ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING BASED APPROACH TO PREDICT THE PREFERENCES OF TARGET CUSTOMERS FOR VARIOUS MARKETING STRATEGIES

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ABSTRACT

Marketing strategies are being revolutionized by the development of consumer-generated data and the expanding accessibility of Machine Learning (ML) tools. Researchers and marketers still have a lot to learn about the numerous potentials that ML applications have for establishing and sustaining a competitive business edge. Based on a thorough analysis of academic and commercial literature, we offer a taxonomy of ML use cases in marketing in this study. We have identified 11 recurrent use scenarios that are grouped into 4 homogenous groups and relate to the core ML in marketing application areas: basics of the shopper, consuming experience, decision making, and financial effect. We analyze the taxonomy's recurrent patterns and offer a conceptual framework for their interpretation and expansion, emphasizing the practical ramifications for marketers.

KEYWORDS: Analytics, Artificial Intelligence, Big Data, Machine Learning, Marketing, and Marketing Analytics.

INTRODUCTION

Companies face both an opportunity and a challenge as a result of the ongoing explosion of data [13, 43,41]. Machine learning algorithms can help operations and allow informed judgments by using such a big volume of structured and unstructured data [2]. Further complicating the situation is the growing availability of IoT, which is a network of physical objects embedded with sensors, software, and other technologies to connect and exchange data with other devices and systems over the internet (e.g., as for smartphones, smart watches, home automation devices, sensors; see Sestino et al., 2020 for a review). It is feasible to analyze collective behavior on huge sizes by using artificial intelligence (AI) and machine learning (ML) technologies to analyze such a massive quantity of data, often known as "Big Data" [13], both spatially and temporally. A machine's capacity to mimic human abilities including thinking, learning, planning, and creativity is referred to as artificial intelligence (AI) [10]: AI systems can adjust their behavior by examining the effects of past acts and functioning independently. [2] define machine learning (ML) as a complicated system of techniques used to develop systems that learn or improve performance based on the data they consume. Due to the variety of devices (IoT, computers, software agents, etc.) that contribute to the generation of these data nowadays, the significance and richness hidden inside Big Data are becoming more and more apparent [3, 41]. Managers and marketers are always working to collect and properly convert such data, into relevant knowledge with suitable research and analysis [43]. In order to investigate data to find correlations, trends, and ultimately predictive models suitable for intriguing marketing applications, machine learning tools may support these efforts [29].

The use of machine learning (ML) techniques enables computers to carry out certain tasks, such as planning and regulating variables and results, without the need for explicit programming and instead by analyzing instances of programmer-provided behavior. Algorithms that can adapt their behavior in response to incoming input make up the machine learning engine, which in a sense learns autonomously. These methods are employed in a variety of fields, including voice or picture recognition as well as sociological research.

Numerous commercial prospects have already been made possible by machine learning algorithms.

For instance, corporate recommendation systems find use for machine learning: These algorithms choose the advertisements that will be displayed to viewers extremely rapidly based on their browsing habits and preferences of users who utilize websites, platforms, or mobile applications.

As a result, this approach takes use of user choices by automatically arranging adverts in accordance with those preferences, without the need to update the algorithm because it can perform better on its own. The use of machine learning in business spans a wide range of areas, including chatbots and virtual assistants, as well as the systematic maximization of performance and budget [2, 10, 20, 29]. As a result, machine learning is transforming marketing by improving its accuracy and enabling real-time action. Numerous significant digital-native companies, like Google, Netfix, Spotify, Facebook, and Uber, are seizing this opportunity and understanding how these technologies can support the creation of platforms and applications capable of understanding people’s needs and providing suggestions based on their interests. With 84% of marketing agencies embracing AI and ML projects and 75% of major organizations increasing customer satisfaction by 10%, machine learning in marketing is becoming a reality in many businesses across the world. The impact of machine learning (ML) and Big Data analysis on the digital transformation of marketing strategies, as well as challenges to be overcome from a data and information management perspective, are revealed in some reviews focusing on machine learning exploitation in marketing (e.g., as for Ma & Sun, 2020; Miklosik & Evans, 2020) [29, 35]; however, an integrative evaluation effort focusing on the strategic marketing perspective is lacking. the creation of platforms and applications capable of understanding people’s needs and providing suggestions based on their interests. Based on the foregoing, the objective of this study is to investigate the present and potential influence of ML and similar technologies in marketing by taking into account such technology as a catalyst for business strategies, illuminating the relevant effects for both businesses and customers.

