Machine learning and artificial intelligence use in marketing: a general taxonomy

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Abstract
The emergence of consumer-generated data and the growing availability of Machine Learning (ML) techniques are revolutionizing marketing practices. Marketers and researchers are far from having a thorough understanding of the broad range of opportunities ML applications offer in creating and maintaining a competitive business advantage. In this paper, we propose a taxonomy of ML use cases in marketing based on a systematic review of academic and business literature. We have identified 11 recurring use cases, organized in 4 homogeneous families which correspond to the fundamentals leverage areas of ML in marketing, namely: shopper fundamentals, consumption experience, decision making, and financial impact. We discuss the recurring patterns identified in the taxonomy and provide a conceptual framework for its interpretation and extension, highlighting practical implications for marketers and researchers.

Keywords Artificial intelligence · Analytics · Big Data · Machine learning · Marketing · Marketing analytics
1 Introduction

The continuous proliferation of data represents both an opportunity and a challenge for companies (De Mauro et al., 2015; Sheth & Kellstadt, 2021; Sestino et al., 2020). By leveraging such a large amount of structured and unstructured data, machine learning algorithms can support operations and enable informed decisions (Agrawal et al., 2020). Moreover, the growing availability of IoT that is the 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, smartwatches, home automation devices, sensors; see Sestino et al., 2020 for a review), complicates the current scenario by generating a continuous massive flow of data. By analysing such a large amount of data, namely “Big Data” (De Mauro et al., 2015) both in space and in time, it is possible to study collective behaviour on large scales, spotting interesting models and anomalies by employing Artificial Intelligence (AI) and Machine Learning (ML) applications. Specifically, AI refers to the ability of a machine to display human capabilities such as reasoning, learning, planning, and creativity (Davenport et al., 2020): AI systems are capable of adapting their behaviour by analyzing the effects of previous actions and working independently. Conversely, among the AI applications, ML refers to the complex system of techniques used to create systems that learn, or improve performance, based on the data they use (Agrawal et al., 2020). For this reason, the relevance and richness hidden within Big Data are increasingly prominent, also by considering the multitude of devices (IoT, computers, software agents, and so on), which today contribute to generating these data (Bessis & Dobre, 2014; Sestino et al., 2020). Marketers and managers are continually attempting to acquire and adequately transform such data, through appropriate study and analysis into meaningful information (Sheth & Kellstadt, 2021). Machine Learning applications may support such efforts, by enabling techniques useful to explore data to derive correlations, patterns, and therefore predictive models, useful for interesting marketing applications (Ma & Sun, 2020).

ML techniques allow computers to perform certain tasks, such as planning and controlling variables and results, without explicit programming, but with the sole analysis of examples of behaviour provided by the programmer. The engine of machine learning is made of algorithms that, in a sense, autonomously learn, and are capable of adjusting their behaviour when exposed to new data. These techniques are used in numerous fields, from social research to speech or image recognition. Machine learning algorithms have proven to unlock vast economic opportunities. For example, machine learning finds application in business recommendation systems: Learning from the behaviour and preferences of users who browse websites, platforms, or mobile applications, these systems very quickly select the advertisements to be shown to users. Therefore, this process exploits the preferences of users by automatically positioning advertisements based on their preferences, without the need to update the algorithm, as it can improve its performance independently. The range of machine learning applications in business is wide, ranging from virtual assistants to chatbots, from the creation of advertisements designed on the profile of a target user to the systematic maximization of performance and optimization of
budget (Agarwal et al., 2020; Davenport et al., 2020; Huang & Rust, 2021; Ma & Sun, 2020; Vermeer et al., 2019). Thus, machine learning is revolutionizing marketing by making it more accurate and capable of acting in real-time. Many big digital-native players such as Google, Netflix, Spotify, Facebook, and Uber, are taking advantage of this opportunity and recognized how these technologies can support the creation of platforms and applications capable of understanding people’s needs and providing suggestions based on their interests. Machine learning applied to marketing is becoming a reality in many companies globally, with approximately 84% of marketing agencies implementing AI and ML projects, and 75% of large companies having improved consumer satisfaction by 10%. Although some reviews focusing on machine learning exploitation in marketing are available (e.g., as for Ma & Sun, 2020; Miklosik & Evans, 2020), revealing the impact of machine learning (ML) and Big Data analysis on the digital transformation of marketing strategies, together with challenges to face from a data and information management perspective, an integrative evaluation effort focusing on the strategic marketing perspective is missing. Based on the above, the goal of this work is to examine the current and future impact of ML and related technologies in marketing, by considering such technology as a trigger for business strategies, shedding light on the related impacts both for companies and consumers.

