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Advancing algorithmic bias management capabilities in AI-driven marketing analytics research

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ABSTRACT

Algorithms in the age of artificial intelligence (AI) constantly transform customer behaviour, marketing programs, and marketing strategies in industrial markets. However, algorithms often fail to perform as expected due to various data, model, and market biases. Motivated by this challenge, this study presents a framework of algorithmic bias management capabilities for industrial markets that contribute to customer equity in terms of value, brand and relationship equity. Drawing on the dynamic capability theory, this study fills this gap by conducting a literature review, thematic analysis, and two rounds of surveys (n=200 analytics professionals and n=200 business customers) in the financial service industry in Australia. The findings show that algorithmic bias management capability consists of three primary dimensions (data, model, and deployment capabilities) and nine subdimensions. These findings have important implications for scholars and managers interested in developing algorithmic bias management capabilities to influence customer equity in industrial markets.

1. Introduction

The momentum of artificial intelligence (AI) driven marketing analytics is well on course to achieve a growth target of $20.83 billion in 2024 to create, communicate and deliver value, and also manage relationships with customers in industrial markets (Coombs et al., 2021; Davenport, Guha, Grewal, & Bressgott, 2020; Kumar et al., 2020; Mariani & Nambisan, 2021; Rai, 2020; Rust, 2020). AI is the building block of the fourth industrial revolution, and 70% of firms will adopt AI technology in marketing operations across the world by 2030 (Bughin, Seong, Manyika, Chui, & Joshi, 2018; Venture Beat, 2021). AI-based analytics methods have enabled marketing managers to formulate strategic decisions leveraging data-driven algorithms, such as transaction data, demographic data, psychographic information, customer product reviews, entertainment content, photos and comments shared on social media, eye-ball movements, food and exercise habits and other clickstream information (Davenport et al., 2020). AI-based marketing analytics methods and recommendation systems accelerate the growth of customer equity (Hagen et al., 2020; Ma & Sun, 2020; Mariani & Wirtz, 2023; Vermeer, Araujo, Bernritter, & van Noort, 2019). As such, firms develop marketing offerings in industrial markets by monitoring post-purchase behaviour and analysing real-time data (Huang & Rust, 2018; Mariani, Perez-Vega, & Wirtz, 2022). However, there is widespread evidence of unethical marketing practices due to discriminatory marketing models (e.g., Akter et al., 2021; Akter et al., 2021; Akter et al., 2022; Dwivedi et al., 2021; Dwivedi et al., 2021). This results in negative customer equity since many customers are restricted equitable access to various marketing offerings (Hartmann, Heitmann, Schamp, & Netzer, 2021; Israeli & Ascazra, 2020; Ma & Sun, 2020).

The sources of algorithmic bias in marketing offerings are often embedded in poor training datasets, weak mathematical models, or historical and social contexts. For example, Google's ad targeting to

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specific business groups based on particular gender profiles (Simonite, 2015), Facebook's gender-specific ad targeting (The Wall Street Journal, 2021), Apple's biased credit card offerings to businesses (Akter et al., 2022) or in other areas of businesses ranging from healthcare to banking (Cao, Duan, Edwards, & Dwivedi, 2021; Coombs et al., 2021; Dalenberg, 2018; Duan, Edwards, & Dwivedi, 2019; Israeli & Ascazra, 2020; Kumar, Dwivedi, & Anand, 2021; Kumar, Sharma, & Dutot, 2023; Lambrecht & Tucker, 2018; Sun, Nasraoui, & Shafto, 2020; Stahl, 2022; Vigdor, 2019). In the context of the Robodebt scheme in Australia, AI-driven service systems wrongfully raised almost $750 million through biased decision-making algorithms (Akter, Dwivedi, et al., 2021). Social and historical biases often disadvantage marketing decision-making either due to incomplete datasets or unreliable models, or poor deployment (Akter et al., 2022). The customer equity of advertisements on the Facebook platform has been questioned as customers with African-American backgrounds could not view targeted ads on housing, credit, and employment (Angwin, Tobin, & Varner, 2017). An unrepresentative training dataset, weak model design, or prejudiced deployment results in unfair customer equity in terms of value, brand, or relationship (Hartmann, Heitmann, Schamp, & Netzer, 2021; Israeli & Ascazra, 2020). Despite the unequal, unjust, and unfair effects of algorithm biases on customer equity, research in this stream is scarce in industrial marketing.

Drawing on the dynamic capability view (Helfat & Martin, 2015; Helfat & Peteraf, 2003; Martin, 2019; Teece, 2007), this study explores how to integrate algorithms effectively within marketing decision-making that adapts to the changing business environment. The theory suggests that distinctive data, model, and deployment capabilities might contribute to building higher-order dynamic capability to reconfigure customer equity (Akter et al., 2022; Israeli & Ascazra, 2020). Furthermore, managers can mitigate the risk of potential bias and reduce the adverse effects on stakeholders by carefully managing algorithms while

