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Algorithmic bias in machine learning-based marketing models

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ABSTRACT

This article introduces algorithmic bias in machine learning (ML) based marketing models. Although the dramatic growth of algorithmic decision making continues to gain momentum in marketing, research in this stream is still inadequate despite the devastating, asymmetric and oppressive impacts of algorithmic bias on various customer groups. To fill this void, this study presents a framework identifying the sources of algorithmic bias in marketing, drawing on the microfoundations of dynamic capability. Using a systematic literature review and in-depth interviews of ML professionals, the findings of the study show three primary dimensions (i.e., design bias, contextual bias and application bias) and ten corresponding subdimensions (model, data, method, cultural, social, personal, product, price, place and promotion). Synthesizing diverse perspectives using both theories and practices, we propose a framework to build a dynamic algorithm management capability to tackle algorithmic bias in ML-based marketing decision making.

1. Introduction

The trajectory of machine learning (ML) is on course to achieve a growth target of $20.83 billion in 2024 from $1.58 billion in 2017, with a compound annual growth rate of 44.06% (Columbus, 2020). Today marketing managers increasingly rely on ML-based models to create, communicate and deliver value and also to manage relationships with customers (Davenport et al., 2020; Dwivedi et al., 2021a; Krishen et al., 2021; Kumar et al., 2020; Rai, 2020; Rust, 2020). ML has enabled marketers to formulate strategic marketing decisions leveraging big data that collates information on customer behavioural traits and characteristics, such as customer spending patterns, eye-ball movements, photos and comments shared on social media, customer product reviews, entertainment content, and food and exercise habits (Davenport et al., 2020; Hagen et al., 2020). ML-based predictive analytics and recommendation systems have been accelerating the entire marketing process, allowing marketers the ability to identify niche customers and reach them through targeted multi-channel campaigns (Ma and Sun, 2020; Vermeer et al., 2019). Thus, ML helps firms develop a sustainable competitive advantage by avoiding brand redundancies, saving on unnecessary advertisements, and monitoring post-purchase behaviour by analyzing real-time data (Huang and Rust, 2018). However, marketing scholars have cautioned that many companies are attempting to increase sales revenues by manipulating ML systems through the development of biased algorithms using non-representative data to create an unfair advantage through marketing. This can be considered as a discriminatory practice whereby a certain group of customers are restricted from equitable access to marketing offerings (e.g., Davenport et al., 2020; Hagen et al., 2020; Ma and Sun, 2020; Vermeer et al., 2019).

Algorithmic bias in ML-based marketing models is rooted in unrepresentative datasets, inadequate models, weak algorithm designs or historical human biases that result in unfair outcomes for customers in terms of value creation (e.g., service offerings), value delivery (e.g., channels) or value management (e.g., pricing and promotion) (Balducci and Marinova, 2018; Caliskan et al., 2017; Hartmann et al., 2021; LeCun et al., 2015). Examples include Optum's racial bias in a medical algorithm in serving patients (Blier, 2019), Facebook's gender bias in ad targeting (Lambrecht and Tucker, 2018), Orbitz's customized travel

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service offerings only to Mac users (Israeli and Ascarza, 2020), and Uber's or Lyft's expensive pricing for destinations with large African-American populations (Pandey and Caliskan, 2020). Algorithmic bias and more broadly ethical issues related to artificial intelligence have also been discussed in relation to other areas of business and management (Ashok et al., 2022; Alter, 2021; Coombs et al., 2021; Stahl, 2022).

In addition to structured data, bias can be perpetuated in ML-based marketing models in the processes of analyzing a large amount of unstructured data. In the real world, unstructured data (UD) accounts for about 80% of all business data, including emails, text files, websites, images, video, voice, facial and gestural cues, customer reviews, live chats, and IM (Michigan State University, 2019). According to Balducci and Marinova (2018, p. 558), UD is "a single data unit in which the information offers a relatively concurrent representation of its multi-faceted nature without predefined organization or numeric value". Although structured data has a utility in defining or identifying particular behavior, UD provides a comprehensive description, and an explanation of customers' underlying perceptions towards a particular product or service. This UD data trove allows marketers to precisely predict future product-demand and to identify crucial innovations in product design and delivery in order to remain competitive in the market (Batra and Keller, 2016). But despite the invaluable potential for UD to better recognize customers' needs and preferences in real-time, indiscriminate use of UD in ML-based marketing models can generate biased outcomes. Unlike structured data, where data is gathered, categorized and quantified using standardized approaches, the processing of UD and its analysis requires data analysts to quantify a large amount of qualitative data to yield generalizable insights (Balducci and Marinova, 2018). Scholars argue that while processing a large amount of unstructured qualitative data for ML models, anchoring bias can permeate into the training dataset as people can assign subjective weights to the study variables that conform to their personal beliefs, values, and prejudices (Baer and Kamalnath, 2017). Caliskan et al. (2017) found that language itself can maintain historical biases, and many of these can be problematic towards a particular race or gender. For example, due to the abundance of texts embedded with historic language biases, Natural Language Processing (NPL) often tends to suggest 'Man is a computer programmer' while it is less likely that 'Woman is a computer programmer.'

Despite the unequal, unjust and unfair effects of algorithm bias in ML-based marketing models, research in this stream is largely anecdotal, fragmented and has yet to be developed into an integrated conceptualization. As such, drawing on the theories of microfoundations of dynamic capability (DC) (Felin et al., 2012; Barney and Felin, 2013; Teece, 2007) and dynamic managerial capability (Helfat and Peteraf, 2003; Helfat and Martin, 2015; Martin, 2011), this study identifies the sources of algorithmic bias in ML-based marketing models and addresses the following research question: *What are the dimensions of algorithmic bias management capability in machine learning-based marketing models?*

To answer the research question, the study conducts a systematic literature review and in-depth interviews with ML professionals in marketing to develop a conceptual framework of algorithmic bias management capability, identifying various dimensions. The study makes several contributions. First, using the microfoundations of dynamic capability (DC), the study identifies three primary dimensions (i.e., design bias, contextual bias and application bias) and ten sub-dimensions of algorithmic bias management capability in ML-based marketing models. Second, the findings show that microfoundations of bias are interconnected, and an understanding of these sources contributes to developing a dynamic managerial capability to address bias in models. Finally, from a practical perspective, our findings address concerns regarding the unfair effects of algorithmic bias on certain groups of customers based on race, gender, sexual orientation, class, age, religion, ethnicity etc. The structure of the paper is as follows. Section 2 focuses on the literature review on ML-based marketing models and the theories on the microfoundations of DC and dynamic managerial capability (DMC). Section 3 explores the methods of the literature reviewed, qualitative insights and corresponding triangulation. Section 4 discusses the conceptual model on algorithmic bias management capability and pertinent propositions. Section 5 discusses research implications with future research directions.

2. Literature review

2.1. Machine learning

Artificial intelligence is a distinctive capability of computer applications that can exhibit characteristics of human intelligence (Huang and Rust, 2018; Syam and Sharma, 2018) through interpreting external data and exhibiting flexible adaptation through learning from data (Kaplan and Haenlein, 2019). ML is a key technology in developing AI-based applications (Davenport 2018) and is considered the most promising method towards the fulfilment of human-level AI (Syam and Sharma, 2018; Duan, Edwards and Dwivedi, 2019). Arthur Lee Samuel (1995) first coined the term ML as computer applications that do not require explicit programming to perform the assigned task. ML methods are built on mathematical models and robust algorithms such as Bayesian networks, reinforced learning or support vector machines that use supervised learning models with associated learning algorithms that are applied to data and analytics applications for the purposes of classification (Ahani et al., 2019; Dwivedi et al., 2021b; Motamarri, Akter and Yanamandram, 2020). It follows, therefore, that the practice of ML requires a high volume of data and high processing power to perform tasks (Syam and Sharma, 2018), and *better* data than *more* data is preferred. ML is the basis of numerous critical AI-based applications that include web search, speech recognition, recommendation engines, etc., that are of great significance in today's business environment (Ng, 2018).