Previous works (Brei, 2020; Huang & Rust, 2021) have offered systematic reviews of ML applications in marketing. Although such reviews resulted in lists of meaningful clusters, which ultimately corroborate our findings, we found the need to develop a structured interpretation framework. By leveraging a qualitative research approach, we obtain a taxonomy of machine learning use in marketing. The taxonomy is organized hierarchically and by following a business-oriented perspective to investigate the activation of ML in marketing: Each branch describes a family of repeatable application ways (which we call “activation recipes” in the remainder of the paper) for utilizing machine learning algorithms to meet certain business needs. The leaves of the hierarchy correspond to practical activation scenarios. We explore this taxonomy of machine learning for marketing applications, particularly discussing how these techniques evolved to deal with marketing-specific needs, such as consumer understanding and segmentation.

Findings may be useful to a managerial-oriented conceptualization concerning the use of machine learning in marketing, also able to synthesize insights from the literature in order to glean practical applications and possible future research directions, both from a business and consumers perspective.

The paper is organized as follows: Sect. 2 provides some theoretical background on Big Data, Machine Learning, and their applications in Marketing. Section 3 illustrates the methodology we adopted for conveying the information gathered in business and scholarly research into a structured taxonomy. Section 4 presents the findings and describes each portion of the taxonomy, providing examples of real-world application of each use case. Finally, the last section discusses conclusions and acknowledges the limitations of the study, highlighting opportunities for further research.
2 Theoretical background

2.1 Big data and its contribution to machine learning

The vast amount of data that inundates every business nowadays, also known as “Big Data”, is getting larger and larger, duplicating in size every 1.2 years (Shankar, 2018), and therefore becoming too complex to be processed with traditional methods (De Mauro et al., 2018). Nevertheless, new technologies are emerging to allow advanced computing storage capability and high-speed data processing machines (Duan et al., 2019). These technical advances are needed to handle the extensive volume, variety and velocity of big data, with the ultimate objective to improve business digitalization and transition strategies (Sestino et al., 2020). In this context, Artificial intelligence (AI) is gaining great importance, due to its ability to exploit large data sets and transform them into business insights, reshaping companies’ strategic decision-making processes in every industry (Sestino & De Mauro, 2021). AI has been defined in previous research as “programs, algorithms, systems and machines that demonstrate intelligence” (Shankar, 2018, p. 7), and also as the “technology able to replicate cognitive functions that belong to the human mind, especially being able to solve problems and learn” (Jarek & Mazurek, 2019, p. 48).

In computer science, AI research is defined as the study of “intelligent agents”, meaning any device that perceives its environment and takes actions that maximize its chances of achieving a goal (Wirth, 2018). Moreover, AI is increasingly being used to support a wide range of consumer-brand relations, thus enriching marketing strategies (e.g., in Vlačić et al., 2021). Many companies use AI and machine learning (ML) to better understand consumers’ needs, predict future demand, optimize consumer service, and enable bots to answer simple service queries to improve the consumer experience. AI applications are also increasingly adopted in automating operations, like in Amazon.com’s Prime Air, which is currently using drones for shipping automation (Huang & Rust, 2021), and in Lowe, now using an autonomous retail service robot—LoweBot—to identify miss helved items in grocery stores and to guide consumers to the products they need (Davenport et al., 2020).

ML is generally considered as a subfield of AI (Ma & Sun, 2020) and it has drawn greater attention within AI research. Mitchell (1997) gave a precise definition of Machine Learning in terms of a “computer program is said to learn from experience E concerning some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E” (p. 114). ML algorithms enable computers to learn and improve by themselves, as they can find links in the input data and identify the correct output, improving upon themselves as they process new data points. ML is a powerful tool for mining large sets of consumer data, allowing marketers to gain new insights about people’s behaviour and to boost marketing operations efficiency. We can observe ML applications in a variety of fields of modern society, including recommender systems, web searches, speech recognition, computer vision, natural language processing and many more (Jordan & Mitchell, 2015).
These ML systems have been categorized into different groups of algorithms in terms of: (1) supervised learning; (2) unsupervised learning; and (3) reinforcement learning. In supervised machine learning, algorithms model relationships and dependencies between the input variables and expected outcomes (Osisanwo et al., 2017). For instance, the system could learn how to spot the difference between images of cats and dogs. In this case, it would receive as training data many labelled examples (pictures of cats and dogs with their label) and would ultimately identify patterns and detect the most useful features to infer a prediction. Once the algorithm has been trained, the ML system creates a predictive function that is able to estimate the right label from a random input. A variety of algorithms can be used for supervised learning tasks, including decision trees, decision forests, logistic regression, support vector machines, neural networks, kernel machines, and Bayesian classifiers. The different algorithmic approaches can be compared by validating their performance using the holdout data. Some examples of supervised learning applications are spam classifiers of email, face recognizers, text classifiers.