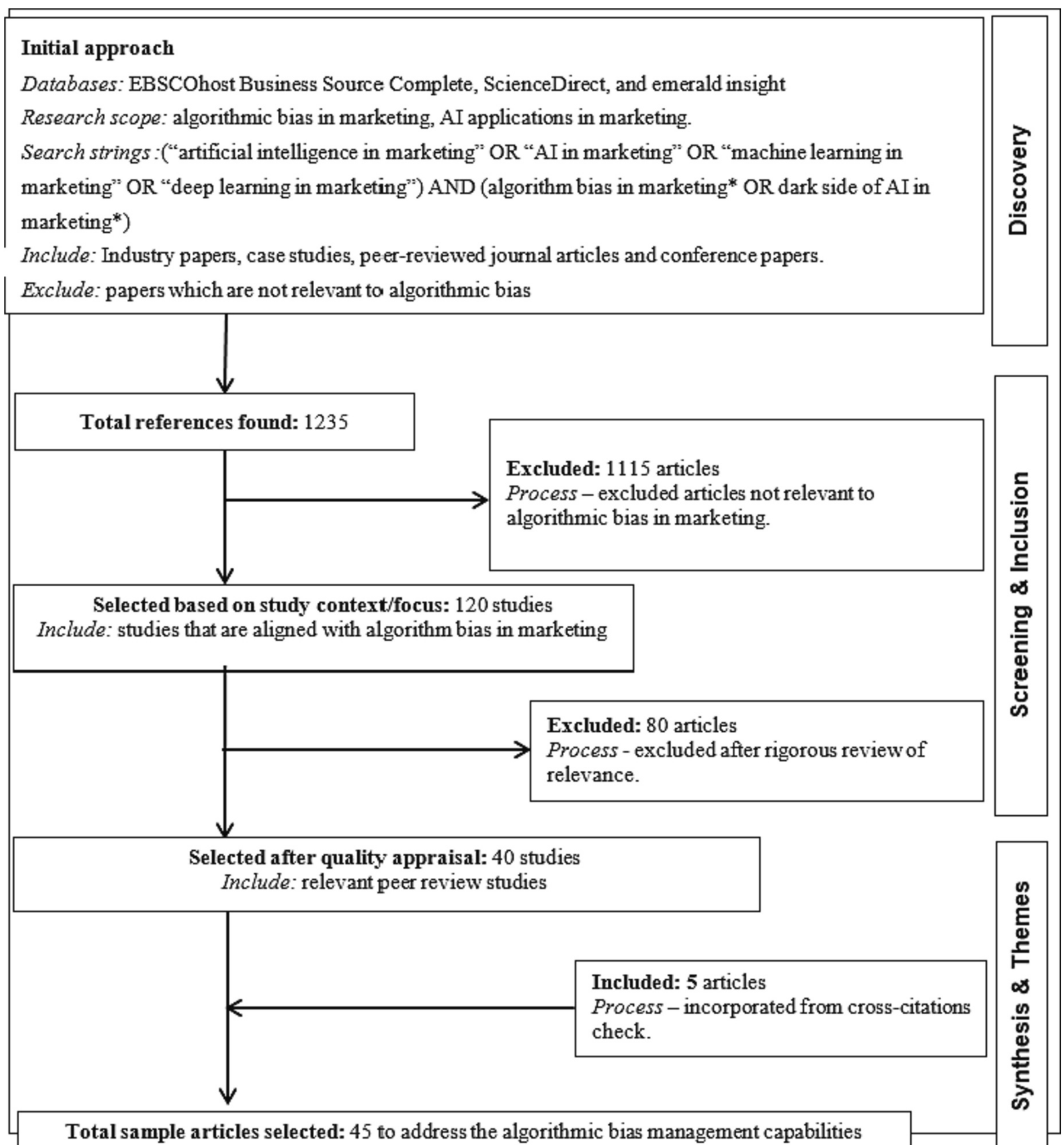

Fig. 1. Literature review protocol.

applying AI in various marketing programs ranging from data products to promotion decisions (Israeli & Ascazra, 2020; Rozado, 2020). Thus, this study aims to identify the sources of algorithmic bias in AI-based analytics methods and their effects on customer equity to address the following research question:

RQ. What are the dimensions of algorithmic bias management capabilities in industrial markets, and how do they influence customer equity?

To answer the research question, this research adopts a three-stage research process: (i) a systematic literature review to identify the gaps in this stream (Christofi, Vrontis, & Cadogan, 2021; Durach, Kembro, & Wieland, 2017; Mariani, Machado, Magrelli, & Dwivedi, 2023; Tranfield, Denyer, & Smart, 2003) (ii) a thematic analysis to identify the themes in algorithmic bias (Braun & Clarke, 2006) and (iii) finally, two cross-sectional surveys focusing on analytics professionals (n=200) and customers (n=200) to test hypotheses and validate the model using PLS-SEM based higher-order modelling (see Figure 1).

The study makes several contributions. First, using dynamic capability (DC) theory, the study identifies the primary dimensions (e.g., data bias, model bias, and deployment bias) and nine subdimensions of algorithmic bias management capabilities. These findings advance this line of literature and address marketing uncertainty in a dynamic environment. Theoretically, the findings present a significant transition from contemporary AI research in marketing, which has shed light on analytics bias in a broader context and limited our knowledge of on their microfoundations. Second, the study models the effect of algorithmic bias management capabilities on customer equity and extends this research stream by developing a transdisciplinary and translational application of ethical AI in industrial markets. In order to enhance customer equity through algorithmic decision-making, our findings show how to address the challenges of data, model, and deployment biases and achieve a competitive advantage through brand, relationship, and value equity. Finally, the study identifies the partial mediating roles of model and deployment capabilities in modelling the effects of data bias management capability on customer equity. These findings clearly highlight the role played by data bias management capabilities as a building block in the establishment of model and deployment bias management capabilities to reduce unjust and unfair outcomes in service offerings. From a practical perspective, our findings address various algorithmic bias-related concerns and provide future research directions to avert the algorithmic uncertainties in industrial markets.

