Science Core Collection database. We chose the Web of Science platform as it is a more widely used research tool that employs various search and analysis capabilities. Moreover, SCIE and SSCI cover most high-quality refereed social science and management literature (Sharplin & Mabry, 1985), and refereed journal papers represent advanced research outputs (Ngai & Wat, 2002). We used the following retrieval string in SCIE and SSCI: TS= (“machine learning” OR “neural network” OR “artificial intelligence”) AND TS= (“marketing” OR “retailing”). A total of 962 articles were initially retrieved using the query on October 1, 2021. After the first selection stage, 905 articles were obtained. Next, as this study aimed review ML applications in marketing based on the 7Ps marketing mix, articles that were not related to the 7Ps marketing mix and ML technologies were excluded. We then cross-checked the classification results. Finally, 140 articles were identified for the analysis. Fig. 1 shows the selection criteria and evaluation process.

2.2. Conceptual framework for ML application in marketing

Based on the findings of the literature review and the nature of ML technology studied, a two-layer conceptual framework for ML applications in marketing is proposed (see Fig. 2). The framework shows the marketing mix in which ML is applied and the key tools and algorithms used to support the development of major marketing applications. Fig. 2 comprises two blocks/layers. The upper block shows the ML application in marketing based on the 7Ps marketing mix, that is, product (product recommendations, brands and trademarks management, and purchase decision prediction), promotion (advertising management, demand prediction, and chatbots), people (churn prediction, targeting prediction, engagement, and facial recognition), price, place, process, and physical evidence. The lower block depicts ML technologies encompassed by a wide variety of ML tools (e.g., text analytics, voice analytics, and image and video analytics) and algorithms (e.g., supervised learning, unsupervised learning, and reinforcement learning). Based on this conceptual framework, the selected papers are studied to determine whether they are relevant to the topic under study. The selected papers are later analyzed and classified in terms of the ML tools or algorithms used to support ML-based applications along the 7Ps marketing mix (see Fig. 2).

2.3. 7Ps marketing mix framework

McCarthy (1964, p. 35) states that “marketing mix is a combination of all of the factors at the command of a marketing manager to satisfy the target market.” He proposes the famous 4Ps marketing mix, that is, product, price, promotion, and place, which guides the marketing activities. Boom and Bitner (1981) then add process, people, and physical evidence to this framework, extending 4Ps to 7Ps. The 7Ps marketing mix has received wider acceptance in marketing research as it is comprehensive and detailed (Loo & Leung, 2018).

ML has numerous marketing applications. Several research papers report that ML approaches can be utilized to predict outcomes in emerging environments (Cui & Curry, 2005) and consumer interactions (Miklosik et al., 2019). Based on the 7Ps marketing mix, we present the various applications of ML in marketing (see Table 1).

3. Literature analysis

3.1. Product

Product is an important component of the 7Ps marketing mix. Extant literature applies ML technologies to analyze product-related marketing activities, including product recommendations, brands and trademarks management, and purchase decision prediction. These applications are described in detail below.

3.1.1. Product recommendation

With advances in information technology and the booming online shopping landscape, consumers have gained access to a tremendous amount of product information. Determining the suitable products or services through an overwhelming amount of information affects consumers. Simultaneously, the era of big data has enabled companies to obtain real-time data from consumers. Product recommendations have become increasingly personalized (Cheung et al., 2003).

Researchers have examined how to improve the performance of recommendation systems from different perspectives. They explore relevant and timely recommendations (Alabdulrahman & Viktor, 2021), the problems of consumers’ preference ratings or ranking of products (Cheung et al., 2003), travel search engines (Ghose et al., 2012), the robustness of collaborative recommendations (O’Mahony et al., 2004), users’ interests (Wei et al., 2005), and listener-perceived expression of music (Lepa et al., 2020).

Other researchers have taken an interest in recommendations based on customer characteristics; for example, designing recommendation-based strategies according to the quality of new customers referred to the cashback website (Ballestar et al., 2019), recommending products or services to customers of Internet storefronts according to demographics or past purchasing behavior (Kim et al., 2001; Esmaeilpour et al., 2012), and giving customers personalized recommendations based on what similar people with similar portfolios have (Qazi et al., 2020) and shoppers’ preferences using real-time in-store videos (Lu et al., 2016).

3.1.2. Brand and trademark management

As brands and trademarks play a major role in marketing and enhance enterprises’ brand equity and global competitiveness (Trappey et al., 2020), scholars are interested in brand and trademark management.

Some researchers explore brand photos posted on social media to predict brand loyalty (Kaiser et al., 2020) and measure how brands are portrayed (Liu et al., 2020). In addition to the visual content of a brand, researchers explore the textual content of brands to analyze brand reputation (Ducange et al., 2019), the response-worthy electronic world of mouth (eWOM) of brands (Vermeer et al., 2019), brand-relevant valence and volume (Kübler et al., 2020), brand competition (Tirunillai & Tellis, 2014), and brand personality traits (Chen et al., 2015). Carpineto & Romano (2020) focus on the brand search domain to detect