Conversely, in unsupervised machine learning systems, algorithms do not attempt to predict a specific outcome. On the contrary, they aim at identifying the underlying structural properties of the input data, to determine useful representations of the data set (Campbell et al., 2020). They look for associations within the given data, without the need for any labelled input. The two most common paradigms of unsupervised learning are dimension reduction and clustering. The first one aims at transforming the data from a high-dimensional space into a low-dimensional space. It includes several methods, such as principal components analysis, manifold learning, factor analysis, random projections and autoencoders (Jordan & Mitchell, 2015). An example of dimension reduction is topic modelling, which is used to discover hidden semantic structures in text documents. In the unsupervised learning system, the clustering techniques attempt to identify segments in the observed data, without specific labels illustrating the desired partitions. The detected segments are then used as rules to classify future data. Examples of unsupervised learning applications include consumer and markets segmentation, classification and outliers’ detection.

Finally, reinforcement machine learning algorithms operate without a set of training data. In this case, the algorithm acts in an unknown dynamic environment and learns through immediate and continuous feedback (reward function), that allows the system to improve while building the data set. An application of reinforcement learning is advertising on Facebook; the algorithm tests the ad across the entire targeting spectrum, and if it proves to be successful, the algorithms will analyse the data to fine-tune its target (Campbell et al., 2020). Recommender systems use reinforcement learning as well to be able to match consumers’ constantly evolving preferences.

However, among such systems, some hybrid forms coexist. Specifically, hybrid systems are a blend of the previous three machine learning methods (e.g., in Phoemphon et al., 2018). Semi-supervised learning, for example, takes as input unlabelled data to enlarge the labelled data in a supervised learning environment. This allows the ML system to be accurate, without requiring all the training data to be labelled.
2.2 Marketing applications of ML and AI

Despite the rising interest in AI within marketing, it remains a relatively new field with several unexplored research opportunities. Several significant attempts to classify ML and AI applications in marketing have appeared in recent times, particularly from 2017 onwards. For instance, in a joint research with Deloitte, Davenport and Ronanki (2018), AI cognitive technology projects that are making use of AI-based systems across a variety of business functions and processes have been examined reporting interesting results. Specifically, the study allowed Davenport to classify AI applications into three categories: (1) Robotics and cognitive automation, which aims at automating back-office administrative and financial tasks, using robotic process automation; (2) Cognitive insights, which aim at finding patterns in the data and transforming it into useful knowledge through machine learning algorithms; and (3) Cognitive Engagement, which aims at engaging consumers and employees thanks to chatbots, intelligent agents and machine learning. Other attempts to systematize AI and ML applications in marketing provide more common classifications based on marketing strategies, Segmentation, Targeting and Positioning (STP), and marketing actions, Product, Price, Place and Promotion (4Ps).

Accordingly, marketers and managers could leverage AI and ML to improve three strategic areas: Segmentation, Targeting, and Positioning (Corbo et al., 2022). An example of an ML application in this scheme is personalized advertisement. Data mining can help define segments, discovering patterns that human intuition and experience alone would not detect. The marketing 4Ps, or ‘marketing mix’, originally proposed by McCarthy in 1960, are a conceptual framework referring to the four areas of marketing actions: Product, Price, Place, and Promotion. Jarek and Mazurek (2019) conducted an analysis of many examples of AI applications in marketing, showing how the examples reflect the marketing mix. Jarek brings as examples of AI application in product actions, hyper-personalization, automatics recommendations, and new product development. AI technologies are also used for price actions to automate payments (e.g., Apple Pay, Google Pay, PayPal), and reinforcement learning algorithms are able to dynamically adjust prices, taking into account consumer choices, competitor actions, and supply parameters. With regards to price actions, retail processes can be optimized using IoT (Amatulli et al., 2021; Nguyen & Simkin, 2017), while frontend presence can be automated with 24/7 consumer service chatbots (de Cosmo et al., 2021; Kurachi et al., 2018). Finally, AI technologies can support promotion actions in many of their applications, such as social media marketing, mobile marketing, and search engine optimization (Miklosik et al., 2019), automating advertising media planning, keywords researching, real-time bidding, and social media targeting (Kumar et al., 2019).