Supervised and unsupervised learning are two broad categories of ML methods (Syam and Sharma, 2018). Supervised learning aims to construct a statistical model to estimate or predict an output following one or multiple inputs through applying algorithms such as linear regression, logistic regression and neural networks (Syam and Sharma, 2018; Gareth et al., 2013; Ng, 2018). In supervised learning, the utilized data sets are considered to possess the possible outputs already, given that a set of explanatory variables and the right value for the dependant variable is provided to the model, whereas in unsupervised machine learning, unlabelled data that is untagged is utilized to learn patterns in order to determine the underlying structure of the data with no well-specified output variable (Syam and Sharma, 2018). Table 1 shows various ML algorithms and their applications in marketing. ML techniques can be used to explore and leverage unique characteristics from big data to achieve highly accurate segmentation for marketing contexts (Ahani et al., 2019; Ernst and Dolnicar, 2018). ML has a far superior predictive capacity than traditional statistical techniques, given that it has no prior assumptions about the data, and ML models can accommodate highly nonlinear and complex associations between inputs and outcome variables (Syam and Sharma, 2018). However, ML models often lack the ease of interpretability that can be observed in traditional models (Friedman et al., 2017).

2.2. Foundations of algorithmic bias in machine learning

We define an algorithm as a "finite, abstract, effective, compound control structure, imperatively given, accomplishing a given purpose under given provisions" (Hill, 2016, p. 47). In ML-based marketing models, algorithmic bias reflects a "deviation from standard" (Danks and London, 2017, p. 4692) that can originate from algorithm design, socio-cultural contexts or marketing applications (Israeli and Ascazra, 2020). Algorithmic bias should not be confused with "bias term" in a machine learning model, such as $y' = b + w_1x_1 + w_2x_2 + \ldots w_nx_n$ in which bias-term is referred to as b or w_0. This study rather focuses on the bias

Table 1
Algorithms used in ML-based Marketing Models.

Unsupervised Learning (Clustering)	Unsupervised Learning (Dimension reduction)
• Hierarchical • K-means • Gaussian Mixture Models (GMM) • Density-based spatial clustering of applications with noise (DBSCAN)	• Principal Component Analysis (PCA) • Singular Value Decomposition (SVD) • Linear Discriminant Analysis (LDA)
Marketing applications: recommendation systems, risk management, segmentation of customers, identification of product attributes, fake images/ads analysis, performance monitoring, sales functions, associations.	
Supervised Learning(Classification)	**Supervised Learning (Regression)**
• Neural network • Decision Tree • Logistic Regression • Naïve Bayes • Random Forrest • Gradient Boosting Tree • Support Vector Machines • Discriminant Analysis	• Linear Regression • Neural network • Gradient Boosting Tree • Random Forrest • Ensemble methods
Marketing applications: Sales forecasting, pricing, financial performance comparison, language detection, spam filtering, search and classification, computer vision.	

that reflects prejudice, stereotyping, or favouritism towards a specific customer or a group of customers over others due to the poor quality of training data, improper model deployments, analytics methods, deep-rooted socio-cultural factors or marketing variables (Akter et al., 2021; Walsh et al., 2020). A biased algorithm design often fails to identify causality, discovers meaningless correlations/patterns and provides inconclusive evidence (Tsamados et al., 2021). Since every ML model is trained and assessed on data, the model is very unlikely to predict a robust outcome if the dataset is misrepresentative, the model is inadequate in terms of attributes, traits and values, or the method is flawed to design, develop and deploy ML applications in marketing (Walsh et al., 2020). An inadequate model might reflect unwanted biases if the deployment context does not match training data. As such, the overall methods might result in correlation fallacy or over-generalization of findings. In a similar spirit, Taddeo and Floridi (2016, p. 4) state, "While they are distinct lines of research, the ethics of data, algorithms and practices are obviously intertwined … [Digital] ethics must address the whole conceptual space and hence all three axes of research together, even if with different priorities and focus". Hence, the microfoundations of bias may be rooted in algorithmic design, socio-cultural contexts or marketing applications.

2.3. Bias in ML-based marketing models

Algorithmic bias has become a key concern due to the adoption of ML-based applications to aid decision making and fulfil various marketing activities. For example, Lambrecht and Tucker (2018) reveal that because of the embedded bias of Facebook's advertisement placement algorithm, career advertisements of science, technology, engineering, and math (STEM) on Facebook were shown more frequently to males over females despite originally aiming to be gender-neutral in targeting prospective job candidates. Israeli and Ascazra (2020) further clarify that this kind of result may also be due to the fact that it costs more to reach the female audience than their male counterpart, and companies may purposefully target a specific customer segment based on criteria such as gender, age etc. Similarly, there is empirical evidence showing a discriminatory preference of online advertisement placement algorithms in promoting products to specific customer groups or market segments (Israeli and Ascazra, 2020; Dalenberg, 2018; Vigdor, 2019). Algorithmic bias can result in discriminatory pricing practices, such as minorities and women receiving stricter credit conditions for approval of bank loans or credit cards and young female drivers paying a higher insurance premium due to the perception of greater risk (Israeli and Ascazra, 2020). With regard to the marketing channel, Ingold and Soper (2016) point to the discriminatory pricing of Amazon's same-day delivery service based on demographic features of given locations. Furthermore, recommendation engines and curation engines that generate content based on an individual's characteristics and personal preferences maximize the discovery and engagement of content that reflects past behaviour (Israeli and Ascazra, 2020). Therefore, algorithmic bias has been recognized as critical for business managers in the present data-driven business landscape. Table 2 provides an overview of the seminal studies on algorithmic bias in ML-based marketing models.

3. Theories

3.1. Microfoundation perspective

Dynamic capabilities have become a valuable theoretical lens in management research (Schoemaker, Heaton & Teece, 2018; Di Stefano, Peteraf & Verona, 2014; Teece, Pisano & Shuen, 1997). A microfoundation view of routines and capabilities has earned the attention of scholars in explicating the heterogeneity of organizational performance (Felin et al., 2012; Teece, 2007). Scholars have pointed to micro-level components that underlie routines and capabilities such as distinctive skills, procedures, decision rules, design of decision-making activities, organizational disciplines and structures, knowledge development and sharing, information processing, coordination, and integration activities that generate the context for interactions with the external environment as the microfoundation of dynamic capabilities. Individual managers are perceived as a critical microfoundation of capabilities and routines of an organization (Felin et al., 2012; Teece, 2007); therefore, individual managerial roles in building and applying dynamic capabilities are considered as theoretical lens for this research. Table 3 presents a summary of the seminal scholarly studies on dynamic managerial capabilities that will be reviewed.

3.2. Dynamic managerial capabilities

Dynamic capability view considers that managerial capabilities can effectively integrate new technologies within the business for successful innovation in a changing business context (Augier and Teece, 2009; Teece, 2009; 2007; Sirmon and Hitt, 2009; Kor and Mesko, 2013; Adner and Helfat, 2003, 2009). Scholars have coined the term dynamic managerial capabilities to emphasize the distinctive managerial role that is critical to successfully developing and executing dynamic capabilities (Helfat and Peteraf, 2003). The notion of dynamic managerial capability suggests that managerial human capital, cognitive ability and social capital play pivotal roles in building higher-order organizational dynamic capabilities such as sensing, seizing and reconfiguring (Helfat and Peteraf, 2003). Individual managers' human capital provides the managerial capacity to integrate managers' knowledge, skill and innovation capability, leveraging their educational background and experience (Castanias and Helfat, 2001). Adler and Kwon (2002) suggest that managerial social capital derived through an organizational and personal social network can act as a bridge to connect the organization with informational channels, critical resources and opportunities to create a firm-specific advantage (Adler and Kwon, 2002). Finally, cognitive managerial capacity is the managerial ability to perform tasks that require a considerable degree of cognitive engagement, such as attention, perception-based reasoning or problem-solving (Helfat and Peteraf, 2015).

In the context of ML-based marketing models, managers need to be vigilant to carefully mitigate the risk of potential bias that may originate and adversely affect key stakeholders, including customers, while utilizing ML applications to fulfil marketing activities (Israeli and Ascazra, 2020; Rozado, 2020). Rozado (2020), therefore, emphasizes accurately detecting, scrutinizing and addressing bias to mitigate risk through an

Table 2
Seminal studies on algorithmic bias in ML-based marketing models.