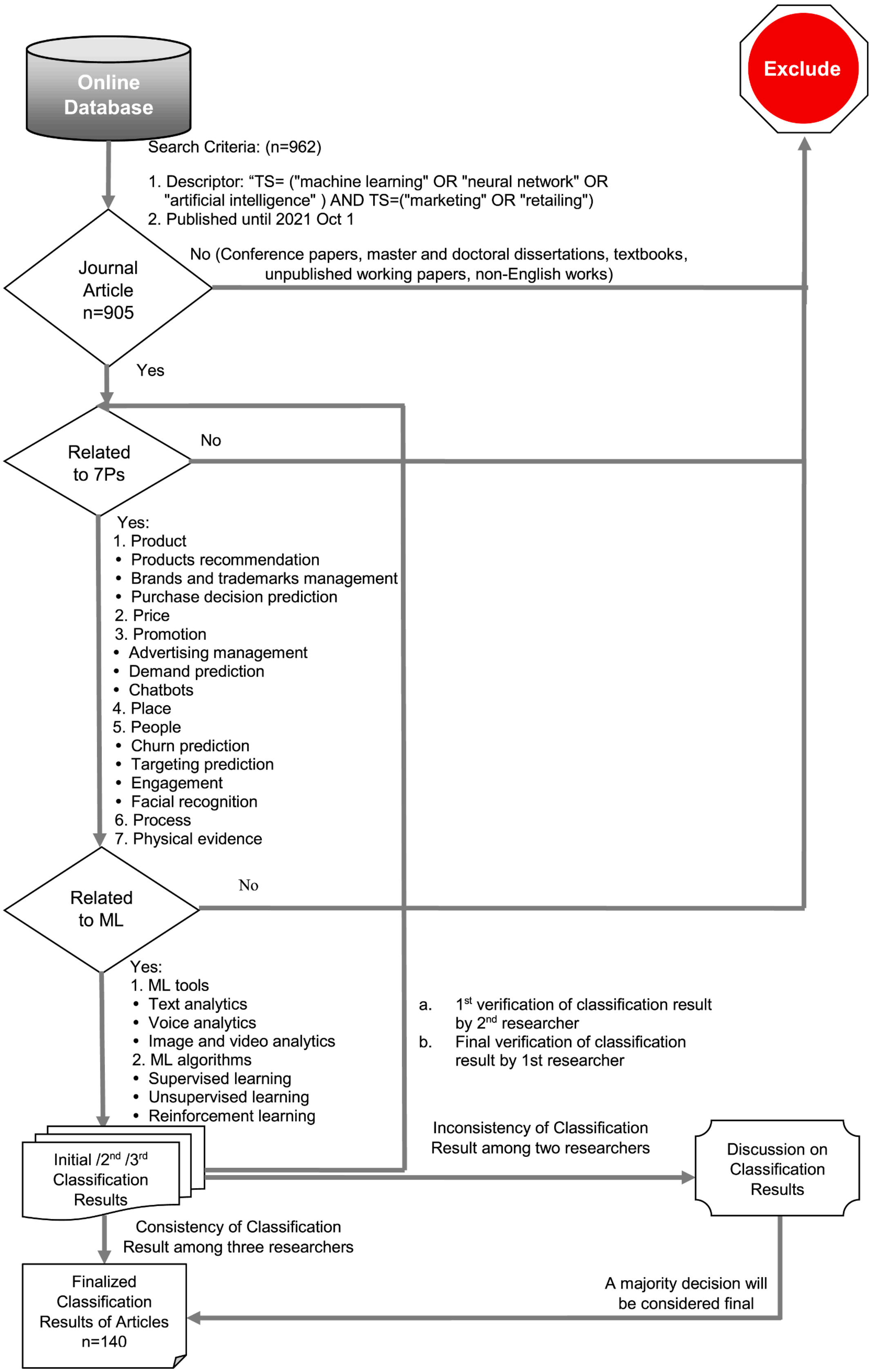

Fig. 1. Selection criteria and evaluation framework.

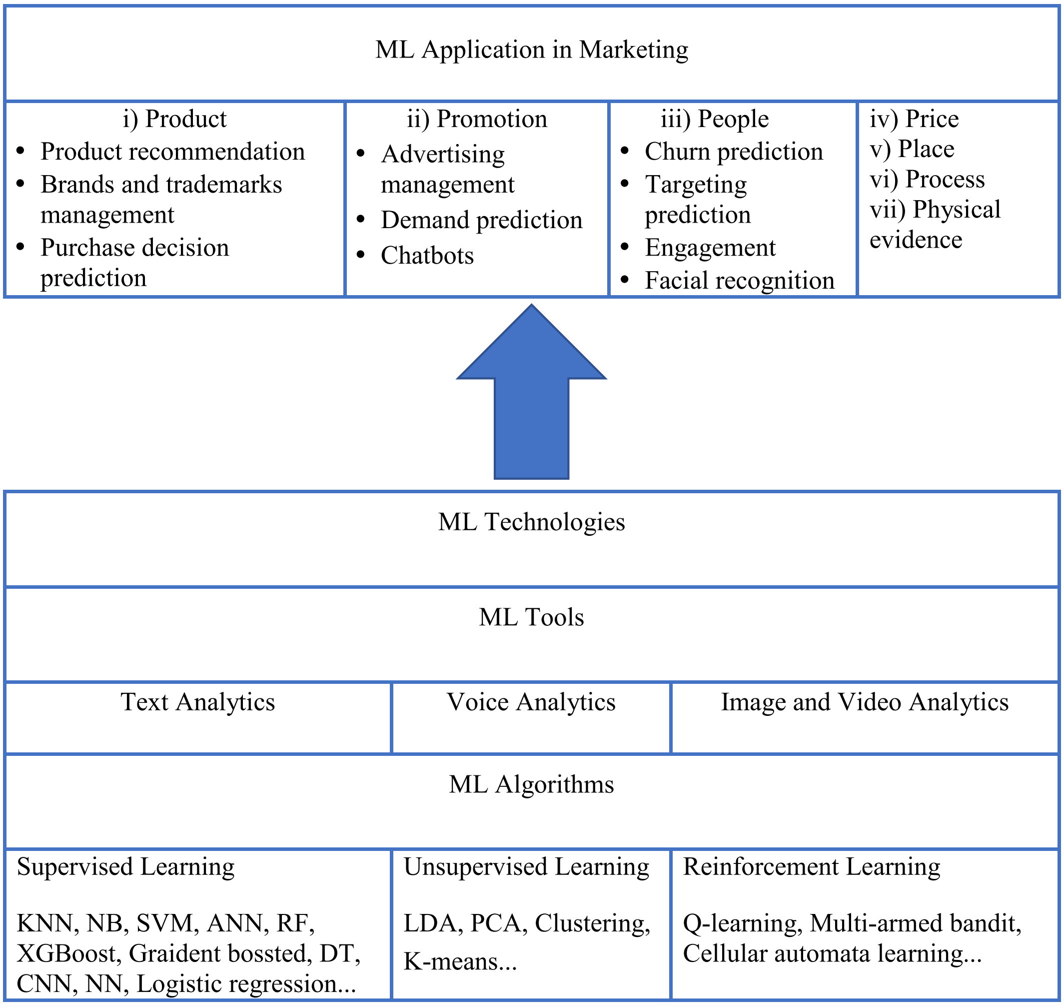

Fig. 2. Conceptual framework for ML application in marketing.

e-commerce websites present in the list of brand search results and fraudulent websites, which is useful for targeted anti-counterfeiting actions.

For trademarks, Trappry et al. (2020) develop advanced trademark similarity assessment models that cover similarities in spelling, pronunciation, and image to protect trademarks.

3.1.3. *Purchase decision prediction*

Predicting consumer purchase decisions and behavior is important for the effective marketing of companies. Knowing who is likely to purchase products or which products are popular is useful for allocating resources efficiently in sales and marketing departments (Martínez et al., 2020). Recent information systems and data processing technologies enable firms to capture real-time transaction records about customers' purchase behavior in a cost-effective manner to predict their purchase decisions (Peker et al., 2017).

Therefore, this application has attracted many researchers' interest. They apply ML and data mining technologies to predict customer purchase preferences (Arasu et al., 2020) or willingness (Ghatasheh et al., 2020; Martínez et al., 2020) and customer behavior by analyzing customers' characteristics (Li et al., 2019a), shoppers' movement in stores and interaction with products (Zhang et al., 2014; Paolanti et al., 2020), customers' repeat purchase incidence (Schwartz et al., 2014), and customers' probability of responding to a promotion (Shin & Cho, 2006). Other researchers concentrate on which product consumers select (van Wezel & Potharst, 2007; Hauser et al., 2010; Behe et al., 2020), the time when customers buy products (Droomer & Bekker, 2020), and market structures (Gabel et al., 2019).

3.2. *Price*

Price is another component of the 7Ps marketing mix that has attracted researchers' attention. Wolkenfelt & Situmeang (2020) examine the effect of application pricing structures on product evaluations regarding the assertiveness and sentiments expressed in reviews. They find that the pricing model affects consumer review sentiment and that removing upfront payment obligations positively impacts consumer sentiment. Casamatta et al. (2022) investigate the month-by-month price differences between professional and non-professional players on Airbnb. They find that the price differential exists during the peak season and that the platform will enhance its profit if the share of professional hosts is sufficiently large.