2. Literature review and theory

2.1. Algorithmic biases and customer equity in marketing

While generating customers' value through sustainable marketing performance (Shamma & Hassan, 2013), customer equity has been envisaged as a strategic approach that connects consumers and businesses (Lemon, Rust, & Zeithaml, 2001). Customer equity is defined as the discounted lifetime values of all customers (Rust, Zeithaml, & Lemon, 2000), with brand equity, value equity, and relationship equity as its three primary components (Kim, Kim, & Hwang, 2020; Lemon et al., 2001; Razzaq, Yousaf, & Hong, 2017). While value equity is the customers' objective assessment of a brand in terms of cost, quality, and convenience (Kim et al., 2020), subjective evaluation of a brand encompassing brand awareness, brand attitude, and corporate ethics is the primary focus of brand equity (Keller, 2003; Vogel, Evanschitzky, & Ramaseshan, 2008). Relationship equity provides unique relationship components that connect brands and consumers (Rust, Lemon, & Zeithaml, 2004).

Being considered a critical indicator of marketing success (Kim et al., 2020), customer equity (CE) has been widely researched in the marketing management literature (i.e., Sun et al., 2020; Yu & Yuan, 2019). Researchers have consistently emphasized the significance of CE in industries like service (Hussain, Mu, Mohiuddin, Danish, & Sair, 2020; Ou, Verhoef, & Wiesel, 2017), manufacturing (Ho & Chung, 2020), telecommunication (Seo, Fu, & Song, 2023), pharmaceuticals (Moradi & Vazifehdust, 2022), and retail (Puspita & Chae, 2021). However, unlike the business-to-customer (B2C) market, CE has attracted little scholarly attention in relation to its implications in business-to-business (B2B) contexts (Grewal, Lilien, Petersen, & Wuyts, 2022). Identifying right customers, managing the customer relationship, handling customer-specific terms, maintaining brand image, integrating appropriate technologies, and sustaining long-term profitability are some of the key challenges that a firm needs to deal with while operating in B2B contexts (Grewal et al., 2022). Hence, taking these challenges into consideration, CE - including brand equity, value equity and relationship equity - is considered to be a critical success factor of B2B business (Cartwright, Liu, & Raddats, 2021). For instance, developing and maintaining solid connections with clients can result in repeat purchases and increased sales (Hawkins & Hoon, 2019) in the B2B market since the existing clients can considerably affect one another's buying choices (Almquist, Cleghorn, & Sherer, 2018). Ramaseshan, Rabbanee, and Hui (2013) revealed that the longevity of stakeholders' relationships in the B2B market depends on the degree of their mutual trust and satisfaction. As such, establishing relationship equity can aid in building long-lasting commitment, which is of utmost priority for B2B marketers to attract and retain customers (De Visser et al., 2020). Moreover, loyal customers are more inclined to concentrate on long-term gains and take cooperative initiatives that are advantageous to both parties in a B2B setting (Doney & Cannon, 1997). Likewise, favorable corporate brand equity provides B2B managers with additional advantages in quality, innovation, technical support as well as customer service (Ryan & Silvanto, 2013). Scholars like Anees-ur-Rehman and Johnston (2019) and Petzer, Verster, and Cunningham (2019) found that B2B firms can enjoy constant financial growth and lasting competitive advantage by establishing a strong brand value.

Similarly, in recent years, the big data analytics capability literature has recognized customer equity as a focal outcome for building such capability (see Kitchens, Dobolyi, Li, & Abbasi, 2018; Moon & Iacobucci, 2022). For example, based on Kitchens et al. (2018), the application of advanced customer analytics, which incorporates customer intelligence data (i.e., relationship-oriented big data) can facilitate a profound comprehension of consumer behavior as well as provide valuable insights for generating customer engagement and equity. However, in search of more accurate and efficient ways of managing customer equity, scholars are now investigating it in terms of AI-driven marketing (see Schweidel, Reisenbichler, Reutterer, & Zhang, 2023; Xu, Zhu, Metawa, & Zhou, 2022). For instance, Dash, McMurtrey, Rebman, and Kar (2019) explain how employing AI-based predictive algorithms not only aids firms in targeting the right customers and forecasting their demand but also in developing marketing mix strategies more accurately and efficiently, which in turn, boosts customer equity. Likewise, Schweidel et al. (2023) suggest that utilizing generative AI provides novel opportunities to marketers for creating text and image content that they can exploit for customer acquisition and retention, as well as customer relationship management. Moreover, the exploitation of AI-driven analytics and algorithms is also prevalent in the realm of customizing marketing campaigns (Lee & Lee, 2020), predicting customer behavior (Gkikas & Theodoridis, 2022), observing customer experience (Batra, 2017), and streamlining interactions and insights to enhance consumer engagement and devotion (Indriasari, Gaol, & Matsuo, 2019).

However, along with its enormous benefits, AI-driven analytics also comes with diverse algorithmic biases (Kordzadeh & Ghasemaghaei, 2022). Literature shows that if those biases are not identified and managed, they can create customer disappointment (Jones-Jang & Park, 2023) and, thus, affect customer equity in the long run. Although many scholars have considered algorithmic bias as their study area in recent times, virtually no study has linked algorithmic bias management capabilities with customer equity. As an example, Akter et al. (2022) proposed a dynamic capability framework for identifying algorithmic biases in ML-based marketing decision-making but did not examine how managing these biases can influence customer equity. Hence, the role of algorithmic bias management capability in enhancing customer equity remains a research gap in the extant literature.