Huang and Rust (2021) have created an interesting classification of AI applications, by crossing the marketing mix explained above, and the multiple AI intelligences: mechanical AI, thinking AI, and feeling AI. The first level of AI intelligence, mechanical AI, involves the automatization of standard processes; thinking AI deals with processing data to provide insights that support decision-making and help gain competitive advantage; feeling AI involves a two-way interaction with humans, analysing consumers’ needs and emotions.
All previous attempts of systematizing AI and ML knowledge in marketing have proposed good theoretical frameworks for consumer-facing applications, concerning consumer experience and personalized communications. However, to the best of the authors’ knowledge, they seem to lack an in-depth study of the business-facing processes, concerning companies’ decision making processes and financials optimization. Furthermore, a complete evaluation effort from a strategic marketing perspective, with practical activation use cases, is missing.

3 Methodology

The main goal of this paper is to examine how ML and AI technologies are leveraged to improve business strategies, through the creation of a taxonomy of applications used to solve marketing-specific needs. We have first collected a large number of use cases, following a systematic search process. Given the broad range of possible applications that we could consider, we based our choice on a set of four specific selection criteria: we collected only (1) real-life use cases from existing companies, (2) with the availability of references on the case, (3) from published works in business or scholar literature, and (4) with some information about the ML implementations (such as the class of algorithms that have been adopted). We conducted a systematic, wide-ranging research of literature on Scopus and Google Scholar bibliometric databases. We looked for papers that referred to ‘Machine Learning’ and ‘Marketing’, or ‘Artificial Intelligence’ and ‘Marketing’ in their title or as keywords. In order to identify the key classification variables for each application, we have used the Structured Content Analysis approach (SCA), as done by Kohlegger et al. (2009). As described in Fig. 1, SCA is an iterative process that aims at grouping findings, i.e., as for relevant portions of text, into meaningful categories (Mayring, 2008). The collection of such categories provides a structured description of the subject under analysis as most of the relevant text will fall under those categories.

We decided to adopt this approach to identify the categories to be used in our taxonomy. For each use case that fulfilled the four selection criteria specified above, we collected information about the required data, technologies, and algorithms used, together with the business value generated for the company. We iteratively went through the full description of each application and, using our judgement, assigned each application to one or more of the existing categories that would most closely encompass its essential features. We chose to allocate each application to one or more categories as done by Cuccurullo et al. (2016) in order to account for the multifaceted nature of some use cases. The initial categories utilized during the preparation phase were based on our general understanding and previous studies. We started by categorising each use case into categories defined by previous researchers in similar studies or well-known frameworks, such as marketing 4Ps. At the end of every iteration, we critically reconsidered the category definitions and assessed whether they could be improved to better match the overall content encountered in the papers. We iteratively redefined the categories and codified each case into the most appropriate category, leveraging spreadsheet software to keep track and update the mapping between the categories and the use cases. The iterative coding process
stopped when the authors reached a consensus on the solidity of the mapping, obtaining meaningful categories of machine learning applications in marketing.

4 Results and discussion

4.1 Description of the taxonomy

During May 2021 we have collected 75 use cases of ML and AI in Marketing and removed 35 cases that failed to meet one or more of the four selection criteria described above. By applying the SCA methodology as described in Sect. 3, we obtained 11 activation recipes in a taxonomy organized on three levels. We linked each of the 40 different real-life implementations found in the literature to a recipe, which represents the most appropriate ML area of application, at the lowest level of the taxonomy. We have then grouped the 11 recipes into four categories, which correspond to the second level of the hierarchy, to give a clear framework of ML applications from a strategic marketing perspective. On the consumer-facing side we classified the recipes into (1) improve shopping fundamentals, and (2) improve consumption experience, while on the business-facing side, we classified them into (3) improve decision making, and (4) improve financial applications. Figure 2 shows a visual tree rendering of the resulting taxonomy where branches correspond to the split in conceptual classes while leaves correspond with the identified recipes. In this section, we are going to describe the essential features of each class of recipes (highlighted in the text in italic) and provide a selection of use cases as an illustration.
4.1.1 Improve shopping fundamentals

Improving shopping fundamentals deals with the opportunity of enriching the consumer experience at the time of purchase, irrespectively from its location (in-store or e-shelf). Our analysis suggested that AI can be used to increase consumer satisfaction through the personalization of the experience. Personalization refers to the creation of consumer-level tailored communications based on socio-demographic patterns and previous purchase behaviour. ML algorithms can be leveraged not only to predict consumers’ needs but also to define segments of look-alike consumers, allowing the company to address precise personalized offers (Campbell et al., 2020; Corrigan et al., 2014).