Some researchers focus on price forecasting in the power market. Sueyoshi and Tadiparthi (2005, 2008) focus on the US wholesale power market to examine how price changes occur under different economic environments (Sueyoshi & Tadiparthi, 2005) and understand the dynamic price changes for effective decision- making (Sueyoshi & Tadiparthi, 2008). Yang et al. (2022) study electricity price forecasting. They develop a novel forecasting model that offers the advantages of adaptive data preprocessing, advanced optimization method, kernel-based model, and optimal model selection strategy, which can achieve more effective electricity price forecasting.

Table 1
ML applications in marketing based on 7Ps marketing mix framework.

7Ps marketing mix	Applications	Articles (author name, year: type of ML)
Product	Product recommendation	(Alabdulrahman and Viktor, 2021: EM/kNN/DT/EL); (Cheung et al., 2003: SVM); (Ghose et al., 2012: Text mining); (O'Mahony et al., 2004: kNN); (Wei et al., 2005: Q-learning); (Lepa et al., 2020: SVM/RF/PCA); (Ballestar et al., 2019: ANN); (Kim et al., 2001: DT); (Qazi et al., 2020: BN); (Esmaeilpour et al., 2012: Cellular automata); (Lu et al., 2016: SVM).
	Brands and trademarks management	(Kaiser et al., 2020: ANN); (Liu et al., 2020: DNN); (Ducange et al., 2019: SVM/NB/kNN); (Kübler et al., 2020: SVM); (Tirunillai and Tellis, 2014: LDA); (Chen et al., 2015: FA); (Carpineto and Romano, 2020: NB/SVM); (Trappey et al., 2020: CNN/word2vec).
	Purchase decision prediction	(Arasu et al., 2020: Text mining); (Ghatasheh et al., 2020: ANN); (Martínez et al., 2020: LR/gradient boosting); (Zhang et al., 2014: HB); (Li et al., 2019a: DT/NB); (Paolanti et al., 2020: CNN); (Schwartz et al., 2014: DT/HMM); (Shin and Cho, 2006: SVM); (Behe et al., 2020: RF); (Hauser et al., 2010: Bayesian methods); (van Wezel and Potharst, 2007: Bagging/boosting); (Droomer and Bekker, 2020: RNN/ANN/LR/gradient boosting); (Gabel et al., 2019: SG model/PCA).
Price		(Wolkenfelt and Situmeang, 2020: Topic model); (Sueyoshi and Tadiparthi, 2005: Adaptive learning); (Sueyoshi and Tadiparthi, 2008: NN/GA); (Casamatta et al., 2022: double machine learning); (Yang et al., 2020: Kernel-based extreme learning).
Promotion	Advertising management	(Goodrich et al., 2015: FA); (Schwartz et al., 2017: MAB); (Lee et al., 2018: LR/NB/SVM); (Peng et al., 2020: EL); (Simmonds et al., 2020: LR); (Fan and Chang, 2010: SVM); (Fan and Chang, 2011: Text mining); (Miralles-Pechuán et al., 2018: LR); (Couwenberg et al., 2017: LR); (Matz et al., 2019: LR); (Quesenberry and Coolsen, 2019: LR); (Bai et al., 2019: DNN); (Chapelle et al., 2014: LR); (King et al., 2015: NB/LR/DT/SVM); (Xu et al., 2018: NN); (Yang et al., 2020: NN); (Haider et al., 2018: EL); (Hu et al., 2020: CNN); (Kanei et al., 2020: RF); (Aswani et al., 2018: K-means); (Hou et al., 2021: CNN); (Wang et al., 2020: CNN); (Liang et al., 2019: Graph analysis); (Li et al., 2019b: CNN).
	Demand prediction	(An et al., 2021: DT/RF/gradient boosting); (Tang and Dong, 2020: DT/gradient boosting); (Liu et al., 2016: LDA/PCA); (Bassamzadeh and Ghanem, 2017: BN); (Zhang et al., 2017: CNN); (Kim et al., 2008: SVR); (Kumar et al., 2020: NN).
	Chatbots	(Van den Broeck et al., 2019: LR); (Luo et al., 2019: LR); (Zarouali et al., 2018: Regression).
Place		(Danaher et al., 2020: Variational bayes); (Bhowmick and Mitra, 2019: NB); (Leguina et al., 2020: LR/NB/RF/SVM).
People	Churn prediction	(Ascarza, 2018: RF); (Schaeffer and Rodriguez Sanchez, 2020: SVM/KNN/RF); (Ullah et al., 2019: RF/k-means).
	Targeting customer prediction	(Cui et al., 2006: BN); (Lessmann et al., 2021: EL); (Ameer et al., 2019: NB/LR/RF/J48); (Hsieh et al., 2015: SVM/Adaboost); (Jeon et al., 2020: DNN); (Abernethy et al., 2008: RN); (Fiore et al., 2017: PCA); (Luaces et al., 2015: SVM); (Chen et al., 2017: Sparse ML); (Evgeniou et al., 2007: HB/LR); (Dew et al., 2020: LDA); (Buckinx et al., 2007: RF); (Chen et al., 2020: RF).
	Engagement	(Cheng and Huang, 2020: Classification mining); (Kim et al., 2015: NB/DT/NN/SVM); (Kwok et al., 2020: SVM); (Taecharungroj and Mathayomchan, 2019: NB/LDA); (Pantano et al., 2019: Markov mothod); (Luo and Xu, 2019: SVM/NB/LDA); (Srivastava and Kalro, 2019: LDA); (Li and Zhang, 2020: PCA/K-means); (Ryoo et al., 2020: LDA); (Chatterjee et al., 2021: RF/DT/XGboost/LR); (Liu et al., 2019: NN); (Yu et al., 2019: unsurpervised matrix iteration algorithm); (Khurshid et al., 2019: EL); (Cagnina and Rosso, 2017: SVM); (Dong et al., 2018: LDA); (Hazim et al., 2018: XGBoost); (Rajamohana and Umamaheswari, 2018: NB/kNN/SVM); (Zhang et al., 2016: SVM/NB/DT/RF); (Arora et al., 2019: KNN/SVR); (Fang and Hu, 2018: DT); (Feng et al., 2020: CNN/LDA); (Montañés et al., 2014: LR); (Jung and Jeong, 2020: DT/RF/NN/gradient boosting).
	Facial recognition	(Su et al., 2020: SVM/CNN); (Yolcu et al., 2020: CNN); (Masui et al., 2020: SVR); (Alvarez-Pato et al., 2020: NN); (Renigier-Biłozor et al., 2021: CNN); (Wahab et al., 2021: CNN/KNN).
Process	Marketing segmentation	(Jiang et al., 2015: CL); (Ahani et al., 2019a: CL); (Nilashi et al., 2019: LDA); (Ahani et al., 2019b: CL); (Florez-Lopez and Ramon-Jeronimo, 2009: DT); (Buckley et al., 2014: Topic modeling); (Huiru et al., 2018: SVM); (Koehn et al., 2020: RNN); (Jagabathula et al., 2018: CL); (Kühl et al., 2019: SVM/RF); (Timoshenko and Hauser, 2019: CNN); (Mostafa, 2009: NN); (Yu et al., 2020: CL/K-means).
	Planning process	(Smirnov and Huchzermeier, 2020: Gradient boosting).
Physical evidence	Content marketing	(Poecze et al., 2019: kNN); (Tsao et al., 2019: Text mining); (Rietveld et al., 2020: StarSpace model); (Vazquez et al., 2014: Text mining); (Chapelle et al., 2015: LR); (Jai et al., 2021: SVM); (Salminen et al., 2019: RF/KNN/NN).