The rise of AI-Based models in marketing aims to create, communicate and deliver value and manage sustainable customer relationships (Columbus, 2020). Although powerful algorithms leveraging big data contribute to the robust recommendation engines for cross-selling and customisation, churn modelling, and market-basket analysis, algorithmic biases currently present a grim picture of such applications (Akter, McCarthy, et al., 2021). Table 1 synthesizes the sources of these biases either through spurious datasets or, unreliable models or, or deep-rooted societal biases in marketing offerings. For example, the extant literature shows a discriminatory placement of online advertisements on gender-specific pages (Israeli & Ascazra, 2020; Lambrecht & Tucker, 2018), discriminatory pricing practices (Dalenberg, 2018; Vigdor, 2019) or, unjust offerings based on postcode/locations (USA Today, 2020). In this context, algorithmic bias management capability indicates how to manage deviation from the standards in AI-based marketing models that can stem from training datasets, types of models or market applications (Danks & London, 2017). Despite the prevalence of unfair, unjust and unequal effects of AI-driven marketing models and their corresponding algorithmic biases, research in this emerging domain is still fragmented and anecdotal. Table 1 shows findings and research gaps in this line of research through an analysis of key studies.

Considering its far-reaching impacts, algorithmic bias is being studied widely in the context of its identification, understanding, and mitigation with regard to education (Baker & Hawn, 2021; Yang, Ogata, Matsui, & Chen, 2021), healthcare (Panch, Mattie, & Atun, 2019; Seyyed-Kalantari, Zhang, McDermott, Chen, & Ghassemi, 2021), human resource management (Newman, Fast, & Harmon, 2020; Raghavan, Barocas, Kleinberg, & Levy, 2020), economics (Cowgill & Tucker, 2020), data-driven innovation (Akter, McCarthy, et al., 2021), computational linguistics (Markl, 2022), public administration (Wirtz, Weyerer, & Sturm, 2020), social research (Thiem, Mkrtchyan, Haesebrouck, & Sanchez, 2020) and many others. However, though the extant literature on marketing management has recognized the multiple benefits of AI (Schweidel et al., 2023; Varsha, Akter, Kumar, Gochhait, & Patagundi, 2021), there are very limited studies on identifying and mitigating algorithmic biases that are generated during the deployment of AI-driven solutions in marketing-related functions (Akter, Dwivedi, et al., 2021; van Giffen et al., 2022; Wan, Ni, Misra, & McAuley, 2020). Furthermore, these current studies are deemed to be conceptual, disintegrated, and experimental in nature. For example, Wan et al. (2020), in their research, theoretically addressed the sources of marketing bias that caused an underrepresentation of specific niche markets while developing personalized product recommendations and proposed approaches to optimize recommendation fairness. Similarly, Akter, Dwivedi, et al. (2021) identified how the application of AI-enabled analytics created various socio-economic biases in the process of customer engagement as well as provided solutions for overcoming such biases. Even though scholars like them developed a conceptual base for tackling biases to bring out the best outcome from AI-based applications, it is still unexplored how managing such biases from a capability viewpoint can strengthen customer equity. Hence, in light of the abovementioned limitations in the present literature, this research claims its originality in empirically investigating the impact of algorithmic bias management capabilities, including data bias, model bias, and deployment bias management capabilities, on enhancing customer equity.

2.2. Dynamic capabilities theory

Dynamic capabilities (DC) theory has an established tradition in industrial marketing management literature and has steadily become a

Table 1
Selected studies on algorithmic bias management capabilities.

Study	Study type	Main findings on algorithmic bias
Kordzadeh and Ghasemaghaei (2022)	Conceptual	Reviews, summarizes, and thematically analyzes the extant literature of algorithmic bias and based on that develops a theoretical model including eight propositions. Findings from thematic analysis provide a holistic view regarding how social, ethical, philosophical, and technical components contribute to developing algorithmic bias; as well as imply the significant role of laws and regulations, and socio-technical design principles in addressing and mitigating bias. The authors further propose that algorithmic bias negatively affects the perceived fairness of ML-generated recommendations and system adoption.
Hooker (2021)	Conceptual	Highlights the misconception that model bias emerges from the existing dataset; and, therefore, sheds light on the unique contribution of ML model bias along with the data bias in creating algorithmic bias.
Akter, Dwivedi, et al. (2021)	Conceptual	Using a systematic literature review, thematic analysis, and case study approach, the authors identify that algorithmic bias across the data-driven innovation process primarily comes from data bias, method bias, and societal bias and emphasize the role of dynamic managerial capabilities in identifying and combating such biases.
Akter et al. (2022)	Conceptual	Drawing upon a systematic literature review and in-depth interviews, the research presents design bias, contextual bias, and application bias that significantly affect machine learning-based marketing strategies and decision-making.
Rozado (2020)	Empirical	The authors warn that widely applied ML applications such as Word embedding models and vector predictions, if not implemented appropriately, can produce negative biases against a group of people belonging to a specific socio-economic status.
Grote and Keeling (2022)	Conceptual	Underlines how the growing prevalence of algorithmic bias coming from machine learning technologies which is applied with the aim of improving the healthcare capabilities actually aggravates the existing inequalities and injustice in the health system.
Peters (2022)	Conceptual	The author alerts that political biases embedded in society can be reflected while developing algorithms, thus, raising the risk of producing algorithmic political bias. The author also argues that this bias can be more difficult to be identified and cured than any other bias as algorithms can capture data on someone's political preference without his/her consent.
Paulus and Kent (2020)	Review	The research put forwards that any problems related to data sampling and model training in ML

(continued on next page)

Table 1 (*continued*)