Systematic evaluations of ML applications in marketing have been provided in earlier studies [5, 20]. Despite the fact that these assessments produced lists of significant clusters that eventually supported our findings, we still felt the need to provide a systematic framework for interpretation. We are able to create a taxonomy of machine learning applications in marketing by utilizing a qualitative research methodology. To look at the activation of ML in marketing, the taxonomy is organized hierarchically and by adopting a business-oriented perspective: Each branch outlines a set of re-usable application techniques (referred to as "activation recipes" in the remaining sections of the article) for applying machine learning algorithms to specific business requirements. The hierarchy's leaves correspond to real-world activation circumstances. We investigate this taxonomy of machine learning for applications in marketing.

The creation of platforms and applications capable of understanding people's needs and providing suggestions based on their interests. The results could be helpful for a managerial-oriented conceptualization of the use of machine learning in marketing. They could also be used to combine knowledge from the literature to identify potential research directions and practical applications.

The essay is structured as follows: Big Data, machine learning, and its applications in marketing are briefly discussed in Sect. 2. Section 3 provides an example of the approach we used to translate the knowledge discovered via academic and commercial research into a structured taxonomy. The findings and a description of each section of the taxonomy are presented in Section 4, along with illustrations of how each use case has been used in practice. The final portion addresses the study's results and recognizes its limitations while noting areas that might use more research.

2 THEORETICAL CONTEXTS

2.1 The use of big data in machine learning

The enormous quantity of data, commonly referred to as "Big Data," that inundates every firm today is only growing and doubling in size every 1.2 years [42], making it too hard to analyze using conventional methods [11]. However, new technologies are starting to emerge that enable high-speed data processing devices and powerful computational storage capabilities [15]. With the ultimate goal of improving company digitalization and transition strategies, these technological advancements are required to handle the massive amount, diversity, and velocity of big data 41]. Artificial intelligence (AI) is becoming increasingly significant in this context because of its capacity to use vast data sets and translate them into business insights, changing businesses' strategic decision-making processes. the creation of platforms and applications capable of understanding people's needs and providing suggestions based on their interests.

According to earlier studies, artificial intelligence (AI) is defined as "programmes, algorithms, systems, and machines that demonstrate intelligence" (Shankar, 2018, p. 7), as well as "technology able to replicate cognitive functions that belong to the human mind, especially being able to solve problems and learn" [22].

In computer science, "intelligent agents" are defined as any device that can understand its surroundings and take activities to increase its chances of succeeding [50]. Additionally, AI is being utilized more and more to assist a variety of consumer-brand relationships, enhancing marketing tactics (e.g., Vlai et al., 2021) [49]. Many businesses utilize AI and machine learning (ML) to enhance the customer experience by better understanding customer wants, forecasting future demand, improving customer service, and enabling bots to respond to basic service inquiries. For example, Amazon.com's Prime Air is currently automating shipping with drones [20] and Lowe is currently using an autonomous retail service robot (LoweBot) to identify misplaced items in grocery stores and direct customers to the products they require [10] as examples of how AI applications are being used in automating operations.

According to Ma and Sun (2020) [29], ML is typically regarded as a subfield of AI and has received more attention in that field of study. A computer programme is said to learn from experience E about some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, increases with experience E, according to Mitchell's (1997) exact definition (p. 114). ML algorithms provide computers the ability to learn and develop on their own since they can find connections in the input data and recognize the right output, improving as they process additional data points. the creation of platforms and applications capable of understanding people's needs and providing suggestions based on their interests.

Large collections of consumer data may be mined effectively using ML, which gives marketers fresh perspectives on consumer behavior and increases the effectiveness of their marketing operations. Applications of machine learning (ML) may be seen in many spheres of contemporary culture, such as recommendation systems, online searches, speech recognition, computer vision, natural language processing, and many more. (2015) Jordan and Mitchell.

In terms of (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning, these ML systems have been divided into several categories of algorithms. According to Osisanwo et al. (2017) [37], algorithms used in supervised machine learning simulate dependencies and interactions between the input variables and anticipated results. For example, the system may be taught to recognize the differences between photographs of cats and dogs. In this instance, it would be given a large number of labeled samples (images of cats and dogs with labels) as training data, and would eventually find patterns and determine the most helpful attributes to infer a prediction. After the algorithm has been taught, the machine learning system develops a prediction function that can infer the correct label from a random input. For

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supervised learning tasks, a number of algorithms can be utilized, such as decision trees, decision forests, logistic regression, support vector machines, neural networks, kernel machines, and Bayesian classifiers. By evaluating their effectiveness with the use of the holdout data, the various algorithmic techniques may be compared. Email spam classifiers, face recognizers, and text classifiers are a few examples of applications that use supervised learning.