(Note: acronyms of ML methods: NN = neural networks; EL = ensemble learning; SVM = Support-vector machine; LDA = Latent Dirichlet allocation; XGBoost = Extreme gradient boost; NB = Naïve bayes; DT = Decision tree; RF = Random forest; CNN = Convolutional neural networks; BN = Bayesian network; LR = Logistic regression; Adaboost = Adaptive boosting; DNN = Deep neural network; RN = Regularization networks; PCA = Principal component analysis; HB = Hierarchical bayes; RBA = Randomized-by-action; EM = Expectation maximization; ANN = Artificial neural networks; RNN = Recurrent neural networks; SVR = Support vector regression; MAB = Multi-armed bandit; CL = Clustering; HMM = Hidden-markov model; GA = Genetic algorithm; FA = Factor analysis).

3.3. Promotion

Extant literature applies ML technologies to analyze promotion-related marketing activities, including advertising management, demand prediction, and chatbots. These applications are described in detail below.

3.3.1. Advertising management

Recently, online advertising has rapidly developed for promotion. Researchers want to know how to improve advertising effectiveness and how to predict click through rates, which are critical components of any online advertising platform (Bai et al., 2019).

Some researchers examine the impact of observable advertisement attributes (Goodrich et al., 2015; Schwartz et al., 2017; Lee et al., 2018; Peng et al., 2020) and prior brand usage (Simmonds et al., 2020); discover bloggers' immediate personal interests (Fan & Chang, 2010; 2011); optimize the microtargeting technique in direct response (Miralles-Pechuán et al., 2018); and analyze the effects of ad appeals (Couwenberg et al., 2017; Matz et al., 2019), story development (Quesenberry & Coolsen, 2019), and visual information (Li et al., 2019b) to improve advertising effectiveness. Other researchers apply different ML methods for clicks through the prediction of online advertisements (Chapelle et al., 2015; King et al., 2015; Xu et al., 2018; Bai et al., 2019; Yang et al., 2020).

Fraud advertising is another research angle that has received significant attention. Researchers apply ML technologies to detect fraudulent advertisements by leveraging the flexibility of tolerance to different ad servers (Haider et al., 2018), novel weighted heterogeneous graphs (Hu et al., 2020), robust features against attacker evasion (Kanei et al., 2020), insights from social media analytics and bio-inspired computing (Aswani et al., 2018), attention-based learning of self-media data (Wang et al., 2020; Hou et al., 2021), and semantic features in content marketing articles (Liang et al., 2019).

3.3.2. Demand prediction

Accurate prediction of demand and sales is crucial in promotion activities as such information can be used to adjust the distribution of marketing resources. The development of information technology has generated a large amount of consumer behavior data that has prompted many scholars to explore how to use ML methods to predict demand or sales.

In the film and TV industry, scholars predict movie audience numbers on the opening weekend (An et al., 2021), total sales of films (Tang & Dong, 2020), and TV show consumption (Liu et al., 2016). In the electricity industry, Bassamzadeh & Ghanem (2017) predict electricity demand in residential buildings. In the hotel industry, Zhang et al. (2017) predict Airbnb property demand using a scalable image classification algorithm. Additionlly, Kim et al. (2008) focus on a response model to estimate the purchase amounts of responders for direct marketing. Kumer et al. (2020) propose a back-propagation neural network-based model to predict demand by using historical demand and sales data.

3.3.3. Chatbots

Chatbots galvanized by AI and ML (Luo et al., 2019) are one of the latest innovations in marketing and business. Chatbots are defined as "a computer program, which simulates human language with the aid of a text-based dialogue system (Zumstein & Hundertmark, 2018)." They are designed to mimic an interpersonal conversation, characterized by a high degree of personalization (Letheren & Glavas, 2017).

Van den Broeck et al. (2019) study the effectiveness of chatbot advertising by investigating whether and how perceived helpfulness and usefulness of a chatbot consulted on Facebook. The messenger platform affects the perceived intrusiveness of chatbot-initiated advertising in a later stage. Zarouali et al. (2018) test cognitive and affective determinants that influence the effectiveness of chatbots through an adapted CAT model on Facebook for brands. Luo et al. (2019) find that although undisclosed chatbots are as effective as proficient workers in engendering customer purchase, the disclosure of chatbots before a machine–customer conversation reduces the purchase rate. Ngai et al. (2021) propose an intelligent knowledge-based conversational agent system architecture to support customer services in e-commerce sales and marketing. The system is built in a real-world setting and incorporates various technologies, including web crawling, natural language processing, knowledge bases, and AI.

3.4. Place

Place refers to the marketing channels in the 7Ps marketing mix. Researchers have also noticed the influence of place on marketing activities. Danaher et al. (2020) investigate the in-store and online purchases of three retail brands in the clothing category and reveal a sizeable group of customers who shop across multiple brands and both purchase channels. They show that three forms of advertising expenditure (email, catalogs, and paid search) can influence in-store and online sales. Bhowmick and Mitra (2019) focus on geographical proximity to predict business popularity in location-based social networks. They define two types of consumers visiting a business, local and foreign, and find that local customers play a major role in shaping the popularity of business in local cities. Additionlly, Leguina et al. (2020) reveal that the attribution model is an instrument used to assess the return on investment of different channels and explore the impact of the key properties of user paths on attribution models.

3.5. People

People refer to customers who buy products or services and other customers in the service environment (Rafiq & Ahmed, 1995). Extant literature applies ML technologies to analyze people-related marketing activities, including churn prediction, targeting customer prediction, and engagement. These applications are described in detail below.

3.5.1. Churn prediction

Churn management is a top priority for most businesses, and churn prediction plays a central role in churn management programs (Ascarza, 2018). The prediction of customer churn has aroused the interest of researchers.

Ascarza (2018) explores whether targeting those individuals in churn prediction models using ML methods is indeed optimal. Targeting customers who are at the highest risk of churning is not necessary (Ascarza, 2018). Firms should target customers whose propensity to churn decreases in response to interventions (Ascarza, 2018). Schaeffer & Sanchez (2020) propose and test a method to predict client retention using monthly client transactions records in a business-to-business setting. They find that current ML techniques can adequately predict which clients will be lost. Ullah et al. (2019) focus on the telecommunication sector and propose a churn prediction model to identify customers who are inclined to churn and explore the factors behind customer churning.

3.5.2. Targeting customer prediction

Marketing messages are most effective if they reach the right customers (Lessmann et al., 2021). The allocation of different marketing resources to different consumers is important for firms. Several studies have predicted targeting customers and applied direct marketing.

Researchers predict targeting customers from the perspective of customer response (Cui et al., 2006; Lessmann et al., 2021), gender (Hsieh et al., 2015; Ameer et al., 2019; Jeon et al., 2020), preference (Abernethy et al., 2008; Luaces et al., 2015; Fiore et al., 2017), heterogeneity (Evgeniou et al., 2007; Chen et al., 2017; Dew et al., 2020), and loyalty (Buckinx et al., 2007). Additionally, Chen et al. (2020) use a randomized field experiment to explore direct-to-patient outreach marketing through ML to implement personalized healthcare marketing programs.