Study	Study type	Main findings on algorithmic bias
		applications can entail unreliable and biased anticipations of consumer behavior resulting in discriminatory outcomes towards distinct customer groups.
Rust (2020)	Conceptual	While emphasizing on ML as a critical instrument for optimizing marketing performance, the author, at the same time, alerts marketers to gain comprehensive skills and knowledge from distinct fields in order to cautiously handle the socio-economic diversity and inclusion as well as geopolitical concerns in dealing with bias emerging from ML practices.
Lee (2018)	Conceptual	The research asserts that apart from the explicit bias, the implicit or unconscious social bias equally contributes to the design model of algorithmic bias against a particular racial group in the market resulting in unequal profiling of customers. In order to uproot such bias from the surface level, this study emphasizes on maintaining workforce diversity in the tech-giant industries as well as developing public policy conducive to the sustainability of bias-free algorithmic advancement.
Adomavicius, Bockstedt, Curley, Zhang, and Ransbotham (2019)	Conceptual	Sheds light on the possible dark sides of digital recommendation engines as intrigued by machine learning biases, these engines can manipulate customer preferences and behaviors for future purchases. Innovating both algorithms and user interface design are suggested to mitigate such biases in the recommendation system.
van Giffen, Herhausen, and Fahse (2022)	Conceptual	Recognizes eight different machine learning biases, including social bias, measurement bias, representation bias, label bias, algorithmic bias, evaluation bias, deployment bias, and feedback bias as well as offers a number of mitigation methods in order to handle ML biases in the marketing context.
Lambrecht and Tucker (2018)	Empirical	While examining how an algorithm-powered advertisement promotes job opportunities in the discipline of Science, Technology, Engineering and Math (STEM), the research finds that an algorithm solely based on cost-optimization in ad delivery creates discrimination in terms of targeting candidates based on gender. Instead, to be gender-neutral, the advertisement reached more men than women.
Parikh, Teeple, and Navathe (2019)	Conceptual	Although AI itself impetuously contributes to bias, the authors suggest heedful use of AI technologies, like, the application of AI decision support tools, unified collection of the diversified dataset, and appropriate algorithm prediction, can mitigate the risk of biases.
Ntoutsi et al. (2020)	Conceptual	In addition to the technical solutions like generating a balanced dataset, refining classification models, and modifying the regression model's predictions; the authors additionally suggest considering legal issues and deploy algorithmic accountability to manage biases in data-driven AI.
Akter, Dwivedi, et al. (2021)	Conceptual	The study demonstrates how AI-driven algorithms applied in customer management can produce biased decisions, which further results in inappropriate exploitations of customers based on their age, gender, race, religion, and socioeconomic status. Findings suggest marketers can apply both a priori and post-hoc approaches to identify and reduce such biases while responsibly managing targeted customers.
Ransbotham, Kiron, Gerbert, and Reeves (2017)	Empirical	The authors recommend using both published (positive) data and unpublished (negative) data, as well as deploying sophisticated algorithms in some cases in order to develop an unbiased training dataset. Positive data is biased towards successful experiments, whereas negative data contains data sets coming from failed experiments.
Israeli and Ascazra (2020)	Teaching Note	Stresses how algorithmic biases generated throughout the marketing decision process regarding product, price, promotion and place can bring outcomes that indiscriminately affect customers based on their age, gender, race, religion, and sexual orientation.
Sun et al. (2020)	Technical Report	The study substantiates that rather than being static; bias is a dynamic and iterative process. The authors also propose an iterated-learning framework to study the interactions between ML algorithms and human; and discover that three types of iterative algorithmic bias, along with imbalanced training data and human action, can impact the performance of ML.
Chui et al. (2018)	Discussion Paper	The research identifies the potential bias in data and algorithms as a limitation of AI and labels such bias as more socio-cultural and less technical in nature. To mitigate such bias, the study further suggests carrying out holistic approaches, such as a comprehensive understanding of the training data collection process that influence the algorithm model behavior.

dominant conceptual framework in big data analytics and AI research (Mikalef, Conboy, & Krogstie, 2021). This theory has injected new vigour into dynamic algorithmic bias management capabilities to sense, seize and transform uncertainties (Akter et al., 2022). This view is rooted in managerial capabilities that can effectively integrate new technologies to adapt to the changing business environment (Teece, 2007). More specifically, capabilities have been defined as the 'firm's capacity to deploy resources for a desired end result' (Helfat & Lieberman, 2002: p. 725). We define DC as "a firm's behavioural orientation constantly to integrate, reconfigure, renew and recreate its resources and capabilities and, most importantly, upgrade and reconstruct its core capabilities in response to the changing environment to attain and sustain competitive advantage" (Wang & Ahmed, 2007: p. 35). We refer to DC as organizational abilities to combine, recombine and exploit resources to gain a competitive advantage (Eisenhardt & Martin, 2000; Teece, Pisano, &

Shuen, 1997). They are firm-specific and information-based, intangible or tangible processes that are developed over time (Amit & Schoemaker, 1993). For example: Commonwealth Bank Australia (CBA) provided AI-driven repayment holidays to its business customers considering the hardship and disruption in a business environment (Eyers, 2020). This study views algorithmic bias management capabilities as DCs which can change swiftly to fit the shifting business environment and are conducive to adapting, integrating, and re-configuring resources (Teece & Pisano, 2003). For example, based on robust algorithmic bias management capabilities, Amazon's merchant services provide automated notification services, Deloitte's audit practice and GE's data curation services provide cognitive insights for suppliers (Davenport & Ronanki, 2018). Given the nature of their components, these capabilities cannot be sold or purchased but grow as the organization develops. More specifically, DCs pertain to "the capacity of an organization to purposefully create, extend, or modify its resource base" (Helfat et al., 2007: p.7).