Segmentation is becoming more and more fine-grained, capturing a large number of precise micro-segments. This continuous refinement can ultimately lead to the point where each consumer becomes a specific segment and can be targeted with customized offers and advertisements based on his or her singular profile (Ma & Sun, 2020). This extremely personalized 1:1 communication is enabled by machine learning algorithms, such as propensity modelling, cluster analysis, and decision trees, as well as reinforcement learning and text-mining techniques.
(Huang & Rust, 2021). Harley-Davidson NY could be an illustrative example of this ML application; the company has implemented Albert AI, an AI-driven marketing platform, to target high potential consumers, and personalize the marketing campaign appropriately, leading to an increase in sales by the third month (Power, 2017). In addition to personalized offers and personalized 1:1 communication, several companies are also implementing personalized recommendations to boost sales and consumer engagement. Recommender systems analyse consumers’ purchasing history, as well as similar consumers’ behaviour, to predict and suggest other items that the consumers could be interested in (Boyd, 2010). Netflix uses an advanced recommendation system that predicts what users would enjoy watching and sends suggestions accordingly (India, 2019; Suryawanshi & Narnaware, 2020). Similarly, LinkedIn uses this technology to recommend “people you may know” to extend users’ network (Marr, 2016). The last recipe belonging to the ‘improving shopping fundamentals’ category is assortment optimization. This includes prediction and optimization of distribution, inventory, store displays, and store layouts (both brick-and-mortar and online), as well as voice and visual search enablers (Campbell et al., 2020). Robotics plays an important role in this area, especially in inventory management and stocking. AI-based automation together with AI-backed demand forecasting enables retailers to meet buyers’ needs at any time (Shankar, 2018). For example, Lowebot at Lowe’s Home Improvement stores can understand consumers’ requests, check if the item they are looking for is in stock and guide them to the precise shelf in the store where they can find it (Davenport et al., 2020; Harriet, 2016).

4.1.2 Improve consumption experience

This second class refers to the consumers’ experience while using products or services and to the behaviour that they will exhibit in response. It involves product improvement, experience improvement and digital consumer service. Internet of Things (IoT) technologies based on AI are providing great innovations in this area, especially for product development, product support, and consumer relationship management. By leveraging on to Internet-based devices, companies may collect actual real-time, in-depth data about the consumer’s usage of the product. Therefore, IoT enables a deeper consumer understanding, allowing companies to develop better products, and improve consumer value (Nguyen & Simkin, 2017). The home automation company June for instance developed a “do-it-all oven”, which encapsulates seven appliances in one. It may be able to identify and cook food thanks to machine learning and computer vision technologies, and recommend a cooking program accordingly (Tariq et al., 2020). In addition to product improvement, IoT devices can gather information on each individual consumer and provide personalized experiences by addressing their specific needs, resulting in higher consumer satisfaction and engagement. An illustrative use case of experience improvement is Walt Disney’s ‘MagicBand’, a wristband that tracks guests’ movements around the park and resorts in Orlando and collects information on the consumers’ behaviour. The band acts as a room key and pass for attractions, as well as an electronic wallet for payments, allowing guests to shop whatever they want with a simple touch of
the wrist. In addition to the data that Walt Disney tracks with the wristband, consumers can provide their preferences on the website before their arrival, to have a completely personalized experience in the park (Marr, 2016). The last recipe, digital consumer service, is about automation and improvement of consumer support. The most used technology to reach this goal is AI chatbots.

Through natural language processing chatbots can answer a number of different questions, and provide immediate and accurate support 24/7 to consumers. They are easy to implement, cost-efficient and they scale up easily (Huang & Rust, 2021). However, their impact on consumer satisfaction is not clear, some consumers still do not feel at ease in speaking to a chatbot and prefer a human being to support their requests. Nearly 50% of consumers in the U.K and 40% in the U.S. prefer a human over a chatbot (Elliott, 2018). Companies in a variety of industries have adopted this technology. For instance, the Japan Professional Football League has implemented the CHORDSHIP Digital Agent in their official app, an AI chatbot technology that enables quick and easy communication with the audience, as well as reliable and non-stop consumer service (Kurachi et al., 2018).