Facial recognition is important for targeted marketing and draws researchers' attention. Facial features like skin color, gender, appearance, emotion, and facial marks can be extracted from facial images using different ML technologies (Mane & Shah, 2019). Facial recognition technology is used to classify individuals based on their facial features. These features are salient for understanding consumer preferences (Su et al., 2020), and such information is used for interactive targeted marketing.

Su et al. (2020) apply facial expression analysis to develop a novel model to automatically personalize clothing recommendations. To obtain consumers' multi-interest, the authors combine expression intensity and expression duration, which improves the recall of the recommendation. Yolcu et al. (2020) present a deep learning-based system for monitoring customer interests. They use local part-based features with holistic facial information for robust facial expression recognition. Masui et al. (2020) analyze facial expressions and physiological responses through facial videos to estimate advertising effectiveness in the natural environment and purchase intent. Álvarez-Pato et al. (2020) introduce a novel sensory analysis system, including facial emotion recognition, to predict consumer acceptance of food samples. Renigier-Biłozor et al. (2021) propose a method that correlates the emotional states of buyers with the visualization of selected attributes of properties in the real estate market. They verify the significance ranking determined by unconscious facial emotions. From the method perspective, Ab Wahab et al. (2021) propose a hybrid CNN and KNN model for facial expression recognition to recognize users' emotions. The ability of facial recognition technology to determine user emotions and influence buying decisions is part of a digital marketing strategy that is important for marketing.

3.5.3. Engagement

Social media platforms, such as Facebook, Twitter, and Instagram, have created new ways of interaction, communication, and engagement (Hanna et al., 2011). People post opinions and use "like," "share," or "comment" for exchanging information (Kwok & Yu, 2013) via these platforms. The engagement level can gauge the effectiveness of firms' social media marketing efforts (Jung & Jeong, 2020). Huge volumes of opinions, expressed in real time, has great appeal as a novel marketing application (Ikeda et al., 2013). Hence, extensive studies on ML in engagement and interaction have been conducted.

As customers prefer to post reviews to share their experiences after consumption, researchers examine customer reviews in different domains and from different perspectives. They focus on reviews of movie (Kim et al., 2015; Cheng & Huang, 2020), travelers (Taecharungroj & Mathayomchan, 2019; Kwok et al., 2020), fast fashion retailers (Pantano et al., 2019), and health-product (Chatterjee et al., 2021), and the helpfulness of online reviews (Luo & Xu, 2019; Srivastava & Kalro, 2019). Other researchers pay attention to lurkers, who do not post reviews after purchasing (Li & Zhang, 2020), and spoiler reviews to find new insights (Ryoo et al., 2020).

However, as e-commerce grows, so does the prevalence of fake online reviews (Wu et al., 2020). Fake reviews are utilized to manipulate product reputations (Yu et al., 2019) and consumer purchase decisions. Several researchers attempt to detect fake reviews by applying ML methods (Zhang et al., 2016; Rajamohana & Umamaheswari, 2018; Khurshid et al., 2019; Liu et al., 2019), such as a novel individual–group–merchant relation model (Yu et al., 2019), character n-grams (Cagnina & Rosso, 2017), Gibbs' sampling algorithm (Dong et al., 2018), and statistical-based features (Hazim et al., 2018) for detection.

Other researchers are actively exploring influence marketing on social media. They measure the social media influencer index across popular social media platforms (Arora et al., 2019), predict top persuader prediction (Fang & Hu, 2018), explore the role of narratives (Feng et al., 2020), and study the influence of superstars on spectators (Montañés et al., 2014).

3.6. Process

Process refers to the procedures, mechanisms, and plowing of activities (Rafiq & Ahmed, 1995). Researchers pay attention to how managers perform the marketing segmentation.

Marketing segmentation is the division of the mass market into groups with similar needs and wants (Yu et al., 2020). Customer segmentation is the practice of grouping customers into non-overlapping segments such that customers in the same segment have similar needs and preferences this sense, the two concepts have the same meaning. As traditional market segmentation approaches are ineffective in analyzing big data, ML methods can solve large amounts of data better. The literature review shows that several researchers explore marketing/customer segmentation from different perspectives.

Researchers mine hotel reviews to conduct segmentation (Jiang et al., 2015; Ahani et al., 2019a; Nilashi et al., 2019) or evaluate market segmentation by assessing traveler satisfaction (Ahani et al., 2019b). They also apply customer relationship management (Florez-Lopez & Ramon-Jeronimo, 2009), customer behavior (Buckley et al., 2014; Huiru et al., 2018; Koehn et al., 2020), customer preferences (Jagabathula et al., 2018) and needs (Kühl et al., 2019; Timoshenko & Hauser, 2019), psychographic and cognitive factors (Mostafa, 2009), and game players' attributes (Yu et al., 2020) to conduct marketing/customer segmentation. Smirnov and Huchzermeier (2020) integrate customer arrival forecasting, service time estimation, and staffing into a labor planning process.

3.7. Physical evidence

Physical evidence refers to the environment in which the service is delivered and tangible goods/clues that facilitate the performance and communication of the service (Rafiq & Ahmed, 1995). The extant literature applies ML technologies to investigate physical evidence-related marketing activities. Content marketing is about tangible information and persuading audiences with solid content to motivate customers to buy goods or services (Kee & Yazdanifard, 2015).

For example, Poecze et al. (2019) measure the success of different types of posts on Facebook to optimize brand communication on social media. Tsao et al. (2019) develop a novel ML-based method for measuring marketing constructs through the passive analysis of consumer-generated textual data. Rietveld et al. (2020) explore how emotional and informative message appeals influence customer engagement on Instagram. They find that positive high and negative low-arousal images drive customer engagement. Informative appeals do not drive customer engagement except for informative brand-related appeals. Vazquez et al. (2014) classify user-generated content according to the different stages of the consumer decision journey and marketing mix elements. Chapelle et al. (2015) explore how to model response prediction in display advertising, which is a form of online advertising where advertisers pay publishers to place graphical ads on their web pages. Jai et al. (2021) investigate the effect of different types of visual sensory information on brain activation preceding purchase decisions. Salminen et al. (2019) compare the ML approach to automatically tag and classify different types of online news articles for content marketing efficiency.

3.8. ML technologies

ML, which applies different analysis tools and learning algorithms to generate predictions needed to make decisions (Agrawal et al., 2018) in the era of big data, has entered marketing research (Hagen et al., 2020). We focus on articles that are directly related to ML tools, including text, voice, and image and video analytics. We divide the technology category into the following sub-categories: supervised learning, unsupervised learning, and reinforcement learning. In this subsection, we provide a list of the major types of analysis tools and algorithms with a brief discussion on how they are adopted in support of the system development of ML applications in marketing. Table 2 summarizes the major ML tools and algorithms and their applications, as outlined in the papers reviewed.

3.8.1. ML tools

Based on the characteristics of the analyzed data, we describe ML analysis tools that are algorithmic applications of ML in marketing. These tools provide systems with the ability to learn and help improve business decisions by leveraging ML/AI using text, voice, and image and video analytics into business insights. In the following section, we provide a detailed discussion of these ML tools and technologies.