Extant research in analytics and AI has emphasized that resources only are not sufficient to generate considerable performance gains; rather, they have to be transformed into distinctive capabilities (e.g., Mikalef et al., 2021). For example, managers in industrial markets need to be vigilant to carefully mitigate the risk of potential bias that may originate and adversely affect key stakeholders, including customers, while utilizing algorithms to meet customer needs (Akter, Dwivedi, et al., 2021). Those studies suggest that technological resources (e.g., data, model) should be combined with other organizational resources, such as intangible components (e.g., benevolence and integrity) to develop algorithmic capabilities to enhance customer equity, thus overcoming one of the dark side of algorithmic bias. Accordingly, to our knowledge, this work is one of the first attempts to theorize and understand how different types of DCs regarding algorithmic bias management capabilities can influence customer equity.

3. Qualitative exploration

Following the guidelines of Tranfield et al. (2003) and Watson, Wilson, Smart, and Macdonald (2018), the study has conducted a systematic literature review to plan the search protocols, identify the screening rules and develop the themes to address our research quest of algorithmic bias management capabilities that influence customer equity in marketing. A thorough review of the key databases, such as ABI/Inform Collection (ProQuest), Emerald Insight, ScienceDirect, Business Source Complete (EBSCO) and Wall Street Journal, was conducted using the following search strings: "artificial intelligence", "bias" and "marketing", "artificial intelligence in marketing", "algorithmic bias in marketing", "bias in artificial intelligence", "machine learning in marketing", "deep learning in marketing", "dark side of AI in marketing" etc. In addition to all other database, the Wall Street Journal was included as our research context is the financial industry and this business and economic-focused international daily newspaper has reported a significant number of news articles in recent years on the bright and dark side of AI applications in this context. The overall process has resulted in 45 studies after a careful review following the protocol in Figure 1. The exclusion of articles throughout the process was based on relevance, quality, and duplication criteria. Whereas relevance refers to the degree the articles were aligned with the research question on the dimension of algorithmic bias management capabilities, quality refers to the studies that offer depth, rigor and some novel insights beyond a recitation of past findings (Palmatier, Houston, & Hulland, 2018; Snyder, 2019). We excluded papers that are not directly linked to our research topic, such as physics, chemistry, geology and biology. As such, the criteria used to

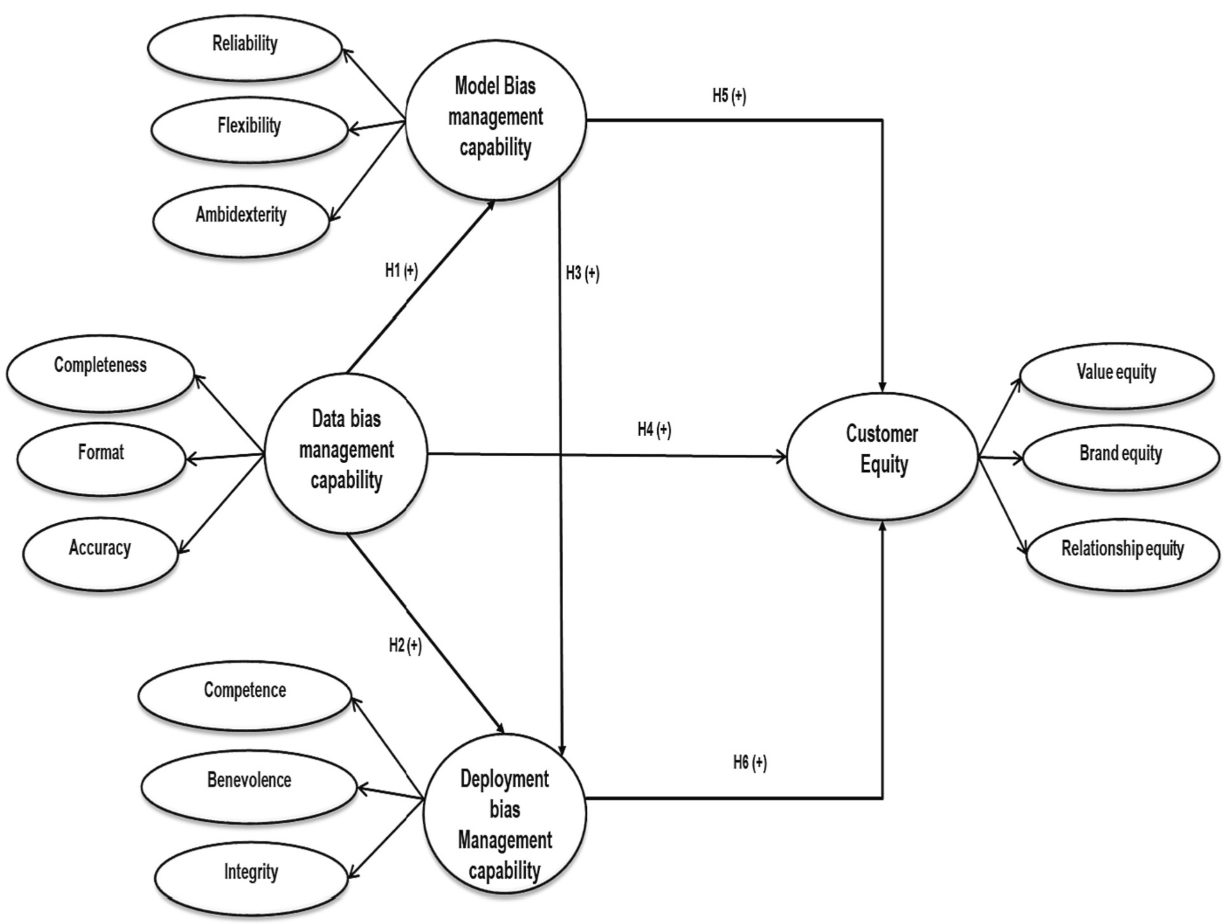

Fig. 2. Research model.