Study type	Study	Definition of ML	Main findings on algorithmic bias in ML in the marketing process
Conceptual	Davenport et al. (2020)	ML method is considered a key technology for AI application development.	Confirm the advantage of AI applications based on machine learning in marketing and business applications. The authors emphasise on the training data set and the opacity of the underlying algorithms used in ML models as important sources of algorithmic bias.
Conceptual	Rai (2020)	Articulates that the deep learning (DL) method within ML is inscrutable and suggests that ML algorithms provide greater structure and supervised learning through a considerably less of underlying elements such as features, rules or paths capable to produce transparency and traceability of decision making.	Highlights the complexity associated with scrutinizing the nature of many ML algorithms, such as understanding deep learning results based on neural networks algorithms, trust deficit on AI-based systems and scope of bias in algorithm to negatively impact vulnerable customer segments and the community at large.
Conceptual	Rust (2020)	Consider ML as an important tool for marketing activities and suggest integrating knowledge from different disciplines to enhance the quality of the underlying algorithms.	The author confirms the role of artificial intelligence in rapidly advancing marketing activities based on traditional approaches as critical. The author warns that marketing professionals need to carefully tackle the serious socio-economic concerns of inclusion and diversity in addressing bias resulting from AI applications such as ML practices.
Review	Chouldechova and Roth (2020)	Note that ML methods are designed to fit the data and are widely used for batch classification and generating outcomes useful for decision making.	The research reveals concerning findings of the scope of introducing discriminatory and unfair practices by the data-driven ML models as these methods can embed human bias and also can introduce new ones within the applications.
Technical report	Sun, Nasraoui, Shafto (2020)	Define ML algorithms as computer programs that can be trained to predict future recommendations. Suggest that due to interaction with the end-user, the machine learning model can produce three types of iterated algorithmic bias such as personalization filters, active learning, and random.	This study demonstrates in detail the trade-off between variances and bias within ML applications. The authors recommend adopting a systematic procedure to address the scope of algorithmic bias in AI driven-applications.
Review	Paulus and Kent (2019)	Define ML as a type of reference class forecasting that measures the probability of outcomes specified by a user through analysing the outcome ranges within a group of users carrying similar characteristics.	The authors suggest that ML methods may contain data or sampling issues that can lead to biased predictions resulting in harmful or unfair consequences across different customer groups.
Empirical	Rozado (2020)	Consider the generally accepted conception of ML definition.	The authors suggest that widely adopted ML applications such as recidivism prediction or language modelling are subject to societal biases and prejudices.
Teaching note	Israeli and Ascazra (2020)	Consider the generally accepted conception of ML definition.	The authors note that algorithmic bias in marketing practices can produce results that may disadvantage or privilege a specific group of users or customers based on demographic features such as religion, age, sexual orientation or race.

adversarial collaboration within intellectually heterogeneous working groups. Israeli and Ascazra (2020) provide an example of an ML application that was deployed in a credit card company and failed to detect images of women of a specific background as a direct result of having less diversity in the team of developers.

Developing an ML application requires a range of skills, including data collection, integration and building algorithms for training purposes, and finally supervising the training of the algorithm. Therefore, it is important to mobilize people from diverse backgrounds for building necessary organizational expertise on ML and AI in general (Ransbotham et al., 2017). Developing ML applications necessitates superior cognitive engagement, as the applications are heavily data-intensive to effectively train for prediction (Paulus and Kent, 2020). Further, ML algorithms require reliable labels from experts (Sun et al., 2020), although some ML algorithms deliberately do not use labels or tags. Moreover, Ng (2018) notes that a significant portion of the algorithm's knowledge will come from human insight in the case of a very small training data set. Thus, we suggest that humans should not be completely out of the loop. Due to their highly iterative and complex nature, ML processes require superior problem-solving capabilities to generate innovative approaches to tackle novel problems (Ng, 2018). It is important to develop a dynamic managerial capability to anticipate, detect and reduce potential biases to ensure fairness through audits (Israeli and Ascazra, 2020), precisely describe the algorithmic behaviour through empirically supported diverse viewpoints (Rozado, 2020), and

Table 3
Seminal studies on dynamic managerial capabilities.

Study type	Study	Main findings
Theoretical	Helfat & Peteraf (2003)	Following the dynamic resource-based view (RBV), this article introduces the term dynamic managerial capability. The authors recognize individual managers' cognitive ability, social capital and human capital as critical microfoundations of dynamic managerial capabilities.
Theoretical	Augier & Teece (2009)	Based on behavioral and evolutionary theories, the authors emphasize critical managerial roles in the economic system for developing dynamic capabilities.
Review	Helfat & Martin (2015)	Through examining the empirical evidence related to dynamic managerial capabilities, the authors argue that microfoundations of dynamic managerial capabilities such as cognitive ability, social capital and human capital can influence strategic change and organizational performance.
Empirical	Peteraf & Reed (2007)	The paper confirms that dynamic managerial capabilities are necessary for adaptive organizational change to obtain fit under changing environmental conditions.
Theoretical	Ambrosini, & Altintas (2019)	The authors emphasise that managers need to transform the organizational resource base to maintain and develop competitive advantage and superior performance through utilizing the antecedents of dynamic managerial capabilities such as cognitive ability, social capital and human capital.
Theoretical	Helfat & Peteraf (2015)	The study introduces the term managerial cognitive ability to highlight the capacities required to perform mental activities to sense and seize business opportunities following changes in the external environment and successfully modify organizational resources and capabilities to exploit the identified opportunities.
Empirical	Sirmon & Hitt (2009)	The authors argue that dynamic managerial capabilities pay attention to managing resources through asset orchestration to attain superior firm performance. Further, managers make decisions by effectively matching resource investments, and deployments play a critical role in a firm's success.
Theoretical	Martin, & Bachrach (2018)	The authors conceptualize dynamic managerial capabilities as managerial capabilities to create, extend, and modify a firm's value creation mechanism and suggest that dynamic managerial capability is a useful perspective to explain the relationship between strategic change, and organizational performance and the quality of managerial decisions.
Empirical	Eggers, & Kaplan (2009)	The authors recognize managerial cognition as a dynamic managerial capability that can positively impact organizational adaptation within established firms. The findings reveal that managerial attention on emerging technology is related with the rapid entry and growth of the firm.
Empirical	Widianto et al. (2021)	The authors confirm the significant role of mid-level managers dynamic managerial capabilities for organizational change and superior performance outcomes.

acknowledge the limitations of machine learning.

4. Method

This study explores the sources of algorithmic bias through a systematic review of the extant literature followed by in-depth interviews. Following are established guidelines for the systematic literature review and thematic analysis (Durach et al., 2017; Tranfield et al., 2003). In this paper, we identified various dimensions of bias management capabilities in ML-based marketing models. The research results have been triangulated in the findings of the review of extant literature, and 25 in-depth interviews were also conducted (Carter et al., 2014; Akter et al., 2020). To complement the systematic literature review, qualitative interviews were conducted to capture the sources of various algorithmic biases at the individual, organizational and societal levels. Specifically, this study incorporated in-depth qualitative interviews to investigate the microfoundations of the algorithmic bias management capability within the context of ML applications in marketing practices.

4.1. Literature review and thematic analysis

To conduct a literature review on the algorithmic bias in ML-based marketing activities, the following major data sources were utilized: ScienceDirect, EBSCOhost Business Source Complete and Emerald Insight. With regard to journals, we focused on the Chartered Association of Business Schools (ABS)/Academic Journal Guide (AJG) ranking tier 3/4/4* and the Australian Business Deans Council (ABDC) ranking tier A/A* benchmark following the review protocol of Akter et al. (2021). Different keyword search strings were employed in the data collection process of relevant extant literature that incorporated empirical enquiry (Dada, 2018; Vrontis and Christofi, 2019).

The keyword search "algorithmic bias in marketing" returned three records in both Scopus and Web of Science. These findings probably suggest sparse attention to the sources of algorithmic bias on ML application-based marketing activities in the extant literature. The search strings used included algorithmic bias, bias in AI applications, algorithmic bias in machine learning, algorithmic bias in analytics, algorithmic bias in AI, ethical issues in machine learning, ethical concerns of machine learning, fairness in machine learning and the dark side of AI. The initial search result yielded 250 articles. We excluded duplicate articles, book parts, and articles that do not reflect study context adequately in terms of the title of the article, keywords, abstract and the body of the main article. This exclusion process resulted in a total of 45 articles. Through further refinement based on quality appraisal and full-text review, the initial list was reduced to 33 articles. Finally, a total of 25 articles were selected due to their rigor and relevance to answering our research questions for the purposes of thematic analysis. Reviewing these articles enabled the visualization of the various themes associated with algorithmic bias in marketing.

Using thematic analysis by drawing on the process of systematic literature reviews defined by Akter (2020), Braun and Clarke (2006) and Ezzy (2002), three primary themes and ten secondary themes were identified, categorized as follows: *design bias (model, data and method), contextual bias (cultural, social and personal) and application bias (product, price, place and promotion)*. The themes were cross-checked and validated through applying Krippendorff's alpha (or, Kalpha), a reliability measure adopted in the content analysis study. First, Kalpha was calculated by analyzing each of the 25 articles under ten categories, then interrater reliability was calculated on the identified themes following the procedure recommended by scholars (De Swert, 2012; Hayes, 2012; Hayes and Krippendorff 2007). Finally, the Kalpha value of 0.88 on the analysis findings was determined, which is considerably higher than the threshold level (>0.80), indicating evidence of sufficient reliability.