3.8.1.1. Text analytics. Text analytics (or text mining) is defined as "the discovery by computer of new, previously unknown information, by automatically extracting information from different written resources" (Hearst, 2003, p. 1). It uses natural language processing to transform unstructured text into structured data for analysis. Text analytics involves data pre-processing, domain identification/classification, and statistical association analysis; it is widely used to understand social/economic phenomena (Xiang et al., 2015).

Examples of text analytics in the reviewed papers are online reviews of products or services (Ghose et al., 2012) and posts on social media platforms (Jeon et al., 2020). Researchers apply different ML methods to mine textual information in multiple applications. They identify textual features and sentiments to detect fake reviews (e.g., Dong et al., 2018; Liu et al., 2019), predict customer targeting (e.g., Ameer et al., 2019; Jeon et al., 2020), and design ranking systems for recommendations (Ghose et al., 2012). They also use text analytics in the application of engagement and communication, such as predicting start-up firms' marketing engagement levels (Jung & Jeong, 2020), examining customer engagement on social media (Lee et al., 2018), and identifying customer needs (Kühl et al., 2019; Timoshenko & Hauser, 2019). Additionally, text analytics are used to predict demand and customer segmentation (e.g., Jiang et al., 2015; Liu et al., 2016; Nilashi et al., 2019).

3.8.1.2. Voice analytics. Voice analytics refers to the use of a voice recognition tool to analyze and mine voice data to understand the physics and psychology of speech formation as well as how to extract and analyze vocal features (Hildebrand et al., 2020). Hilderbrand et al. (2020) develop a conceptual framework linking vocal features in the human voice to experiential outcomes and emotional states. They also provide several future directions for voice analytics applications in business research and practice, which use vocal features as input to supervised ML models to obtain insights from specific business activities.

However, in the review process, compared with other forms of analytics, voice analytics is rarely applied in marketing. Hence, available research is limited. For example, Lepa et al. (2020) use music to predict listener-perceived musical expression for a recommendation system.

3.8.1.3. Image and video analytics. Image analytics refers to the extraction of information from images by means of digital image process techniques, such as supervised classification learning and unsupervised clustering learning (Solomon & Breckon, 2011). According to our selected papers, researchers explore several marketing activities using image data. Examples of such image data are human face, visual product presentation, and brand-related images. Researchers detect facial and torso information to distinguish the gender of potential customers for predicting targeting (Hsieh et al., 2015; Jeon et al., 2020). Other researchers study the effect of visual product presentation on customer purchase decisions (Jai et al., 2021). Additionally, image analytics is

Table 2
Major ML tools and technologies used in marketing applications.

Groups of tools and technologies		Application areas
ML tools and technologies	Text analysis	Engagement (e.g. (Liu et al., 2019, Jung and Jeong, 2020, Dong et al., 2018)); Advertising management (e.g. (Lee et al., 2018, Kühl et al., 2019, Timoshenko and Hauser, 2019)); Demand prediction (e.g. (Liu et al., 2016)); Targeting customer prediction (e.g. (Jeon et al., 2020, Ameer et al., 2019)); Product recommendation (e.g. (Ghose et al., 2012)); Marketing segmentation (e.g. (Jiang et al., 2015, Nilashi et al., 2019)).
	Voice analysis	Product recommendation (e.g. (Lepa et al., 2020)).
	Image and video analysis	Targeting customer prediction (e.g. (Hsieh et al., 2015, Jeon et al., 2020)); Product recommendation (e.g. Lu et al., 2016)); Content marketing (e.g. (Jai et al., 2021, Rietveld et al., 2020)); Purchase decision prediction (e.g. (Paolanti et al., 2020, Zhang et al., 2014)); Advertising management (e.g. (Matz et al., 2019, Couwenberg et al., 2017, Goodrich et al., 2015, Quesenberry and Coolsen 2019, Simmonds et al., 2020, Li et al., 2019b)); Demand prediction (e.g. (Zhang et al., 2017)); Brands and trademarks management (e.g. (Kaiser et al., 2020, Liu et al., 2020, Trappey et al., 2020)).
Supervised learning algorithms	K-nearest neighbors (KNN)	Engagement (e.g. (Arora et al., 2019)); Content marketing (e.g. (Poecze et al., 2019)); Facial recognition (e.g. (Wahab et al., 2021)); Product recommendation (e.g. (O'Mahony et al., 2004)); Churn prediction (e.g. (Schaeffer and Rodriguez Sanchez, 2020)).
	Naïve Baye (NB)	Product recommendation (e.g. (Alabdulrahman and Viktor, 2021); Engagement (e.g. (Kim et al., 2015)); Targeting customer prediction (e.g. (Ameer et al., 2019, Cui et al., 2006)); Brands and trademarks management (e.g. (Carpineto and Romano, 2020); Purchase decision prediction (e.g. (Li et al., 2019a, Hauser et al., 2010)).
	Support-vector machine (SVM)	Recommendation system (e.g. (Cheung et al., 2003); Targeting prediction (e.g. (Luaces et al., 2015)); Customer segmentation (e.g. (Huiru et al., 2018)); Engagement (e.g. (Ikeda et al., 2013, Kübler et al., 2020, Kwok et al., 2020)); Purchase decision prediction (e.g. (Jai et al., 2021, Shin and Cho, 2006)); Facial recognition (e.g. (Su et al. 2020)).
	Artificial neural networks (ANN)	Recommendation (e.g. (Ballestar et al., 2019)); Predict targeting (e.g. (Buckinx et al., 2007)); Purchase decision prediction (e.g. (Droomer and Bekker, 2020, Ghatasheh et al., 2020)); Engagement (e.g. (Kaiser et al., 2020)).
	Random forest (RF)	Churn prediction of customer (e.g. (Ascarza, 2018, Ullah et al., 2019)); Recommendation (e.g. (Lepa et al., 2020)); Targeting

(continued on next page)

Table 2 (*continued*)