select each paper contained an explicit or implicit indication of algorithmic bias management capabilities in broader business decision-making. Applying QSR NVivo 12 software and following the guidelines of thematic analysis (Braun & Clarke, 2006), the study identifies three major dimensions (data, model, and deployment) and nine subdimensions in algorithmic bias management capabilities (see Figure 2). A panel of 5 experts consisting of two academics and three analytics professionals analyzed and scored the subdimensions and each primary dimension by applying the Q-soring method. We estimated an inter-rater reliability score of 0.82, exceeding the cut-off value of 0.70. The findings of this qualitative exploration show that data bias management capability consists of completeness, format, and accuracy of data; model bias management capability includes reliability, flexibility, and ambidexterity of a model and, finally, deployment bias management capability represents competence, benevolence and integrity of a marketing model in a particular context.

4. Conceptual model and hypotheses development

Building on the findings of the literature review and theoretical underpinnings of dynamic capabilities (DC), this study proposes the conceptual model (Figure 2) to extend algorithmic bias research in marketing. We define *data bias management capability* (DABMC) as the dynamic capability of analytics practitioners to manage the characteristics of datasets ensuring completeness, format, and accuracy in a dynamic environment (Gebru, Morgenstern, Vecchione, Vaughan, & Wallach, 2020). Drawing on data quality literature (e.g., Fosso Wamba, Akter, & De Bourmont, 2019; Nelson, Todd, & Wixom, 2005), *completeness* of the training dataset refers to the extent to which all possible attributes pertinent to the target population are reflected. Whereas *currency* represents the degree to which the dataset is up to date, *format* refers to the extent datasets are well integrated and presented in a way that is understandable and interpretable. Since training datasets are the primary source of algorithmic bias (Akter et al., 2022; Israeli & Ascazra, 2020), the inability to train data management capability in terms of completeness, currency and format results in sample selection bias. For example, Apple's credit card algorithms unfairly rejected female applicants over males since the dataset represents a higher ratio of male applicants.

Similarly, *model bias management capability* (MOBMC) refers to the dynamic ability of analytics practitioners to manage methodological and procedural guidelines concerning model reliability, flexibility, and ambidexterity that influence the design and development of marketing models (Walsh et al., 2020). Model bias occurs due to incorrect specification of the AI models or improper methodological choices used in algorithmic decision-making (Akter et al., 2022). Model *reliability* refers to the extent to which a marketing model is dependable (e.g., technically sound) over time (e.g., Fosso Wamba et al., 2019; Nelson et al., 2005). For example, a recommendation engine may not work if the statistical principles or rules fail to associate the outcome variables and antecedents (Tsamados et al., 2021). Model *flexibility* refers to the degree of versatility of a marketing model which can adapt to a variety of needs and changing contexts (Nelson et al., 2005). For example, the model allows to include of various demographic, geographic, psychographic, and social variables to predict consumer behaviour (Rozado, 2020). Finally, *ambidexterity* refers to the degree a marketing model can exploit current opportunities while exploring new ones in a dynamic environment (De Luca, Herhausen, Troilo, & Rossi, 2021). For example, the algorithms have the capacity to maximize customer lifetime value by offering personalized pricing and services (Deloitte & Salesforce, 2018).

Finally, *deployment bias management capability* (DPBMC) represents the dynamic ability of analytics practitioners to embrace competence, benevolence, and integrity to address societal biases emanating from social status, religion, sexual orientation, subcultures, age groups, gender, and other social groups (Akter, Dwivedi, et al., 2021; Akter, McCarthy, et al., 2021). *Competence* refers to the degree to which the marketing analytics team has the skills and abilities to achieve the marketing goals with regard to marketing mix or marketing programs (Mayer, Davis, & Schoorman, 1995). For example, developing a transparent credit rating algorithm that can offer real-time bias-free credit solutions to a customer (Akter et al., 2022). *Benevolence* refers to the extent analytics practitioners serve customers with good intentions rather than only profit motives, which is also identified as the caring nature of the algorithmic reducing social uncertainty or the possibility of any undesirable behavior (Colquitt, Scott, & LePine, 2007; Mayer et al., 1995). For example, during the COVID-19 pandemic, Commonwealth Bank Australia identified at-risk/most vulnerable customers using AI to provide financial support, such as loan repayment deferral for business customers who have experienced massive business disruptions (Commonwealth Bank Australia, 2020). Finally, *integrity* refers to the ability of the marketing analytics practitioners to uphold honesty, fairness, and justice (Colquitt et al., 2007) or, fairness and moral character (Lind, 2001) or value congruence (Sitkin & Roth, 1993). For example, the ability of a financial institute to offer algorithm-driven bank loans to customers, which is free from discrimination in terms of race, age, gender, education level, and zip code.