4.2. Interviews and thematic analysis

The study undertook in-depth interviews of professionals involved in ML-based marketing model development and execution to obtain rich insights. We have selected 25 respondents aged between 18 and 65 for 45–60 min interviews following both snowball and convenient sampling techniques (Saunders et al., 2018). The respondents were screened based on at least three years of experience working as an ML professional in the stream of marketing. As illustrated in Appendix 1, the sample represented diversity in demographic criteria such as age, profession, education, income, and location. The sample size was sufficient to ensure variety and to achieve thematic saturation (Guest et al., 2006). The interviews were recorded and transcribed, and a thematic analysis was also applied to this distinct dataset to reveal overarching themes. The underlying expression of the themes is reflected in the transcribed interviews. The thematic analysis identified the meaning or threads in the interview data that repeatedly emerged within microfoundations of algorithmic bias (Braun and Clarke, 2006). Through exploring repeated patterns, the thematic analysis revealed ten sources of algorithmic bias (Braun and Clarke, 2006; Fereday and Muir-Cochrane, 2006). Fig. 1 illustrates the final ten themes identified from qualitative interviews that are aligned with the result of the literature review: design bias management capability (data, model and method), contextual bias management capability (cultural, social and personal) and application bias management capability (product, price, place and promotion).

4.3. Triangulation

To confirm the validity of the findings, triangulation is a well-established technique in qualitative research. Since qualitative approaches do not offer the statistical reliability or validity that survey research does (Golafshani, 2003), the practice of triangulation in qualitative research may be evident in different variations, such as theory, investigator, measures, data sources or methods (Carter et al., 2014). This research validates the findings identified from the literature review based on in-depth interviews. Therefore, this investigation validates two distinct sources of evidence: findings from the literature review and findings from in-depth interviews. This also confirms the validation of insights from two separate sources: existing literature is considered as a secondary source of evidence, and perspectives expressed by individual practitioners and managers are considered as a primary source of evidence. This study complements the findings of the systematic literature review based on 25 semi-structured interviews through methodological triangulation. Through this triangulation, we have utilized semi-structured interviews in integrating various views and perspectives and also validating the dimensions identified from the thematic analysis of the literature (Fusch et al., 2018).

5. Conceptual model

Algorithmic bias management capability in ML-based marketing models is an emerging area, and the findings of our study identify 3 primary dimensions and 10 subdimensions (see Fig. 1). The study identifies the subdimensions as the microfoundations of three major sources of algorithm bias, which contribute to overall algorithm bias management capability in marketing models. We argue that understanding these microfoundations will help managers achieve dynamic algorithm management capability to tackle bias in marketing models.

5.1. Design bias

Design of ML applications may cause algorithmic bias that may originate due to improper datasets, inadequate ML model specification and inappropriate methodological choices across the analytics lifecycle (Davenport et al., 2020; Walsh et al., 2020; Paulus and Kent, 2020; Israeli and Ascazra, 2020; Martínez-Villaseñor et al., 2019; Sun et al., 2020; Walsh et al., 2020; Ng, 2018). The following section discusses how these three microfoundations of design bias: training data bias, model bias and method bias, cause negative outcomes.

5.1.1. Training data bias

Training data sets are a critical source of algorithmic bias in ML applications (Israeli and Ascazra, 2020; Davenport et al., 2020; Sun et al., 2019; Martínez-Villaseñor et al., 2019). The inability of training data to adequately represent a random sample from the target population may result in sample selection bias (Cawley and Talbot, 2010). Similarly, out-group homogeneity bias can occur when developers attempt to identify members from faulty sample units to target the intended population group based on personality, attributes, traits,

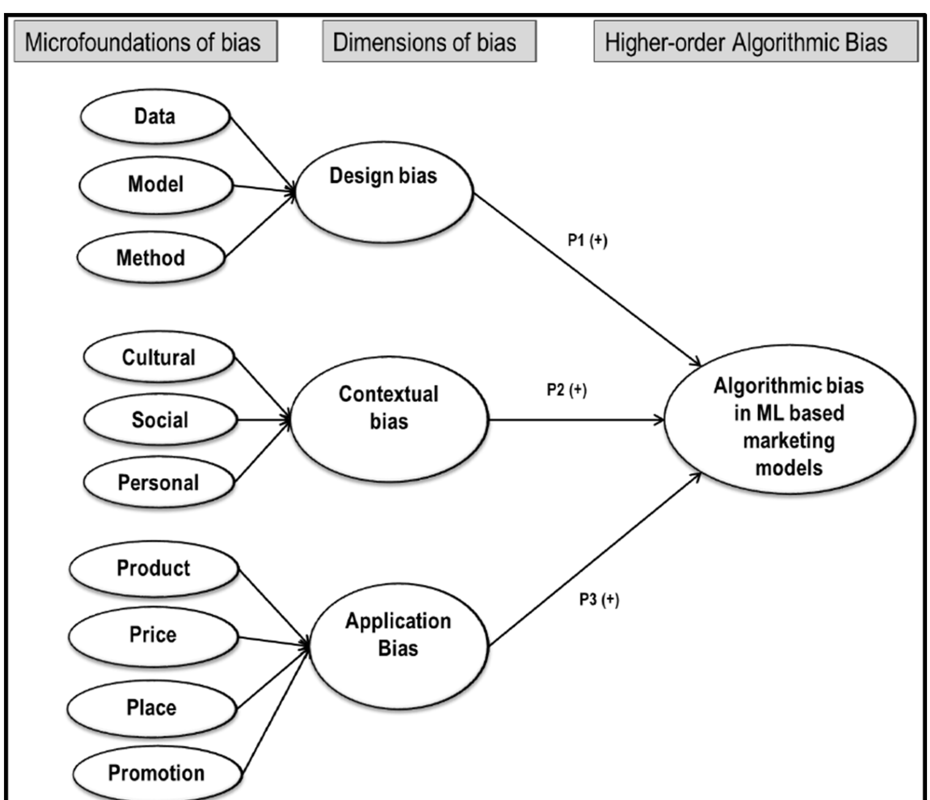

Fig. 1. Algorithmic bias management capability in ML-based marketing models.

attitudes and values (Ramkumar et al., 2019). For example, female applicants are unfairly rejected by Apple's ML-based credit card application due to the higher representation of successful male applicants in the training data set. Further, Amazon's ML-based recruitment application contained primarily successful male applicants' data that caused unfair outcomes to the female candidate (Martínez-Villaseñor et al., 2019; Davenport et al., 2020). Finally, individual belief induced confirmation bias may perpetuate into training data in cases where relevance is determined based on observable evidence (Sun et al., 2019).

The feature selection technique may prove to be useful to reducing bias in cases of small training data set availability (Sun, Nasraoui, Shafto, 2020; Ng, 2018). Further, the popularity of certain items within a training data can cause biased outcomes (Joachims et al., 2017; Collins et al., 2018; Sun et al., 2019). A training data set requires accurate labelling. If the ML model is inadequately adapted in a subgroup or if a proxy is considered as the label or outcome, it may result in label bias (Lesko and Atkinson, 2001; Paulus and Kent, 2020). As the outcome may contain separate meanings across different subgroups, label bias is very challenging to diagnose through analysis of the data. Therefore the ML model performance needs to be examined separately within different subgroups and requires the inclusion of certain interactions across group status and remaining features (Paulus and Kent, 2020). Iteration bias can be traced on a content-based filter or personalization filter, causing a negative effect on relevance estimation affecting item discovery (Sun et al., 2019; Shafto et al., 2012). Furthermore, the continuous feedback loop between humans and the recommendation system may cause polarization on rating data, resulting in assimilation bias (Williams et al., 2019).

The findings of the study support the significance of training data bias through the following comments:

"While we collect and prepare data, it is of utmost importance to ensure that the data represent the real context, free from deep-rooted prejudices either in terms of gender or race or ethnicity." (Participant#07, Male 26–35)

5.1.2. Model bias

Model bias is defined as a phenomenon that results in biased outcomes due to inadequate specifications of ML models used in analytics applications. ML models are mathematical models that are not explicitly programmed rather they are developed utilizing statistical principles and rules to associate variables or features within a training data set (Paulus and Kent, 2020; Rozado, 2020). Inaccurate modelling that misses associations between output variables and input features in an ML application may result in biased outcomes, causing an adversarial impact on protected or unprotected groups (Rozado, 2020; Tsamados et al., 2021).