Groups of tools and technologies		Application areas
		prediction (e.g. (Chen et al., 2020)); Advertising management (e.g. (Kanei et al., 2020)); Purchase decision prediction (e.g. (Behe et al., 2020)); Engagement (e.g. (Kühl et al., 2020)).
	XGBoost/gradient boosted trees	Demand prediction (e.g. (An et al., 2021, Tang and Dong, 2020)); Advertising management (e.g. (Peng et al., 2020)); Targeting prediction (e.g. (Hsieh et al., 2015)); Engagement (e.g. (Chatterjee et al., 2021, Jung and Jeong, 2020)); Purchase decision prediction (e.g. (Martínez et al., 2020)).
	Decision tree (DT)	Engagement (e.g. (Fang and Hu, 2018, Vázquez et al., 2014)); Recommendation (e.g. (Kim et al., 2001)); Marketing segmentation (e.g. (Florez-Lopez and Ramon-Jeronimo, 2009)); Purchase decision prediction (e.g. (Peker et al., 2017, Schwartz et al., 2014)).
	Convolutional neural networks (CNN)	Advertising management (e.g. (Bai et al., 2019, Hu et al., 2020, Hou et al., 2021, Wang et al., 2020)); Purchase decision prediction (e.g. (Paolanti et al., 2020)); Engagement (e.g. (Feng et al., 2020, Liu et al., 2020, Timoshenko and Hauser, 2019)).
	Neural networks (NN)	Customer segmentation (e.g. (Mostafa, 2009)); Customer relationship management (e.g. (Xie and Huang, 2020)); Advertising management (e.g. (Xu et al., 2018, Yang et al., 2020)); Facial recognition (e.g. (Alvarez-Pato et al. 2020)).
	Logistics regression	Chatbot (e.g. (Luo et al., 2019, Van den Broeck et al., 2019)); Targeting prediction (e.g. (Gubela et al., 2020)); Advertising management (e.g. (Matz et al., 2019, Miralles-Pechuán et al., 2018); Engagement (e.g. (Lee et al., 2018).
Unsupervised learning algorithms	Latent dirichlet allocation (LDA)	Targeting prediction (e.g. (Dew et al., 2020)); Customer segmentation (e.g. (Nilashi et al., 2019)); Engagement (e.g. (Luo and Xu, 2019, Ryoo et al., 2020, Srivastava and Kalro, 2019, Taecharungroj and Mathayomchan, 2019).
	Principal component /factor analysis (PCA/FA)	Targeting prediction (e.g. (Fiore et al., 2017)); Fraud detection (e.g. (Haider et al., 2018)); Recommendation (e.g. (Lepa et al., 2020)); Engagement (e.g. (Li and Zhang, 2020)); Brands and trademarks management (e.g. (Chen et al., 2015)); Demand prediction (e.g. (Liu et al., 2016)).
	Clustering	Marketing segmentation (e.g. (Ahani et al., 2019a, Ahani et al., 2019b, Jagabathula et al., 2018, Jiang et al., 2015)); Engagement (e.g. (Ikeda et al., 2013)); Recommendation (e.g. (Alabdulrahman and Viktor, 2021)).
	K-means	Advertising management (e.g. (Aswani et al., 2018)); Engagement (e.g. (Li and Zhang, 2020)); Churn prediction of customer (e.g. (Ullah et al., 2019)); Marketing segmentation (e.g. (Yu et al., 2020)).
Reinforcement learning algorithms	Q-learning	Recommendation system (e.g. (Wei et al., 2005)).
	Multi-armed bandit	Advertising management (e.g. (Schwartz et al., 2017)).
	Cellular automata learning	Targeting prediction (e.g. (Esmaeilpour et al., 2012)).
	Randomized-by-action: off-policy evaluation	Targeting prediction (e.g. (Simester et al., 2020)).

used in engagement, advertising management, trademark, and demand prediction (e.g., Zhang et al., 2017; Matz et al., 2019; Kaiser et al., 2020; Liu et al., 2020; Rietveld et al., 2020; Trappey et al., 2020).

Video analytics (or video content analysis) demand is growing in different industry sectors, including government, education, manufacturing, and business, owing to the increasing prevalence of CCTV cameras and advancements in AI/ML. AI-powered production is set to transform how video analytics are used to automatically detect temporal and spatial events in videos.

With the development of bandwidth and widespread availability of video recording and tools, video has become a primary mode of communication, and video-related applications have emerged (Schwenzow et al., 2020). Researchers focus on video analytics in marketing and business research; they find that video data can provide useful information to consumers and managers (Belk & Kozinets, 2005; Lee & Broderick, 2007). Temporal and spatial information of stores as well as psychological information about consumers, such as body movement, facial expressions, and interaction with products or salespersons and shoppers, can be obtained through video data (Lu et al., 2016). Video analytics systems can equip marketers with better decision-making capabilities. For example, exhibition marketers can make use of video analytics to capture visitors to an exhibition booth and determine their reaction to one's exhibit or individual products, inspiring a view to approach them with an offer later.

Several researchers apply ML algorithms and computer vision techniques to analyze video data in marketing. For example, Paolanti et al. (2020) examine how shoppers move in a store's spaces and interact with products on the basis of occlusion-free RGB-D video flow with near real-time performance. Video analytics systems can determine visitors' age, sex, and emotions invoked by products and use this information to modify their product offerings. Zhang et al. (2014) investigate how the social elements of a retail store visit (e.g., salesperson contact, shopper conversations) affect shoppers' product interaction and purchase likelihood through video tracking data.

Other researchers focus on video-advertising management. They investigate how to improve video advertising effectiveness by exploring neural responses to the functional and experiential appeal of advertisements (Couwenberg et al., 2017). They examine the effects of advertisement characteristics on perceived ad intrusiveness (Goodrich et al., 2015), factors influencing an online video's virality or likelihood to be shared and viewed (Quesenberry & Coolsen, 2019), and the effects of visual attention and prior brand usage or familiarity on recall (Simmonds et al., 2020).

Some researchers focus on other marketing applications. Li et al. (2019b) propose two measures—visual variation and video content—to mine video information to improve video marketing effectiveness. Lu et al. (2016) propose a video-based automated recommender system using real-time in-store videos.

3.8.2. ML algorithms

ML algorithms are programs that can learn from data and improve their experience with human intervention. ML algorithms have been applied to many disciplines, including marketing. In this study, with reference to (Ma & Sun, 2020), we broadly categorize ML algorithms into three types: supervised learning, unsupervised learning, and reinforcement learning. Table 2 summarizes the major ML tools and technologies and marketing applications as outlined in the papers reviewed.

3.8.2.1. Supervised learning. The supervised learning algorithm consists of a dependent variable, which is predicted from a given set of independent variables. The algorithms can be used to predict future labels by employing the labelled data available in the dataset. The input and output variables in the supervised learning tasks are observed (Ma & Sun, 2020). Examples of supervised learning used in marketing research are k-nearest neighbors, naïve Bayes, support-vector machine (SVM), artificial neural networks, random forest, XGBoost, and logistic regression. They are applied in the areas of engagement, targeting campaigns, churn prediction of engagement, targeting prediction, recommendation, fake information detection, marketing strategy, purchase decision prediction, customer segmentation, demand prediction, and advertising management.

3.8.2.2. Unsupervised learning. Unsupervised learning is a type of algorithm that learns patterns from untagged data. Unlike supervised learning, it does not have an outcome variable to predict or estimate; only the input variables are known. The typical goal is to find hidden patterns in or to extract information from the data (Ma & Sun, 2020). Examples of unsupervised learning are latent Dirichlet allocation, principal component/factor analysis, clustering learning, and k-means. They are applied in engagement, market segmentation, fake information detection, recommendation, demand prediction, and churn prediction.

3.8.2.3. Reinforcement learning. Unlike supervised learning, reinforcement learning does not rely on labeled datasets. In this algorithm, the machine learns from past experiences and trains itself continually through trial and error. Simply put, the algorithms are trained on a reward and punishment mechanism. The algorithm is rewarded for right moves and punished for wrong moves to make accurate business decisions (Wiering and Otterlo, 2012). Self-driving cars are a widely known application of reinforcement learning. Examples of reinforcement learning algorithms are Q-learning, multi-armed bandit, randomized-by-action, and off-policy evaluation. They are applied in the areas of recommendation, advertising, and targeting prediction (e.g., Wei et al., 2005; Esmaeilpour et al., 2012; Schwartz et al., 2017; Simester et al., 2020).

Table 2 shows that supervised learning is the most widely applied algorithm in the field of marketing as reflected from the selected papers.