4.1.3 Improve decision making

As for the possibilities of improving decision making, our research shows that the main opportunities involve market understanding and consumer sensing. First, companies need to gather knowledge of the specific market they operate in, predict its evolution and future trends, and identify changes in competitors’ behaviour. AI can support traditional market research methods, through machine learning based analysis. Text-mining is a powerful tool for delivering insights from online reviews, opinions and behaviours, in the form of text, image, audio or video. More advanced analysis can be conducted with deep learning algorithms, such as predictive analytics, computational creativity, personalization algorithms, and natural language processing systems (Huang & Rust, 2021). Walmart’s Social Genome Project for example enables the monitoring of public social media conversations to get insights on people’s preferences and predict future trends (Marr, 2016). On the consumer sensing side, companies leverage similar technologies to go beyond traditional interview-based information and incorporate unstructured consumer data, in order to gain a deeper understanding of the consumer’s needs and wants. In addition, when consumers interact with AI (e.g., conversational bots), computer vision and deep learning techniques can detect their emotions from facial expressions, body gestures, voice, and eye movements (Campbell et al., 2020), providing companies with richer insights about consumers preferences.

The software company Autodesk for instance monitors and tracks every interaction of the consumers with their product, allowing them to have a better consumer understanding, and to provide updates or solve problems at any time (Marr, 2016).

4.1.4 Improve financial applications

Finally, we found that marketing use cases of ML can impact financial metrics by optimizing price and media strategies. In order to structure a good pricing strategy,
Managers need to determine how much they should charge for products and services, based on consumer price sensitivity and competitor pricing. ML algorithms can estimate consumers’ price elasticity and adapt prices, accordingly, e.g., by using *dynamic pricing*. AI and ML can assist companies in estimating what consumers want and how much they are willing to pay (Erevelles et al., 2016; Ke, 2018; Stavins, 2001). Being able to change prices dynamically, based on the market conditions and the consumer’s price sensitivity, allows firms to gain a great competitive advantage (Yang & Leung, 2018; Ye et al., 2018). One of the most known pricing strategies is Uber’s “surge price” (e.g., in Guda & Subramanian, 2019). The company constantly monitors traffic conditions and riding requests in real-time, and adjusts prices, accordingly, encouraging drivers to be available only when needed, and optimizing profits (Marr, 2016). Media optimization refers to the automation and improvement of digital marketing strategies. Social media is a critical component of any company’s marketing strategy; billions of posts and images are shared every day on social networks, and this represents a great opportunity for marketers. As explained in the previous section, firms use this data to improve their consumer understanding, but at the same time, social media represents an important communication channel to advertise their products, serving consumers the right promotion at the right moment. AI offers a variety of opportunities for *media optimization*, such as AI-driven A/B testing, reduction of in cart abandonment, contextual ad targeting, keyword bidding, and automation of content creation (Campbell et al., 2020). As an illustration of this use case, in 2018 LEGO engaged Watson Ads Omni for Black Friday to create AI-powered interactive ads (Sweeney, 2018). The AI system was trained with data about previous LEGO purchases and consumers’ interests and needs. This technology enabled the brand to have meaningful, 1:1 conversations with shoppers along their purchase journey, improving consumer engagement and boosting sales.

### 4.2 Description of the proposed taxonomy

In this subsection, we will provide a description of the main findings of the study. To summarize the content of each category of use cases, Fig. 3 shows four-word clouds, illustrating the top 30 words recurring in the description of each one of the conceptual classes presented in the taxonomy. We noticed that words such as ‘personalized’, ‘consumers’, and ‘offers’ are predominant in the first category, *improving shopping fundamentals*, highlighting the importance of customization in this area of the business. Regarding *improved consumption experience*, we see again ‘consumer’, together with ‘product’, ‘improvement’, ‘experience’, which relate to the focus on product improvement to increase consumer experience at the time of usage. Next, we can see the predominance of words like ‘insights’, ‘market’, and ‘understanding’ for *improving decision making*, which show the importance of having a good knowledge of the market and the consumers to propose and implement better strategic decisions. Finally, we have words such as ‘pricing’, ‘strategy’, ‘media’ for *improving financials*, which represents the focus on price and media optimization to improve the company’s P&L.
To deepen our analysis, for each recipe we gathered information regarding the required data for its implementation, the main algorithms used, the KPIs taken into account, the predominance of the recipe, and finally two or more practical use cases. The predominance is based on the relative presence of the recipe in the literature we have collected in our research (● = infrequent, ●●● = very frequent). Table 1 summarizes the recipes discussed in the previous section.