On the other hand, algorithms in unsupervised machine learning systems do not try to forecast a certain result. Instead, to create meaningful representations of the data set, they seek to isolate the underlying structural characteristics of the input data [6]. Without any tagged input, they search for relationships within the available data. Dimensional reduction and clustering are the two unsupervised learning approaches that are most often used. First one seeks to convert data from high-dimensional space to low-dimensional space. Principal components analysis, manifold learning, factor analysis, random projections, and autoencoders are just a few of the techniques it uses [23]. Topic modeling, which is used to unearth latent semantic patterns in text materials, is an illustration of dimension reduction. Without specific labels indicating the intended divisions, the clustering algorithms used in the unsupervised learning system attempt to discover segments in the observed data. The next step is to categorize future data using the discovered segments as rules. Applications for unsupervised learning include outliers' identification, classification, and consumer and market segmentation.

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Finally, reinforcement learning algorithms don't require a set of training data to function. The algorithm in this situation operates in a dynamic environment that is unknown and learns through immediate and ongoing feedback (reward function), which enables the system to advance while compiling the data set. Facebook advertising is an example of how reinforcement learning is used; the algorithm evaluates the ad across all possible targeting options, and if it is effective, it analyses the data to fine-tune its target [6]. Additionally, reinforcement learning is used by recommender systems to fit the continually changing tastes of customers. However, some hybrid forms coexist in these systems. Hybrid systems combine the first three machine learning techniques (see, for instance, Pompon et al., 2018) [38]. For instance, in a supervised learning environment, semi-supervised learning uses unlabeled data as input to increase the size of labeled data. This enables the ML system to be accurate without need the labeling of every piece of training data.

Applications of ML and AI in marketing

Despite the growing interest in AI in the marketing industry, the field is still relatively young and offers several untapped research opportunities. Recent times have seen a number of significant initiatives to categorize ML and AI applications in marketing, notably from 2017 forward. For instance, in a study conducted in collaboration with Deloitte, Davenport, and Ronanki (2018), projects utilizing AI-based technologies across a range of business tasks and processes have been studied, with fascinating findings. In particular, the study enabled Davenport to categorize AI applications into three groups: (1) Robotics and cognitive automation, which aims to automate back-of-office administrative and financial tasks using robotic process automation; (2) Cognitive insights, which aims to find patterns in the data and turn it into useful knowledge through machine learning algorithms; and (3) Cognitive Engagement, which aims to engage customers and employees thanks to cognitive engagement. More widespread classifications based on marketing strategies, such as segmentation, targeting, and positioning (STP), and marketing activities, such as product, price, place, and promotion (4Ps), are provided by other initiatives to systematize AI and ML applications in marketing.

Accordingly, segmentation, targeting, and positioning are three critical areas where marketers and managers might benefit from using AI and ML (Corbo et al., 2022) [7]. Personalized advertising is an example of an ML application in this system. Data mining may assist in defining segments by seeing patterns that human intuition and experience by themselves would miss. The four categories of marketing actions—Product, Price, Place, and Promotion—are referred to as the marketing 4Ps, or "marketing mix," which McCarthy first articulated in 1960. In their research of several instances of AI applications in marketing, Jarek and Mazurek (2019) [22] showed how the examples affected the marketing mix. Jarek uses the activities taken by products, hyper-personalization, automated recommendations, and the creation of new products as examples of AI application. Apple Pay, Google Pay, and PayPal are just a few examples of payment automation tools that leverage AI technology. Reinforcement learning algorithms are able to dynamically modify pricing by taking into consideration consumer preferences, competition activity, and supply characteristics. Regarding price actions, IoT can optimize retail [1, 36]; frontend presence can be automated with 24/7 customer care chatbots (de Cosmo et al., 2021; Kurachi et al., 2018)[12, 28]; and both can be used to automate frontend presence. Finally, AI technologies can automate the planning of advertising media, keyword research, real-time bidding, and social media targeting in many of their applications, including social media marketing, mobile marketing, and search engine optimization [34].

By combining the marketing mix discussed above with the various AI intelligences—mechanical AI, thinking AI, and feeling AI—VAHuang and Rust (2021) have developed an intriguing classification of AI applications. Mechanical AI, the first level of AI intelligence, automates routine tasks. Thinking AI processes data to produce insights that support decision-making and contribute to competitive advantage. Feeling AI engages in two-way communication with humans by analyzing the needs and emotions of customers.

In all prior attempts to organize AI and ML information in marketing, solid theoretical frameworks for applications that directly affect consumers, such as personalized messaging and the customer experience, have been provided. To the best of the authors' knowledge, there doesn't appear to be a comprehensive analysis of the business-facing processes, such as decision-making procedures at corporations and financial optimization. Additionally, a thorough review effort from a strategic marketing perspective is lacking, along with actual activation use cases.