4. Concluding remarks and limitations

AI and ML are buzzwords in business and are one of the most recent disruptive technologies. The applications of AI and ML are exponentially increasing. As AI and ML have become topics of interest in many business sectors particularly in the marketing sector, understanding how AI can be applied in business is important. Currently, studies on the applications of ML and AI in marketing are limited. Only a few studies provide an overview of ML in marketing. This study identifies 140 articles for analysis. Although this review cannot claim to be exhaustive, it provides a reasonable overview and insights and shows the incidence of research on this subject.

This study contributes to existing literature by providing a conceptual framework that explains how ML applications in marketing are supported by various ML tools and technologies. A two-layer conceptual framework for ML applications in marketing is proposed based on the findings of the literature review and nature of the ML technology studied. The framework shows ML tools and algorithms used to support ML-based applications along the 7Ps marketing mix. The conceptual framework is used as an initial research agenda and serves as a roadmap to guide further studies on ML applications in marketing. This can offer a potentially useful starting point for the development of insights into these aspects of emerging AI research in marketing.

Despite its merits, this study has limitations. First, the review of the extant literature may not be exhaustive. More work is required to include relevant papers from different sources. In this study, only AI and ML articles from academic journals were included. Books and research articles from conference proceedings and theses were excluded. Second, the journals covered in this research were limited to particular databases. Third, the keyword searches may not have been extensive enough to cover all possible papers related to ML applications in marketing. Fourth, although the selected articles were reviewed by two authors, the determination of which articles to include in the study was not fully objective. Finally, non-English journal publications were excluded. Future research may consider analyzing publications in non-English journal articles.

5. Agenda for future research

Applications using AI and ML have been spreading from consumers to business marketing, thereby boosting productivity. The possibilities for ML in marketing in the future are continuously increasing. Accordingly, ML for substantial consumer insights and understanding is in-high demand among companies. The goal of developing ML learning algorithms is to gain valuable business insights. Implications for businesses, particularly large businesses in competitive industries, are present to maintain innovativeness in strategic marketing planning. We are convinced that failure to deploy AI in marketing, specifically given the competition presented by firms that have deployed AI, will result in companies lagging in the industry.

Our literature review indicates that the potential of ML techniques in realizing AI applications in marketing has only been explored by a few marketing and AI researchers. Accordingly, there are numerous opportunities for research on the confluence of ML and marketing that address the current market needs and research gaps. One direction for future research is to analyze the progression and development of AI and ML in marketing and the impact of AI and ML findings on business. Some more specific topics and research opportunities are described as follows.

One of the concerns in digital marketing is customer data privacy. An unavoidable aspect is that numerous regulations are being formulated to tighten responsibilities concerning customer data. Privacy regulations, such as the General Data Protection Regulation and California Consumer Privacy Act, aim to protect consumers' rights over their personal information and how their data are used and shared by companies.

Face recognition systems are widely used in marketing. This technology can facilitate the determination of a person's sex and age, thereby making the introduction of new products minimally risky and markedly predictable. In fact, most video analytics solutions on the market are based on face recognition technology for gender and age analyses. The data provided by the system can be used to facilitate various business operations, such as visitor analytics for shops that can help shopkeepers make strategic decisions on product display and personnel deployment. Face recognition technology has also been used to identify regular store customers and offer them discounts or additional perks. However, there are many concerns over the increased use of face recognition technology in society, and governors are still in the process of providing a regulation of governing its use. There is a company-wide approach to end the use of face recognition system. For example, Facebook (Meta) is killing its face recognition system and will delete more than a billion people's individual facial recognition templates (Kaplan, 2021).

In this pandemic, everyone wears face masks. The performance and accuracy of the facial recognition system are reduced because people's faces are no longer recognized by computers. There is indeed a need to develop other algorithms to replace the face recognition algorithm owing to social concerns and personal privacy issues. Soft biometrics (e.g., person's clothes attributes) have emerged as a new attribute-based form of biometrics with a high level of usability and collectability that offer many advantages over hard biometrics (e.g., fingerprints, faces, etc.) (Jaha and Nixon, 2016). With a clothing identification model (containing different clothing attributes) to the video analytics system, marketers can extract full-body clothing characteristics for clothing attribute-based analysis and can obtain information about draw-in rate and people count for store traffic analysis and visitor analytics for physical shops without infringing on personal privacy. Further research can address how customer privacy and protection concerns in the use of rich marketing data generated by AI/IoT systems by developing models and algorithms that can preserve or ensure consumer privacy (Wedel and Kannan, 2016).

Marketers are implementing live streaming and using big data technology in their digital marketing strategies to ensure an uninterrupted user experiences and create a sense of closeness and originality. This can be challenging for organizations faced with hundreds of various data sources at the edge, within the firm, and in multiple clouds in the context of customer interactions, as they try to interact with customers in the moment. A large computing capability is required to run AI in video analytics, with further advances in computational equipment and the power of graphics processing unit cards that have significantly improved the ability for AI modeling training and analytics. Another crucial aspect is measuring human emotions, which can help predict the sales of products intended for introduction. Future research should investigate how this can be done to enable real-time analytics, which can influence customer decisions, leading to a better customer experience.

The use of AI or machine learning-based chatbots boosts marketing strategies, helps automate marketing communication, and ensures immediate and timely responses to customers, thereby maintaining their loyalty. Improved customer interactions with chatbots or conversational chatbots for marketing that can understand users' intent reduce their possible frustration and wastage of time. Natural language processing (NLP) is a field of ML that focuses on the ability of computers to understand, analyze, manipulate, and generate human language. Superior NLP enables chatbots to understand what customers want to achieve and reduces the time consumed in resolving customer issues.

However, most studies on NLP have been conducted using the English language and Mandarin Chinese (Otter et al., 2021). Hence, improving the NLP models in the use of languages other than English and Mandarin Chinese is an important means to improve customers' engagement with chatbot services. Accordingly, further research should be conducted to seamlessly integrate e-commerce at the service level of the customer journey (searching, booking, onsite).

Obtaining high-quality data is challenging with garage-in and garage-out. Regardless of how advanced the ML algorithms are, the results will be poor if the input data are of low quality. The training dataset (historical data) is important for supervising training because it serves as the foundation for building and training the model and how the machine model is built. A training set is an idealized case of a representative population set. However, data bias may occur because of sampling errors, selection bias, and human error. Using a non-representative training set to train and generate a model is unlikely to make accurate predictions. How can the attribution data across media and devices be collected and representative of the marketing mix? ML models are the heart of ML marketing projects. Obtaining marketing data from external digital sources with offline data to build a predication model of the effects of the marketing mix poses challenges. Algorithm-based models are trained using large amounts of data. An algorithm may become overfitting when the model performs well on the training data but does not generalize well. Contrastingly, an underfitting algorithm occurs when a model is too simple to learn the underlying structure of the data. Future research should consider viable data modeling and analysis strategies for the predictive and prescriptive modeling of unstructured marketing data. How can advanced AI/ML techniques and algorithms be further extended to analyze and interpret unstructured marketing data? How can creative elements of the marketing mix be incorporated into predictive and prescriptive analytics, which leads to strategic marketing decisions (Wedel and Kannan, 2016)?

CRediT authorship contribution statement

Eric W.T. Ngai: . **Yuanyuan Wu:** Data curation, Investigation, Visualization, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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