A closely related concept, variance, occurs when ML models fail to perform adequately despite learning the majority of data points (Walsh et al., 2020). Due to the reciprocal relationship between bias and variance, performing a bias-variance trade-off impacts the performance of ML models (Walsh et al., 2020; Ng, 2018). Therefore, Ng (2018) recommends modifying input features based on insights obtained through error analysis, increasing the size of the model by adding more layers of neurons in the neural network, and considering different model architecture to address avoidable bias. However, adding more layers will increase variance and computational cost. But selecting a better alternative model architecture is challenging to develop, and will be unpredictable in producing optimal outcomes (Ng, 2018).

The ML model used in recommendation engines can learn relevant input as irrelevant but can fail to learn irrelevant input as relevant, resulting in polarisation (Sun et al., 2019). Contrarily, within the context of dynamic settings such as reinforcement learning, there are often problems related to fairness due to the algorithm's inability to observe counterfactual data (Chouldechova and Roth, 2020). For example, we cannot observe how a patient would have reacted to a different drug, or whether a loan applicant who is not granted the loan would have actually paid it back, or whether a parole applicant who is rejected parole would have followed the rules (Chouldechova and Roth, 2020). Embedded blind spots within algorithms used in ML models for recommendation engines can result in difficulties in discovering specific items, products or services (Sun, Nasraoui, Shafto, 2019). The findings of the study support the significance of model bias through the following comments:

"A robust model should focus on linking well-established causal variables which are transparent and understandable. Also, marketers should include all the confounding variables that link well between predictors and outcomes." (Participant#01, Female 36–45)

"A bank considers a whole lot of demographic and financial variables to develop an ML algorithm for mortgage customers. It is important to look into all these variables, their nature and weights to identify bias against certain customer groups." (Participant#05, Female 18–25)

"Since machines learn from data, it is critical to consider the sampling error, bias blind spot, within-group bias, data selection and reporting errors and implicit stereotypes and associations." (Participant#11, Male 18–25)

5.1.3. Method bias

Method bias in ML applications is defined as sources of bias caused by methodological choices and procedural approaches undertaken during different stages of the ML application lifecycle, starting from conceptualization of the ML problem to deployment to ongoing maintenance (Walsh et al., 2020). Due to ML model developers' lack of experience in ML application development methods, many ML applications suffer from poorly crafted problem definitions, leading to unintentional discriminatory outcomes (Lorenzoni et al., 2021). The practice of performing a trade-off between methodological correction and strong results using artificial data may result in data inflation bias (Baumgartner and Thiem, 2020). If methodological preference inappropriately applies correlation instead of causation, it may cause a correlation fallacy. Through providing generic insights, inappropriate for a specific context, the methods may cause overgeneralization of findings (Zhou et al., 2016).

Recently, various lifecycle approaches have been adopted to obtain a systematic procedure to tackle algorithmic bias within ML-based marketing models (Paulus and Kent, 2020). Garcia et al. (2018) recommend carefully considering the context surrounding the data, system, and the people involved in the lifecycle of an ML product to effectively address challenges. Furthermore, for hypotheses development or validation, empirical findings suggest that humans tend to favour or confirm information that supports a pre-existing hypothesis or belief. On the other hand, personal belief induced confirmation bias in individuals involved in ML application development teams may resist any initiatives to challenge hypotheses that may emerge from faulty evidence (Thiem et al., 2020). Thus, scholars recommend incorporating explanatory models supported by theoretical underpinning to enable empirical testing of underlying propositions to tackle confirmation bias (Thiem et al., 2020). Comprehensive documentation, explainable and auditable ML models, and pairing data scientists with social scientists may mitigate sampling bias, anchoring bias, confirmation bias and performance bias (Abbasi et al., 2018; Thiem et al., 2020).

Methods scholars suggest instituting robust ML lifecycle management procedures and frameworks to tackle underlying challenges and ensure best practices in enterprise-level adoption of ML applications. Akkiraju et al. (2020) proposed a maturity framework emphasizing continuous improvement and maintaining rich engagement with the key stakeholders to obtain the highest quality results. To effectively mitigate concerns about algorithmic bias in ML-based marketing models, it is critical to attain transparency, explainability and auditability (Satell and

Abdel-Magied, 2020). Overall, we recommend adopting an explainable and auditable ML that is transparent and understandable for managing ML projects in marketing. The following comments from interviewees shed light on method bias:

> *"In order to embrace a robust methodology, ML professionals should carefully select training dataset and testing datasets. Proper data governance guidelines, diversity in teams in data labelling, inputs from multiple sources, tracking errors and making bias testing as a crucial component of ML development cycle can help to tackle bias." (Participant#18, Female 26–35)*
>
> *"Although we are still in the infancy of ML-based methods, bias relating to methods can ruin the whole objective of marketing strategies. Specifically, sample selection bias, outgroup homogeneity bias, correlation fallacy, confirming bias, overgeneralization or automation bias can generate spurious findings." (Participant#22, Male 36–45)*

Proposition 1. *Algorithmic design bias consisting of data, model, or method bias will be significantly more likely to influence marketing strategies in executing ML-based marketing decisions, such as segmentation, targeting and positioning.*

5.2. Contextual biases

Demographic and socio-cultural factors are crucial indicators in modern marketing efforts. A key challenge that we face in algorithm-driven marketing models is the historical and social biases embedded in the datasets that can further intensify historically disadvantaged populations, including people of different color, social status, sexual orientation, religion, gender, age group, subculture and many other social groups. As asserted by Crawford et al. (2016), histories of social discrimination can be integrated into ML platforms. Therefore, identifying and addressing challenges of racial bias, gender bias, and other social and cultural biases that emanate from algorithms and ML are of critical importance. Below, we identify the dimensions of these biases of ML in marketing, namely cultural biases, social biases, and personal biases.

5.2.1. Cultural biases in ML

Culture can be identified as the set of values, norms, beliefs, perceptions and behaviors learned by an individual from the society, family and other social institutions (Hofstede, 1991). Not only main cultures but also subcultures such as Asian Americans and African Americans serve as significant market segments that marketers pursue to offer culturally-tailored products and services (Samaha et al., 2014). In efforts to deliver such products and services to consumers through algorithms, discrimination emanating from cultural biases are evident in practice. A report in 2017 revealed that certain individuals such as African Americans and Jews were excluded from seeing targeted marketing ads on Facebook, including ads for housing, employment and credit (Angwin et al., 2017). Findings in the insurance and lending fields have also shown that historical disparities and discrimination, such as determining credit and loan values based on zip codes, are continued in algorithmic decisions. A study by Bartlett et al. (2019), using 3.2 million mortgage applications and 10 million refinance applications, exposed that racial discrimination occurs in face-to-face lending as well as in algorithmic lending. The study found that Black and Latino individuals not only experience higher rejection rates but they also have to pay higher interest rates.

Several other contexts may generate discrimination occurring from algorithms based on cultural factors. For instance, in 2015, Flickr received criticism for displaying racist results like tagging Black people as animals or apes (Yapo and Weiss, 2018). Likewise, Google faced similar issues for tagging African Americans as 'gorillas' (Kasperkevic, 2015). Google searches also exposed racial bias when searching for 'Black-sounding' names generated ads related to criminal activity. Sweeney (2013, p. 44) argues that this is "raising questions as to whether Google's advertising technology exposes racial bias in society and how ad and search technology can develop to assure racial fairness." In the sharing economy context, Airbnb hosts were found to reject and discriminate against certain customers based on the information produced by the algorithms. Cultural bias was witnessed in Uber and Lyft share rides where African-American customers or riders with 'Black-sounding' names got cancelled or had to face extended wait times (Ge et al., 2016). Also, another study has found that Uber and Lyft trips starting or ending at areas with a large African-American population are found to be more expensive than others (Pandey and Caliskan, 2020). The following comments from an interviewee reflect the impact of cultural bias in ML-based marketing models:

> *"An ML-based marketing model reflects the beliefs, attitudes and values of a culture passed from generation to generation, which often reflects unjust and unfair outcomes focusing on race, religion and gender. Although we try to exclude these variables while developing the model, other cultural variables might still produce biased outcomes if we do not exercise caution." (Participant#25, Female 55 +)*