3. METHODOLOGY

Through the development of a taxonomy of applications used to address marketing-specific objectives, the primary objective of this article is to analyze how ML and AI technologies are utilized to enhance corporate strategy. After doing a thorough search, we first gathered a sizable number of use cases. Given the wide range of potential applications that we could take into account, we made our decision based on a set of four specific selection criteria: we only gathered real-world use cases from existing businesses, references for which were available, published works in business or academic literature, and some knowledge of ML implementations (such as the class of algorithms that have been used). We performed an extensive, methodical literature search using the bibliometric databases Scopus and Google Scholar. We searched for publications that had the terms "Machine Learning," "Marketing," or "Artificial Intelligence" in their titles or keywords. We utilized Kohlegger et al. (2009)'s[25] Structured Content Analysis technique (SCA) to determine the important classification variables for each application. SCA is an iterative procedure that seeks to arrange findings, such as for pertinent passages of text, into meaningful categories, as shown in Fig. 1 [32]. As the majority of the pertinent content will fall under these categories, the compilation of these categories offers a systematic description of the topic under examination.

We chose to utilize this method to choose the categories that would be included in our taxonomy. We gathered data on the necessary data, technology, and algorithms employed, as well as the commercial value produced for the organization, for each use case that met the four selection criteria listed above. Using our best judgment, we iteratively read over the whole description of each application before classifying it into one or more of the pre-existing categories that best fit its key characteristics. In order to take into consideration, the multifaceted character of some use cases, we decided to classify each application into one or more categories, as done by Cuccurullo et al. (2016) [9]. The original categories used during the planning stage were based on our understanding in general.

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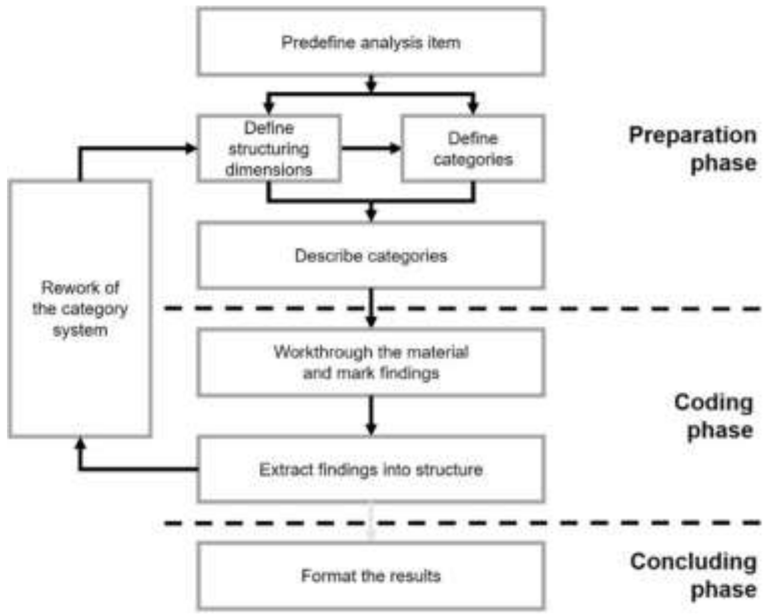

Fig. 1 Process flow of a Structured Content Analysis (SCA)

We began by classifying each use case according to categories established by earlier researchers in related studies or by popular frameworks like the marketing 4Ps. We critically reexamined the category definitions at the conclusion of each iteration and evaluated if they might be altered to better fit the overall content found in the articles. Using spreadsheet software to maintain and update the mapping between the categories and the use cases, we progressively redefined the categories and codified each example into the most pertinent category. When the writers came to an agreement over the validity of the mapping and created useful categories for machine learning applications in marketing, the iterative coding process came to an end.

4 RESULTS AND ANALYSIS

4.1 A taxonomy description

We gathered 75 use examples of ML and AI in marketing during May 2021 and eliminated 35 of them since they didn't fulfil one or more of the four aforementioned selection criteria. By utilizing the SCA technique as outlined in Section 3, we were able to get 11 activation recipes that were organized into a three-level taxonomy. At the lowest level of the taxonomy, we connected each of the 40 various real-world implementations we discovered in the literature to a recipe, which stands for the most suitable ML application field. The 11 recipes have then been divided into four groups, each of which corresponds to the second level of the hierarchy, in order to provide a clear framework for ML applications from the viewpoint of strategic marketing. On the consumer side, we divided the recipes into those that (1) enhance the foundations of purchasing, (2) enhance the consumption experience, and (3) enhance decision-making, (4) enhance financial applications. Figure 2 displays a visual tree visualization of the resultant taxonomy, with leaves representing the identified recipes and branches representing the division into conceptual groups. In this part, we'll go through each class of recipes' key characteristics (which are highlighted in the text in italics) and illustrate them using a variety of use cases.