From our study and use cases collection, based on a systematic research process, we found some patterns in how ML and AI can support marketing strategies. First, we noticed that the number of ML business applications is higher on the consumer-facing side, indicating the high and rising importance of deeply personalized advertisements and recommendations. This is also highlighted by the fact that the most touched KPIs in our taxonomy concern consumer satisfaction and loyalty. This finding explains the recurrent presence of the terms ‘consumer’ and ‘consumer’ in all the four word clouds shown previously. Sector-wide, the most active companies in the usage of ML appear to be the ones operating in technology (e.g., as for Apple, Microsoft), online entertainment (e.g., as for Netflix, EA) and social media (e.g., as for Facebook, LinkedIn); in particular, we noticed that digital-native firms are overly represented, indicating that the larger availability of data is an enabling factor of ML utilization for marketing (Mariani & Fosso Wamba, 2020). Based on the marketing mix classification (Huang & Rust, 2021), most of the implementations fall into the ‘product’ category, which refers again to consumer experience improvement. On the other hand, the area of ‘place’ seems to embrace a smaller number of ML applications; this could be justified by the fact that this sphere depends upon Industry 4.0 technologies since autonomous vehicles and robotics (Aquilina & Michael A., 2020) play a key role in establishing alternative sales channels, corroborating the findings of Jarek and Mazurek (2019). Ultimately, we highlight that each one of the four conceptual categories of our hierarchy requires a specific class of algorithms: the recipes belonging to shopping fundamentals mainly use supervised learning and propensity modeling for personalization, the ones referring to consumption experience

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**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.
| Recipe                        | Predominant data requirements                          | Predominant algorithms                     | Value creation KPIs          | Marketing Mix (4Ps) | Predominance* | Use cases                       |
|-------------------------------|-------------------------------------------------------|---------------------------------------------|------------------------------|---------------------|---------------|---------------------------------|
| Personalized offers          | Consumer-level transactions, sociodemographic contextual data | Supervised learning, classification, propensity modeling | Promotional ROI, repurchase rate | Promotion             | ● ● ● ●       | Etsy, Harley Davidson, Target   |
| Personalized 1:1 communication | Consumer-level transactions, sociodemographic contextual data | Supervised learning, clustering, propensity modeling | Customer satisfaction, loyalty, conversion rate | Promotion             | ● ● ●       | Facebook, Sprint, Zynga, Sofinco |
| Personalized recommendations  | Consumer-level historical data                        | Supervised learning, classification, propensity modeling | Sales                         | Promotion             | ● ● ●       | Netflix, LinkedIn, Amazon, OYO   |
| Assortment optimization      | Store-level and demographic data                      | Optimization                               | Customer satisfaction, sales  | Place                | ●            | Lowe’s, SCARA                   |
| Product improvement          | Sensors’ data                                          | Miscellanea                                | Customer satisfaction, loyalty | Product              | ● ● ● ●       | Rolls-Royce, BBC, Apple, EA, June|
| Experience improvement       | Consumer-level transactions, sociodemographic contextual data | Supervised learning, clustering, propensity modeling | Customer satisfaction, loyalty | Product              | ● ● ●       | Walt Disney, Spotify, L’Occitane |
| Digital customer service     | FAQs and response history, service documentation       | Natural language processing, reinforcement learning | Customer satisfaction, costs reduction | Place                | ● ● ●       | eBay, J-League                   |
| Market understanding         | Customer-level data, market research data, social-media comments | Natural language processing, deep learning | Decision making, costs reduction | Product              | ●            | Walmart, Microsoft               |
| Recipe                  | Predominant data requirements                              | Predominant algorithms                                   | Value creation KPIs            | Marketing Mix (4Ps) | Predominance* | Use cases                                      |
|------------------------|-------------------------------------------------------------|-----------------------------------------------------------|-------------------------------|---------------------|--------------|------------------------------------------------|
| Consumer sensing       | Customer-level data, demographic data, social media comments | Natural language processing, sentiment analysis           | Customer retention, loyalty   | Product             | ●●●          | Apixio, Pendleton&Son, Royal Bank of Scotland, Dickey's Barbecue Pit, Caesars, Autodesk, Experian |
| Dynamic pricing        | Historical and real-time transactions, pricing data         | Optimization                                              | Profits                       | Price               | ●●●          | Airbnb, Uber, Major League Baseball, Hotel-Tonight, EasyJet |
| Media optimization     | Customer-level historical and real-time data, ads content data | Optimization                                              | Media ROI, ROAS in digital marketing | Promotion           | ●●          | Acxiom, Kanetix, Orange                        |