5.2.2. Social biases in ML

Apart from the cultural biases discussed above, other biases emerge from other social factors, such as for individuals who are members of small social groups, as their social roles and social status can be more visible. A good example is Amazon's algorithm that decided to exclude certain geographical areas from its same-day Prime delivery system based on whether a particular zip code has sufficient Prime members, availability of a nearby warehouse, and availability of eligible workers willing to deliver to those areas. Despite the fact that it was driven by profit motivations, this resulted in the exclusion of neighborhoods having a poor economic and social status – predominantly African-American neighborhoods (Lee et al., 2019). O'Donnellan (2020) also provides a hypothetical example to clarify how such social biases can occur. A bank evaluates mortgage applications and determines the creditworthiness of applicants based on an algorithm using its historical mortgage approval data. The historical applications that were approved by previous employees indicated bias against certain social groups such as young people, blue-collar workers, and single-female applicants. As a result, the new algorithm rejects approvals for members of such social groups in the future, further establishing historical discrimination (O'Donnellan, 2020). Other areas where different social groups can face discrimination can include college admissions, where certain applications originating from lower-income or rural areas can be excluded (Lee et al., 2019). In a different context, the users of Grindr – an online dating application for gay, bi, trans, and queer social groups, were prompted by the algorithms to download a sex offender location-tracking app (Ananny, 2011). The above examples indicate that a person's membership in a particular social group makes them susceptible to unfair treatment and outcomes. The following comments reflect such bias against different social groups embedded in data used in ML:

> *"In offering banking services, I have often come across ML models with high weights on variables like gender, education, income, suburb etc., which result in unfair outcomes and undermine the core values of the business. To achieve higher ROI, some firms intentionally make algorithms that discriminate [against] customers based on their social backgrounds." (Participant#23, Female 46–54)*

5.2.3. Personal biases in ML

Biases in ML and algorithms can also be identified in how the algorithm treats individuals differently based on factors such as gender, age, and personality. A credit card provided by Apple received backlash for being sexist – the algorithm rejected a credit line increase for a female while it was approved for her husband. This occurred, surprisingly, when she had a better credit score and other requirements in her favor (Vigdor, 2019). Google search also indicated apparent gender bias when image search on 'CEO' resulted in photos predominantly of white men with just around 11 percent of women's photos and also displayed significantly fewer ads for high-paying executive jobs when the Google engine perceived that it was a female person conducting the search (Yapo and Weiss, 2018).

At present, facial recognition software is used widely for numerous tasks. A study at the Massachusetts Institute of Technology found that among three widely used facial recognition software applications, 99 percent of the time, the program could correctly identify a person's gender. However, that was only among white men. The accuracy dropped to 35 percent when applied to dark-skinned women (Manyika et al., 2019). Another study at Princeton University, where the researchers used ML to analyze and link 2.2 million words, found that European names compared to others, such as African-American names, were perceived as more pleasant. In relation to the personal biases dimension, the study found that words such as women and girls were more associated with the arts, whereas men were more associated with science and math (Hadhazy, 2017). Dutta (2021) also discusses another example where an ML algorithm trained to perform language translation tasks associated female names with words such as 'parents' and 'weddings', whereas male names had a stronger association with words like 'professional' and 'salary'. Lee et al. (2019) show that "in analyzing these word-associations in the training data, the ML algorithm picked up on existing racial and gender biases shown by humans." In the case where these learned associations are in practical use (e.g., search engine rankings), the algorithms can reinforce the racial and gender biases in our societies. These examples were reflected by the following comments:

"In the travel or entertainment industry, we often identify customers based on age, race, gender, lifestyle and personality. Model development in this context is often biased toward a particular customer group. For example, placing ads in FB pages are often controversial due to the application of various filters and the choice of particular personality by the marketers." (Participant#17, Male 46–54)

"Personal bias is a subset of human bias, which is embedded in ML models through gender, race or sexual orientations. Although we try to neutralize these variables in ML models, we often encounter training data with under representative minority and biased outcomes." (Participant#20, Male 36–45)

Proposition 2. *Contextual bias consisting of cultural, social and personal factors will be significantly more likely to influence explicating consumer behavior regarding values, beliefs and attitudes of consumers.*

5.3. Application biases

Marketing scholars asserted that a higher level of customization warrants marketers using sensitive individual data. ML can develop biased outcomes that can adversely impact the entire marketing process as articulated under the four pillars of marketing (i.e. product, price, place and promotion) in the following sections.

5.3.1. Product

Leveraging big data, ML has been accelerating the process of new product development, allowing marketers to better serve individual customers in real-time (Huang and Rust, 2021). In many instances, highly customized new product developments are more susceptible to ML biases if adequate caution is not taken earlier in the design phase. Like all other sectors, ML has been revolutionizing the financial industry to develop new loan products and to create a solid credit matrix to determine in real time appropriate credit limits for individuals. When credit rating algorithms are developed based on relevant financial criteria to determine the merit of loan applications, there is no concern of unfairness. However, the decision output generated by ML is prone to bias if the algorithm favours one group over others. For example, The Washington Post (2019) reported that Apple's black box algorithms used to calculate the credit score of customers applying for a credit limit increase were found to be gender-biased, favouring males over females. They reported this in a headline as "Entrepreneur David Heinemeier Hansson says his credit limit was 20 times that of his wife, even though she has the higher credit score" (The Washington Post, 2019, p. 1).

Many marketers have been using social media to develop and promote new products by analyzing the 'Like' function of Facebook to predict the demand for a new product (Wright et al., 2017). Such 'Likes' can be interpreted as to what extent a new product has been accepted by the market and the likelihood of its future success. However, scholars have warned that using ML, Facebook's Likes could be used to predict a user's highly sensitive personal traits such as political views, sexual orientation, religious views, views towards LGBT and minority groups, and use of addictive substances (Kosinski et al., 2013). Such sensitive, individualized information can be used to design products that may disadvantage a particular group over others. For example, in 2010, it was revealed that Nikon's S630 model digital camera was biased against Asian ethnicities. While capturing a facial image, it was consistently displaying a warning message, 'did someone blink?' Similarly, Hewlett-Packard's new Media Smart webcam was flagged as a racist product as it showed that its camera could track only white users' faces, not black ones (CNN, 2009). Overall, manipulation of ML algorithms using non-representative training data can create inequality and social injustice, which in addition to causing harm to individuals, also may ultimately damage the reputation of the company and challenge its future viability. The following comments of the interviewees reflect the role of algorithmic bias in marketing offerings:

"When we develop new products, our primary objective is to consider diversity, equity and inclusion of customer groups so that customers from all sub-cultures can wholeheartedly embrace a new offering. However, this process is often hampered by wrong training data, weak algorithm design and deep-rooted socio-cultural biases." (Participant#24, Male 26–35)

5.3.2. Price

To maximize profitability and remain competitive in the market, marketers often leverage price-discrimination strategies in the form of discounts, coupons, and loyalty points. According to a study by Deloitte and Salesforce (2018), 40% of brands currently use ML-enabled algorithms to maximize the customer value proposition by offering personalized pricing in order to attract and retain their target customers. Price discrimination is legal in many countries, such as the US. In Australia and the U.K., however, the manipulation of market power and price discrimination is entirely prohibited. Despite regulatory restrictions, ML has been widely used by many reputed firms to gain an unfair advantage in capturing market share. For instance, in the early 1980s, American Airlines (AA) created flight-finding algorithms to facilitate customers making an informed booking decision from a list of competitive prices. The U.S. Congress later revealed that AA manipulated algorithms by putting more weight on factors that favored its own flights over others, regardless of the price and convenience offered by their rivals (Friedman and Nissenbaum, 1996). At the micro-level, there are many instances where it has been found that ML has been used for unfair price discrimination considering only the socio-economic and personal attributes of customers such as their age, income, education level, and zip codes. Many US insurance companies have been penalizing immigrants, ethnic minorities, and vulnerable groups by charging higher health insurance premiums and in some cases denying insurance coverage, considering these groups as high-risk and needing more resources for providing health care (Israeli and Ascarza, 2020). Bartlett et al. (2019)

argue that historically human prejudice tends to cause lending discrimination, whereas ML has been used to create pricing discrimination against classified groups. They found that Black and Latino borrowers were paying a higher interest rate on mortgages, up to half a billion more every year compared to white Americans counterparts. This racial discrimination prompted wide media coverage. As reported by The Washington Post (2018, p. 1), “It’s not just bank loan officers with racial biases who discriminate against black and Latino borrowers. Computer algorithms do, too.” Even Facebook was prosecuted for violating the US Fair Housing Act as it allowed its advertisers to target protected classes for manipulating house selling and rental prices (Miller and Hosanagar, 2019). These pricing issues have been reflected by the following comment:

> *“In our organization, we customize prices for our various categories of online products based on customer’s loyalty scores. This pricing generally targets customers with high recency, high frequency and high monetary value scores. Many times I have observed that it excludes offerings to low socio-economic groups and patronizes customers with a higher share of the wallet.” (Participant#16, Male 26–35)*

5.3.3. Place

Place in marketing denotes the means of how customers can get access to their desired products or services using multiple channels and diverse locations. There are many occasions where marketers optimize product offerings by considering the status of location, and the devices used by their customers. For example, it was revealed that, compared to normal PC users, Mac users paid a premium rate for the hotel booking on Orbitz’s reservation website (Israeli and Ascarza, 2020). In the same vein, ML-based marketing models are used to set different pricing for the same product considering the affluence of a suburb, including whether residents are living in a particular suburb dominated by prime customers who are largely white. For instance, Uber and Lyft have been receiving criticism for racial bias as they were using ML algorithms to determine fares based on the suburb status of riders. Using transport and census data in Chicago with more than 100 million trips between November 2018 and December 2019, scholars at The George Washington University found that Uber and Lyft charged a premium price where pick-up or destination suburbs were predominantly populated by ethnic minorities compared to white residents (USA Today, 2020). Sweeney and Zang (2014) investigated whether online search engines generate unique search outcomes for all. They found that when African-American names are searched out that came up with pop-up advertisements persuading users to buy ‘arrest records’. Surprisingly, such pop-up ads were negligible when searched out for typical White-American names. They also found that advertisers used geographic locations through customers’ IP addresses, cookies, and search histories that enabled ML to generate biased suggestions to show ads with higher interest-bearing credit cards and financial products to the residents of African-American dominated suburbs. The channel discrimination issues have been reflected by the following comment:

> *“Based on my modelling experience in the insurance industry, I have come across ML models that tend to provide higher quotes for those customers who are from poor suburbs or suburbs with high crime records and violence. Such customization based on location or criminal records is grossly wrong. Recently, we have also experienced that in ride-sharing apps. Unfortunately, the marketing team makes such strategies to increase revenues”. (Participant#19, Male 26–35)*

5.3.4. Promotion

According to Business Insider (2021), in 2019, influencer marketing spent more than $6.5 billion (USD) on social media platforms for promoting products and services across the globe, and it will exceed $15 billion by 2022. There is a scholarly consensus that, to a large extent, the success of modern marketing depends on how precisely promotional campaigns can reach out to target customers based on solid analytics generated by ML instead of the traditional ‘spray-and-pray’ approach (Davenport et al., 2020; Hagen et al., 2020). There is a burgeoning criticism that, to better design and deliver customized products, ML needs to collate and analyze users’ personalized demographic data at the expense of customers’ privacy. Moreover, to get ahead of competitors, the way ads are presented by some marketers to different audiences can give rise to potential discrimination against a target group. Many big tech giants such as Facebook and Google have been criticized for optimizing ads in consideration of revenue per click and the return on investment, disregarding their ethical and legal obligations to the society in which they operate. For example, due to the adoption of cost minimising algorithms, Facebook excluded young women from viewing certain ads, given that young women’s “eyeballs” are more expensive to access than young men’s (Israeli and Ascarza, 2020). Facebook has been under continuous scrutiny by many regulators for instilling biases against classified groups. On April 9, 2021, The Wall Street Journal (2021) reported that Facebook’s ML-enabled job ads were criticized as gender-biased; for example, Domino’s Pizza delivery jobs were more likely to be shown to men, whereas women received pops up for shoppers’ roles for Instacart’s grocery delivery. Ali et al. (2019) investigated how Facebook had been purposely manipulating ads to the US protected classes using their race, gender and religious characteristics. They ran a series of identical ads with minor variations in terms of image, text, budget and finally found that a subtle modification on key attributes can dictate who will be shown intended ads. For instance, recruitment ads for janitors and taxi drivers were shown to a relatively higher proportion of ethnic minorities. Again ‘home for sale’ ads were shown to more white users while ‘rentals ads’ were displayed to ethnic minorities and immigrant communities. Simonite (2015) found that Google’s ad targeting was sexist as better paid jobs were offered to more males compared to females, thus leading to an increasing gender imbalance in senior management and thus widening the gender pay gap. The promotional biases through ML algorithms in marketing have been reflected by the following comment:

> *“When we design the display advertisements, the search engine advertisements or the Facebook advertisements, we carefully use keywords to focus on a certain group of customers. To the best of my understanding, the algorithms that drive these platforms aim to gain higher traffic from a specific group and exclude the majority. Overall, these offerings do not serve the mass [of] customers [and] rather [are] skewed toward a particular customer group”. (Participant#05, Female 26–35).*

Proposition 3. *Application bias consisting of product, price, place and promotional factors will significantly influence the operationalization of ML-based marketing programs.*

6. Implications and directions for future research

6.1. Theoretical contributions

In order to answer the research question on the dimensions of algorithmic bias management capability in ML-based marketing models, the findings of our study propose a framework that identifies three primary dimensions and ten subdimensions of algorithmic bias in ML-based marketing models. Extending the microfoundations of dynamic capability research, we argue that the ten subdimensions: model, data, method, cultural, social, personal, product, price, place and promotion are the microfoundations of algorithmic bias, which influence design bias, contextual bias and application bias management capability in ML-based marketing models. These findings are aligned with the core tenet of the dynamic managerial capability theory, which argues that managerial cognitive capital, human capital and social capital can play a pivotal role by leveraging managerial skill-set and specialized knowledge to carry out necessary changes (Helfat and Peteraf, 2015; Kor and Mesko, 2013; Salvato and Vassolo, 2018) to effectively mitigate the risk of algorithmic bias. For example, the findings of design bias (i.e., data, model and method bias) extend dynamic managerial capability theory by highlighting the fact that managers can act as change agents by bridging the gap between existing capabilities and new capabilities to successfully develop new and emerging capabilities such as robust ML-based models in marketing to provide value to customers (Davenport, 2019; Kafle and Kanan, 2017; Lavie et al., 2010; Porter and Heppelman, 2019). Using the findings of application bias across product, price, place and promotion decisions, we extend theory by illuminating the roles of ethical managerial intervention and transformation of existing resources and capabilities to address the concern of unfair and discriminatory practices (Helfat and Peteraf, 2015; Teece, 2009; Hu and Chen, 2018; Israeli and Ascazra, 2020; Paulas and Kent, 2020; Sajib, 2018; Wilson and Daugherty, 2018; Zahra et al., 2006). In a similar spirit, based on the findings of contextual factors (e.g., cultural, social and personal), we suggest developing a diverse and heterogeneous pool of talents to integrate and incorporate disparate ideas and viewpoints to effectively manage biases and trace their origin effectively through perspective-taking (Devenport, 2019; Israeli and Ascazra, 2020; Paulus and Kent, 2020), skilled adaptive action (Nayak, Chia and Canales, 2019) and adaptive collective decision-making (Laureiro-Martínez and Brusoni, 2018). This suggestion is fully aligned with scholars of dynamic managerial capability who have advocated cultivating heterogeneity in organizational resources and talent pools as well as emphasized productive interactions among organizational members through dialogue, learning mechanisms, matured routines and effective information ad knowledge sharing practices (Hatum and Pettigrew, 2004; Helfat and Peteraf, 2015; Salvato and Vassolo, 2018; Teece, 2007). The findings also suggest developing managerial capabilities to successfully access and leverage resources from managers' social networks that may better equip them to handle microfoundations of algorithmic biases that may emerge from individual and societal sources (Kor and Mesko, 2013). Overall, this paper extends dynamic managerial capabilities in addressing algorithmic bias for the fair practice of ML-based marketing models to avoid discriminatory and unfair outcomes.

6.2. Practical contributions

Our findings also contribute to practice in numerous ways. As shown in the analysis, our findings based on the literature were confirmed and augmented by the interviewees. Hence, we inform firms, marketers, AI scientists, and other practitioners to pay serious attention to numerous sources of biases in marketing models, namely, design bias, contextual bias and application bias. Marketers need to be aware that addressing biases in ML is a critical ethical concern (Kirkpatrick, 2016; Sun et al., 2019), which can cause discrimination against certain individuals and groups and, therefore, should be avoided or minimized by their best efforts. Thus, marketers, when using ML for determining product, price, place, and promotion, must strategically balance profit potentials and discriminatory effects. For instance, as the interviewees suggested, the need for customization of products should not be achieved at the expense of racial, social or gender discrimination. This study provides knowledge about the sources of such biases. Businesses can apply the proposed framework in their marketing practices as well in other functions involving ML, such as marketing management. To realize sustainable competitive advantage, ML has become a dynamic managerial capability in organizations, which has moved from a "nice-to-have" functionality to a "have-to-have" capability to develop offerings for customers (Rosenberg, 2018).