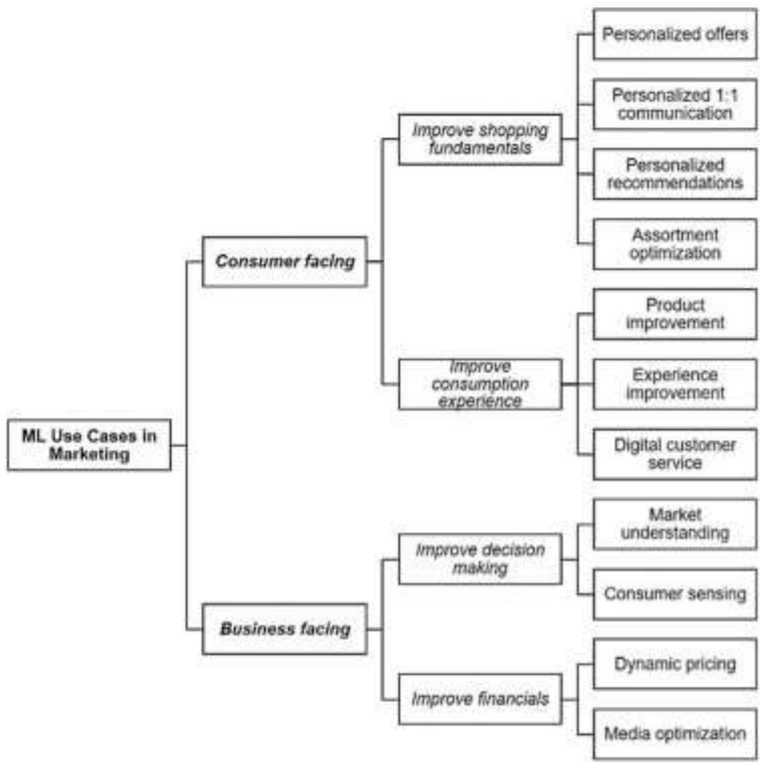

Fig. 2 Taxonomy of Machine Learning use in Marketing

4.1.1 Develop essential shopping skills

The possibility to enhance the customer experience at the time of purchase, regardless of the venue (in-store or online) is what is meant by improving shopping basics. Our findings revealed that by personalizing the experience, AI may be utilized to raise consumer pleasure. Personalization is the process of designing messages specifically for a certain customer based on socio-demographic trends and past purchasing behavior. ML algorithms may be used to define categories of customers who are similar to one another as well as to forecast consumer demands, enabling businesses to target accurate, personalized offers. [6,7]

Increasingly fine-grained segmentation is being used to capture several accurate micro-segments. As a result of this ongoing refinement, each customer may eventually turn into a distinct market group that may be specifically targeted with offers and promotions that are relevant to their unique profession (Ma & Sun, 2020). Machine learning technologies, including propensity modeling, cluster analysis, decision trees, reinforcement learning, and text-mining approaches, enable for highly personalized 1:1 communication [20]. In order to target high potential consumers and tailor the marketing campaign appropriately, Harley-Davidson NY implemented Albert AI, an AI-driven marketing platform. By doing so, the company saw an increase in sales by the third month (Power, 2017). A number of businesses are using personalized suggestions in addition to personalized offers and 1:1 communication to increase sales and customer engagement. In order to forecast and make suggestions for further products that customers might be interested in, recommender systems assess consumers' past purchasing behavior as well as that of comparable consumers [4]. (India, 2019; Suryawanshi & Narnaware, 2020) Netfix employs a cutting-edge recommendation engine that foretells what users will love watching and makes suggestions in line with that prediction. Similar to how Facebook utilizes this technology to suggest "people you may know," LinkedIn does the same to grow users' networks [30]. The final tip under the heading "improving shopping fundamentals" is assortment optimization. This covers voice and visual search, distribution prediction and optimization, inventory, retail displays, and store layouts (both offline and online).