*Predominance is based on the relative presence in literature according to our research (● = infrequent, ●●● = very frequent)
involve IoT technologies and reinforcement learning (Mcinerney et al., 2018), while the area of decision making can be improved through natural language processing (NLP) that enables social media listening, and finally financial applications concern primarily optimization algorithms. This insight is useful to understand which level of AI and ML technologies can be leveraged to improve the different areas of the business. Some ready-made AI components, such as NLP, can be accessed free of charge and easily implemented. Many of the applications that we have presented can be deployed through open access libraries like TensorFlow, through open-source data analytics platforms or languages such as Python or R (Wirth, 2018).

5 Conclusions

In this paper, we analysed the business and scholarly literature dealing with the marketing application of ML to build a structured taxonomy of 11 typical application scenarios. We have found that part of the use cases will directly face consumers and improve their experience at the time of both shopping and consuming the product. Other use cases will be oriented toward the business and its operating model, as ML is proven to effectively improve decision making and impact financial metrics.

Our findings may be useful for marketers and managers in the attempt to understand the multifaceted nature of ML in marketing from both consumers’ and businesses’ perspectives. More specifically, the structured systematic research process, reveals some patterns in how ML and AI can support marketing strategies. From a consumers’ perspective, marketing efforts should be directed both to drive personalized actions required by consumers-related peculiarities and to enrich their overall customer journey. From a business perspective, machine learning can be exploited for consumer sensing and market understanding (and, thus, to ultimately improve decision-making processes) and also for supporting dynamic pricing and media optimization strategies, ultimately impacting financial results. These findings corroborate with the emerging paradigm of Marketing 5.0 (Kotler et al., 2021) in an attempt to fully exploit the application of technologies that imitate humans to create, communicate, offer and increase value along the customer journey, requiring both efforts in the redesign of business-oriented and consumer-oriented activities. Machine learning may importantly contribute to the so-called “next-tech” in marketing (that is the set of advanced technologies able to emulate the ability of human marketers) aiming toward the creation of a new, fluid, and engaging experience (Kotler et al., 2021). Marketers and managers should fully understand how they are required to build a balanced symbiosis between human and computer intelligence, making marketing strategies more accurate and capable of real-time adjustment.

Moreover, by considering previous studies (e.g., as for Ngai & Wu), we advance knowledge in the domain concerning the opportunities of machine learning in marketing by providing a conceptualization of current issues and by offering a theoretical basis to examine its emerging trends, also by including managerial and patricidal use cases. In addition, this contribution is the first to present a structured taxonomy deriving from the combination of ML and AI technologies. Furthermore, the present taxonomy is built on both research and practical shreds of evidence, thus able to
represents a theoretical basis for empirical studies on the phenomenon of machine learning application in marketing, aimed at identifying new variables and patterns that are reliable but still unexplored.

We believe that our study offers three significant contributions to the practice of ML usage in marketing and its conceptual development as a research area. First, we offer a definition and a structured description of ML applications in marketing and provide a theoretical justification of business strategies enabled by ML from a strategic marketing perspective. Second, the taxonomy presented in this work can be used by business managers to assess the completeness of their ML programs by checking the extent of marketing applications that are currently enabled. We believe that this exercise can help firms identify which routes are still unexplored, resulting in further opportunities for leveraging data and ML algorithms at best. Lastly, we provide scholars with a framework that systematizes the broad set of business applications of ML and offer a structured view of the current related literature, enabling the identification of gaps to be filled through further research.

Finally, we recognize that this work displays some limitations to be solved in future studies. Firstly, while SCA is suitable for qualitative exploration and categorization of documents, we envision the possibility to achieve deeper and less subjective findings using quantitative methodologies such as NLP and, particularly, topic modeling. Secondly, our findings could be further expanded by encompassing a larger number of use cases, which might be obtained through a wide surveying activity or a broader review of literature based on more sources. Lastly, this study did not attempt to numerically quantify the impact of leveraging ML on marketing performance indicators, which would greatly help firms prioritize their investment choices.

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**Declarations**

**Conflict of interest** The authors declare that they have no conflict of interest.

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