Table 4
Future research directions.

Future research area	References
Understanding biases and ways to address these biases in ML is a significant concern.	Davernport (2019); Hull (2021); Satell & Abdel-Magied (2020); Sun et al. (2020)
Identify how bias can be emerging in different stages of the AI/ML adaptation process, such as the data preparation stage or variable selection stage.	Ransbotham et al (2017), Vinuesa et al. (2020), Toreini et al. (2019)
Build trust in all stages in the ML life cycle for ensuring fair and non-discriminatory consumer outcomes.	
Explore the significance of corporate social responsibility and the importance of values-based and rule-based approaches to stakeholder management when developing and deploying AI applications.	Yapo & Weiss (2018)
Identify and address individual, organizational, and societal consequences originating from different sources (e.g., design, contextual factors) for effective ML deployment.	Gupta & Krishnan (2020); Obermeyer et al. (2019)
Find mechanisms to address the challenge of differentiating which predictive objectives pursued with ML should be considered useful, unethical, or should be legislated.	Siegel (2020)
Examine the ways in which 'explainable AI' can be used to ensure fairness and also prevent and detect algorithm bias in marketing applications.	Kumar et al. (2020); Ma & Sun (2020); Rai (2020)
Explore the degree of explainability and transparency in ML systems to cater for the needs of customers and other users.	
Examine how ML marketing applications ensure the well-being of consumers by addressing negative consequences of ML bias, such as discrimination and manipulation.	Carmon et al. (2019), Kumar, Ramachandran & Kumar (2020)
Establish sustainable uses of ML applications by striking a balance between organizational harvesting benefits and addressing the dark sides of ML.	Frow et al. (2011); Ransbotham (2018)
Develop an AI culture where diverse stakeholders are engaged to ensure that sources of biases such the design, historical and contextual biases are addressed in ML applications.	Appen (2020); Lee et al. (2018); Wixom, Someh & Gregory (2020)
Researchers and practitioners need to find ways to overcome bias due to economic and competitive reasons.	Satell & Abdel-Magied (2020)

Moreover, managers in the age of AI need to possess greater autonomy, risk-averse behavior, superior performance feedback and technological insights to appropriately explore the avenues to improve the adoption of ML applications and exploit them appropriately to generate fair outcomes and maximize organizational performance. This article paves the way for the application of dynamic managerial capabilities within ML-based applications to prepare business organizations to tackle the underlying challenges associated with algorithmic bias.

Our findings show that it is critical to address ML bias to maintain sustainable competitive advantage through algorithmic decisions. Firms that are using non-representative training data, manipulating contextual factors, and who use flawed algorithms will contribute to inequality and social injustice, which may damage the reputation of the company and challenge its future viability. Therefore, firms should invest for longer and sustainable gains through engaging in ethical and socially responsible ML practices. As highlighted by the interviewees, values such as transparency, fairness, and non-discrimination should be practised and considered at all levels of ML implementation. Also, our interviews exposed that interviewees are aware of different forms and causes of bias. However, it can be perceived that these biases are largely unaddressed by marketers. We suggest that firms address these biases urgently as they not only intensify social inequalities and discrimination, but if they go unaddressed, these unethical practices may come to be considered acceptable by the marketers to increase their profits.

Based on our review of literature, several areas for future research are identified (see Table 4). It is evident that empirical research on algorithm bias is still in its embryonic stages. Therefore, the research directions presented below (Table 4) can significantly contribute to advancing the research in this area. In particular, we highlight the need to examine the three sources of bias that we present in this paper. Moreover, we call for extensive research in this area to address the outcomes of these biases on issues pertaining to fairness, discrimination, manipulation, and trust in AI-driven marketing applications.

Broadly these future research areas can be grouped as falling in the domain of responsible innovation. Most large technology companies have responsible innovation managers whose job is to ensure that business information systems do not negatively impact customers, suppliers, and other company stakeholders. Ethical, legal and social aspects (ELSA) of ML/AI applications can be examined before and after ML/AI implementation phases to ensure that the company is compliant with local laws and that socio-ethical values are built into the design. As ML/AI is considered an emerging technology, it will take some time to understand its capabilities and limitations. So long as business managers are closely monitoring the release of new software suites and programs relying on ML/AI, the field will continue to develop in a manner that is beneficial to society. It is when ML/AI is left without a human in the loop that its diffusion can be catastrophic if left unchecked to a brand or company at large.

7. Conclusions

The marketing landscape has been gradually undergoing digital transformation, particularly since the emergence of big data. Today, as big datasets have been amassed by firms, marketers are increasingly using ML to recommend appropriate content based on user queries via search engines while co-locating the most profitable advertisements alongside the search results. ML also transforms marketing from automatic detection and verification of a face or an individual's voice commands for Internet of Things devices to the real-time navigation of a self-driving car. However, these benefits of ML-based marketing models are increasingly questioned due to the unfair or unjust effects on specific customer groups. Since algorithmic bias research is at a nascent stage in marketing, the proposed framework of our study provides the foundation for future investigation and extends this line of research by discussing its implications for customers, firms and other stakeholders.

CRediT authorship contribution statement

Shahriar Akter: Conceptualization, Supervision, Funding acquisition, Writing – review & editing, Writing – original draft. **Yogesh K. Dwivedi:** Project administration and Software. **Shahriar Sajib:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing, Writing – original draft. **Kumar Biswas:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Ruwan J. Bandara:** Writing – original draft. **Katina Michael:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

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.

Appendix A. Demographic profile of the respondents

Demographic Characteristic	Sub-Level	Count n = 25	(%)
Gender	Male	15	60%
	Female	10	40%
Profession	Sales manager using AI	1	4%
	CRM managers	2	8%
	Travel managers	2	8%
	Marketing analysts in financial industry	3	12%
	Digital marketing experts	3	12%
	Supply chain manager	2	8%
	Marketing analysts in grocery retail	3	12%
	Data scientists in healthcare	2	3%
	Service analysts in big data environment	2	8%
	Business process manager	2	8%
	New service development manager	2	8%
	Web marketing analysts	1	3%
	Others	1	3%
Education	Bachelor	12	48%
	Masters	8	32%
	Research degree	5	20%
Age	18–25	5	20%
	26–35	6	24%
	36–45	5	20%
	46–55	6	24%
	>55	3	12%

Appendix B. Checklist for marketers using ML models

Checklist for marketers using ML-enabled decisions:	4Ps (Promotion, Price, Product and Place)
1. Is the targeted promotion campaign highly personalized based on the individual characteristics of classified groups? For example, STEM career ads on Facebook are more biased towards young men than young women (Lambrecht et al., 2018; Han, Reinartz, & Skiera, 2021).	Promotion
2. Is the targeted promotion campaign excluding a certain group considering the high cost of reaching out to them? For example, young women's eyeballs are more expensive than young men that prompt Facebook to exclude women from viewing certain ads (Israeli and Ascarza 2020).	
3. Is the price discrimination made based on customers' demographic factors? For example, considering sex and age, young women drivers are charged less car insurance premium compared to young men due to perceived behavioral differences. (Balducci and Marinova, 2018; Caliskan, et al. 2017).	Price
4. Does the ethnicity of customers influence what price will be charged to individual customers? For example, ML-enabled pricing ads show higher lending rates and costly credit terms to minorities and women in the US lending market (Israeli and Ascarza 2020).	
5. Is the pricing discrimination made based on the devices customers use to view and book the service? For example, Orbitz's- a travel reservation website, charged a higher rate for Mac users over PC users for hotel booking (Xiong & Bharadwaj, 2014; Israeli and Ascarza 2020).	
6. Do the features of the product provide consistent user experiences to all users irrespective of customers' ethnic identity? For example, some facial detection software used by law enforcement agencies falsely identifies African-American and Asian faces more often than Caucasian faces. (Israeli and Ascarza 2020)	Product
7. Is the product recommendation based on incomplete past behavioral data of customers? (Batra & Keller, 2016).	
8. Does the optimization algorithms generate suggestions to potential customers considering their location status? For example, to optimise cost and efficiency, Amazon's Price Save-Day Delivery service was first rolled out in those suburbs in Boston where prime members reside, dominantly white Americans (Israeli and Ascarza 2020).	Place
Is the website of the organization compatible with all sorts of devices such as smartphones, desktops to provide unique user experiences to all customers? (Bellman et al. (2016; Israeli and Ascarza 2020)	

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Further reading

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