4.1.2 Enhance the experience of consuming

This second category is concerned with the experiences customers have when utilizing goods or services and the actions they take as a result. It entails improvements to the products, the user experience, and digital customer support. Great advancements in this field are being made by Internet of Things (IoT) technologies based on AI, particularly in the areas of product creation, product support, and customer relationship management. Companies may gain access to Internet-based devices and gather detailed information on how customers use the product in real time. As a result, IoT allows a deeper knowledge of consumers, enabling businesses to create better goods and raise consumer value (Nguyen & Simkin, 2017) [36]. For instance, the home automation business June created a "do-it-all oven" that combines seven different appliances into one. With the use of machine learning and computer vision technologies, it could be able to recognize and prepare food and suggest an appropriate cooking programme (Tariq et al., 2020) [47]. IoT devices may collect data on every customer individually and offer personalized experiences by addressing their unique demands, leading to increased consumer happiness and engagement in addition to product enhancement. Walt Disney's 'MagicBand', a wristband that follows visitors' travels around the park and resorts in Orlando and gathers data on the customers' behavior, is an example of a use case for experience improvement. The band serves as a hotel key, an attraction pass, a payment device, and an electronic wallet, enabling visitors to purchase anywhere they

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want with only a flick of the wrist. Chatbots that use natural language processing may respond to a wide range of inquiries and offer customers timely, accurate help around-the-clock. They are simple to put into practice, economical, and easy to scale up (Huang & Rust, 2021) [20].

However, it's unclear how they affect customer satisfaction because some people still find it awkward to communicate with chatbots and would rather speak to a live person. A person over a chatbot is preferred by over 50% of consumers in the U.K. and 40% of consumers in the U.S. (Elliott, 2018) [16]. Many other sectors' businesses have embraced this technology. For instance, the Japan Professional Football League has integrated the CHORDSHIP Digital Agent, an AI chatbot technology, into their official app, allowing for quick and simple connection with the league's players.

4.1.3 enhancing decision-making

Our research reveals that market knowledge and consumer sensing are the two key areas where decision-making may be improved. Companies must first learn about the specific market they serve, forecast its future trends and evolution, and spot changes in the conduct of their rivals. Through machine learning-based analysis, AI may support conventional market research techniques. For offering insights from internet evaluations, opinions, and behaviors in the form of text, picture, audio, or video, text-mining is a potent tool. Deep learning algorithms enable more complex analysis, including predictive analytics, computational creativity, customization algorithms, and systems for natural language processing (Huang & Rust, 2021). For instance, Walmart's Social Genome Project enables the monitoring of open social media discussions to get knowledge about people's preferences and forecast future trends (Marr, 2016) [30]. On the consumer sensing side, businesses use related technology to include unstructured consumer data in addition to traditional interview-based information in order to acquire a better insight of the requirements and desires of the customer. Additionally, computer vision and deep learning techniques can identify emotions from facial expressions, body language, voice, and eye movements when customers interact with AI (such as conversational bots) (Campbell et al., 2020) [6], giving businesses deeper insights into customer preferences.

For instance, the software business Autodesk watches and monitors each time a customer interacts with their product, giving them a greater understanding of their target market.

4.1.4 Boost financial application quality

Finally, we discovered that by enhancing price and media tactics, marketing use cases of ML may influence financial KPIs. Managers must decide how much to charge for goods and services based on customer price sensitivity and rival pricing in order to develop a successful pricing strategy. The price elasticity of customers may be estimated using ML algorithms, which can then be used, for example, to dynamically adjust prices. Inferring what customers want and how much they are ready to spend can help businesses (Erevelles et al., 2016; Ke, 2018; Stavins, 2001)[17, 24, 44]. Businesses can gain a significant competitive advantage by changing pricing dynamically in response to the state of the market and customer price sensitivity (Yang & Leung, 2018; Ye et al., 2018) [51].

Uber's "surge price" is one of the most well-known pricing methods (see, for example, Guda & Subramanian, 2019) [18]. In order to maximize profits, the company continually analyses traffic conditions and ride requests in real-time and changes rates appropriately (Marr, 2016)[30]. This encourages drivers to be accessible only when necessary. Media optimization is the process of automating and enhancing digital marketing tactics. Each day, billions of messages and photographs are exchanged on social networks, providing marketers with a huge opportunity. Social media is a crucial part of every company's marketing plan.

Fms utilize this information to better understand their customers, as was previously discussed, but at the same time, social media is a significant communication channel for product advertising, giving customers the correct promotion at the right moment. A/B testing powered by AI, decreased cart abandonment, contextual ad targeting, keyword bidding, and content creation automation are just a few of the potential that AI provides for media optimization (Campbell et al., 2020) [6].

As an example of this use case, in 2018 LEGO hired Watson advertisements Omni to develop interactive advertisements driven by AI for Black Friday (Sweeney, 2018) [46]. With the use of data on customer interests and demands as well as prior LEGO purchases, the AI system was taught. With the use of this technology, the company was able to conduct deep, one-on-one discussions with customers throughout their purchasing process, increasing consumer engagement and driving up sales.

4.2 A summary of the suggested taxonomy

The major findings of the study will be described in this subsection.

Fig. 3 depicts four-word clouds, illuminating the top 30 terms repeatedly used in the descriptions of each of the conceptual classes offered in the taxonomy, to summarize the substance of each category of use cases. We saw that the first group is dominated by words like "personalized," "consumers," and "offers," enhancing the principles of purchasing and illuminating the significance of customization in this line of work. We see the words "consumer," "product," "improvement," and "experience" again in reference to an enhanced consuming experience.

These words refer to the emphasis on product improvement to improve the consumer experience at the time of usage.

The prominence of words like "insights," "market," and "understanding" for better decision making follows, which highlights the need of having a thorough understanding of the market and the target audience in order to suggest and carry out better strategic decisions. Last but not least, terms like "pricing," "strategy," and "media" for increasing finances signify the emphasis on price and media optimization to raise the company's P&L.

Fig. 3 Word clouds representing the topic content of each conceptual class at the second level of the taxonomy. From the top-left corner in clockwise order: Improve shopping fundamentals, improve consumption experience, improve financials, improve decision making

To thoroughly assess our findings, we gathered data for each recipe's implementation requirements, primary algorithms, KPIs taken into consideration, recipe predominance, and finally two or more real-world use cases. The prevalence is determined by how frequently (frequently, seldom) the recipe appears in the study literature we have gathered.

The recipes covered in the previous section are included in Table 1.

We identified several trends in how ML and AI may assist marketing strategies from our study and use case collection, which was based on a methodical research methodology. First, we noted that there are more machine learning (ML) commercial applications on the consumer side, highlighting the high and growing significance of highly tailored advertisements and suggestions. The fact that the most impacted KPIs in our taxonomy relate to customer loyalty and satisfaction further emphasizes this point. This finding explains why the words "consumer" and "consumer" appear often in all four of the word clouds that were previously displayed. We noticed that digital-native firms are overrepresented, indicating that the greater availability of data is an enabling factor for ML utilization for marketing [31]. Sector-wide, the most active companies in the use of ML appear to be those operating in technology (e.g., as for Apple, Microsoft), online entertainment (e.g., as for Netfix, EA), and social media (e.g., as for Facebook, LinkedIn). Most implementations come under the 'product' area of the marketing mix classification (Huang & Rust, 2021), which again relates to improving the customer experience. However, the concept of "place" appears to encompass a smaller number of ML applications. This may be explained by the fact that this field depends on Industry 4.0 technologies as autonomous vehicles and robotics play a significant role in the establishment of alternative sales channels, supporting the findings of Jarek and Mazurek (2019) [22].

Table1 SummaryofMLrecipesformarketingasidentifiedinliterature

Recipe	Predominantdata requirements	Predominantalgorithms	ValuecreationKPIs	MarketingMix(4Ps)	Predominance*	Usecases
Personalizedoffers	Consumer-leveltransac - tions,sociodemo - graphiccontextual data	Supervisedlearning, classification,propen - sitymodeling	PromotionalROI, repurchaserate	Promotion	●●	Etsy,HarleyDavidson, Target
Personalized1:1com - munication	Consumer-leveltransac - tions,sociodemo - graphiccontextual data	Supervisedlearning, clustering,propensity modeling	Customersatisfaction, loyalty,conversion rate	Promotion	●●	Facebook,Sprint,Zynga, Sofinco
Personalizedrecom - mendations	Consumer-levelhistori - caldata	Supervisedlearning, classification,propen - sitymodeling	Sales	Promotion	●●	Netflix,LinkedIn,Ama - zon,OYO
Assortmentoptimiza - tion	Store-levelanddemo - graphicdata	Optimization	Customersatisfaction, sales	Place	●	Lowe's,SCARA
Productimprovement	Sensors'data	*Miscellanea*	Customersatisfaction, loyalty	Product	●●●	Rolls-Royce,BBC, Apple,EA,June
Experienceimprove - ment	Consumer-leveltransac - tions,sociodemo - graphiccontextual data	Supervisedlearning, clustering,propensity modeling	Customersatisfaction, loyalty	Product	●●	WaltDisney,Spotify, L'Occitane
Digitalcustomerservice	FAQsandresponse history,servicedocu - mentation	Naturallanguage processing,reinforce - mentlearning	Customersatisfaction, costsreduction	Place	●●	eBay,J-League
Marketunderstanding	Customer-leveldata, marketresearchdata, social-mediacom - ments	Naturallanguagepro - cessing,deeplearning	Decisionmaking,costs reduction	Product	●	Walmart,Microsoft

While natural language processing (NLP), which enables social media listening, can help with decision-making, optimisation algorithms are the main focus of financial applications. This information is helpful in determining the amount of AI and ML technologies that may be used to enhance various business functions. Some pre-made AI parts, like NLP, are simply implementable and accessible for free. Many of the applications we've shown may be used with open-source platforms for data analytics, open-access frameworks like TensorFlow, or languages like Python or R (Wirth, 2018) [50].

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Table1 continued

Recipe	Predominantdata requirements	Predominantalgorithms	ValuecreationKPIs	MarketingMix(4Ps)	Predominance*	Usecases
Consumersensing	Customer-leveldata, demographicdata, socialmediacom - ments	Naturallanguage processing,sentiment analysis	Customerretention, loyalty	Product	●●●	Apixio,Pendlenton&Son, RoyalBankof Scotland,Dickey's BarbecuePit,Caesars, Autodesk,Experian
Dynamicpricing	Historicalandreal-time transactions,pricing data	Optimization	Profits	Price	●●●	Airbnb,Uber,Major LeagueBaseball,Hotel - Tonight,EasyJet
Mediaoptimization	Customer-levelhistori - calandreal-timedata, adscontentdata	Optimization	MediaROI,ROASin digitalmarketing	Promotion	●●	Acxiom,Kanetix,Orange

*Predominanceisbasedontherelativepresenceinliteratureaccordingtoourresearch(● = infrequent, ●●● = veryfrequent)

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5 CONCLUSIONS

In order to create a systematic taxonomy of 11 common application scenarios, we examined the academic and industry literature on the marketing use of machine learning. We have discovered that some of the use cases will directly impact customers and enhance their experience when shopping for and using the product.

As machine learning has been shown to significantly enhance decision-making and have an influence on financial measures, further use cases will be focused on the business and its operational model.

In their efforts to comprehend the complex nature of ML in marketing from the viewpoints of both customers and businesses, marketers and managers may find our findings to be helpful. In further detail, the organized, methodical research methodology identifies certain trends in the ways that ML and AI might enhance marketing initiatives. From a consumer's point of view, marketing efforts should be focused on enhancing both the overall customer journey and the personalized activities demanded by consumer-related idiosyncrasies. From a corporate standpoint, machine learning may be used for customer sensing, market comprehension (and, eventually, improving decision-making processes), as well as enabling dynamic pricing and media optimization techniques, all of which have an effect on financial outcomes.

These findings are consistent with the emerging paradigm of Marketing 5.0 [26], which seeks to fully exploit the use of technologies that mimic humans in order to create, communicate, offer, and increase value along the customer journey. To do this, it is necessary to redesign both business-oriented and consumer-oriented activities.

The development of the "next-tech" in marketing, which refers to a group of cutting-edge technologies that may mimic the skills of human marketers, may significantly benefit from machine learning [26]. Marketers and managers need to thoroughly comprehend how they must create a harmonious synergy between human and machine intelligence to increase the accuracy and adaptability of marketing plans.

Additionally, by taking into account earlier research (such as that of Ngai & Wu), we contribute to the body of knowledge in the field of opportunities for machine learning in marketing by conceptualizing current problems, providing a theoretical framework for analyzing its emerging trends, and including managerial and patricidal use cases. A systematic taxonomy resulting from the fusion of ML and AI technologies is also being presented for the first time in this contribution. Additionally, the current taxonomy is based on both theoretical and empirical evidence, making it capable of serving as a theoretical foundation for empirical studies on the phenomenon of machine learning application in marketing, with the goal of discovering novel variables and patterns that are reliable but have not yet been fully explored.

Our research, we feel, makes three significant additions to the practice of using ML in marketing and the conceptual growth of this field of study. In order to theoretically justify business strategies made possible by ML from a strategic marketing viewpoint, we first define and present a formal definition of ML applications in marketing. Second, by examining the breadth of presently enabled marketing applications, company managers may utilize the taxonomy offered in this paper to gauge the completeness of their ML programmes. We think that by identifying untried paths, frms may find more possibilities to use data and machine learning techniques to their fullest potential.

Finally, we acknowledge that there are certain gaps in our study that need to be filled in further investigations. First,000 while SCA is appropriate for categorizing and exploring texts qualitatively, we envisage the potential to reach deeper and less subjective conclusions utilizing quantitative approaches such as NLP and, in particular, topic modeling. Second, by including new use cases, which may be discovered by a thorough surveying exercise or a wider assessment of the literature based on more sources, our findings could be improved even more. The influence of leveraging ML on marketing performance indicators was not attempted to be numerically quantified in this study, which would have substantially aided firms in prioritizing their investment decisions.

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