The study proposes that a dynamic data bias management capability influences model bias management capability (H1) and deployment bias management capability (H2). Both data bias and model bias management capabilities jointly influence deployment bias management capability (H3). All these three types of bias management capabilities significantly influence customer equity, which consists of value equity, brand equity, and relationship equity (H4-H6). We define *customer equity* as the outcome of dynamic algorithmic bias management capabilities, which is a sum total of the discounted lifetime values of a firm's entire customer group (Kim & Ko, 2012; Kumar & George, 2007; Lemon et al., 2001). It is critical to investigate the impact of algorithmic bias management capabilities in marketing models in order to grasp the strategic perspective and holistic understanding of these dynamic capabilities on value equity, brand equity, and relationship management (Lemon et al., 2001).

4.1. The association between data bias, model bias, and deployment bias management capabilities

Algorithmic bias may result from incorrect statistics, ineffective machine learning framework, and poor analytical decisions made throughout the analytics process when designing marketing models (Akter et al., 2022). According to Balayn, Lofi, & Houben (2021, p.741) "data bias is observed if data instances belonging to certain classes show a systematically different label distribution compared to instances belonging to other classes." On the other hand, Akter et al. *(2022, p.207) defined model bias as "a phenomenon that results in biased outcomes due to inadequate specifications of ML models used in analytics applications."* Mathematical models which are not deliberately coded but rather are constructed using statistical rules and guidelines to correlate variables or characteristics in a training data set are known as AI-driven marketing models (Walsh et al., 2020). The datasets occasionally contain various mistakes or flaws, including repeated entries, inaccurate data formats, and incomplete data or fields (Akter et al., 2022), which make it challenging for the algorithms to analyze them. Reportedly, incomplete data has a negative effect on how well machine learning models function (Slaughter, Kopec, & Batal, 2020). As such, if an algorithm for machine learning is employed to be trained from substandard inputs, the resulting model may also be incomplete and faulty (Grote & Keeling, 2022). Subsequently, such an incomplete model may exclude a specific group of people, which can also lead to incorrect forecasts for particular communities (Gianfrancesco, Tamang, Yazdany, & Schmajuk, 2018). For example, Amazon developed a machine learning algorithm to recruit potential candidates, which favored male candidates over female candidates. Later, the investigations revealed that a large portion of the candidate information that was used to develop the ML algorithm over a ten-year timeframe was provided by men. Thus, the lack of data bias management capability in this particular case of Amazon caused a model bias in the recruitment tool (Dastin, 2018). *Additionally, biased data also produce systemic discrimination and less accurate results because they do not even truly reflect usage applications for machine learning models. As a consequence, marketing programs may be prejudiced due to consuming unregulated data like biased selections and classifications (*Sun et al., 2020*). The precision and dependability of a model's forecast are impacted by its capacity to regulate data bias (*Smith, Rustagi, & Haas, 2020*). However, from the dynamic capability view,* researchers have emphasized ensuring effective format (Akter et al., 2022; Janssen, Brous, Estevez, Barbosa, & Janowski, 2020), accuracy (Gudivada, Apon, & Ding, 2017; Sengupta, Garg, Choudhury, & Aggarwal, 2018) and completeness (Rozado, 2020; Salvato et al., 2018; Slaughter et al., 2020) of data as capabilities to manage data bias. As such, introducing the feature selection technique (Sun et al., 2020) and precise labeling as well as adopting random sampling in data selection can be an example of a dynamic capability to create a balanced training dataset which in turn helps in producing reliable and flexible marketing models (Zhang & Qu, 2019). For example, gender-specific interpretations were made available by Google Translate in 2018. While converting questions that are gender-neutral in the original language, this functionality gives users a choice between male and female sound versions (Castaneda et al., 2022). Similarly, IBM unveiled AI Fairness 360 in 2018. With this extendable free software toolbox, one may investigate, monitor, and reduce prejudices and biases in machine learning algorithms across AI applications (Thompson, 2021). Therefore, based on the abovementioned discussion, we posit the following hypothesis focusing on an individual analytics practitioner.

H1. Perception of data bias management capability has a significant positive impact on model bias management capability.

Any data bias added to machine learning can result in significant deployment bias (Parikh et al., 2019). Deployment bias takes place when algorithm designers unintentionally use or interpret the analytical and artificial intelligence (AI) systems in inappropriate ways. As a dynamic capability in data science, deployment starts as soon as the ML algorithmic system is brought into action as part of a business project (Davenport & Malone, 2021). Among other reasons, when incomplete, outdated, and unreliable data is fed into AI applications, the deployment of the AI-driven marketing model loses its integrity, transparency, and competence (Valentine, 2019). For example, Facebook denied some specific groups of people (e.g., African Americans) for showing tailored advertisements for property, jobs, and finance (Akter et al., 2022). This happened due to the company's heavy reliance on an automated AI system for the deployment of such advertisements, which makes the system vulnerable to biases during the learning process (Angwin et al., 2017). Studies in the banking and finance sectors have also shown that the deployed models brought on by data bias reinforce historical imbalances and prejudice in the market (Bhutta, Chang, & Dettling, 2020; Fairlie, Robb, & Robinson, 2022 and Hassani, 2021). For example, Vigdor (2019) asserted that despite being engineered to be unbiased to the fact, the Apple Credit system gave males better credit levels as compared to females.

Additionally, the extant cultural and societal biases embedded in the data sources can worsen the situation for previously marginalized groups from particular races, socioeconomic backgrounds, faiths, genders, and age groups. Based on findings from MIT research, three facial recognition software which was commercially deployed to the market failed to provide accurate identification for darker-skinned female (Hardesty, 2018) as the training datasets were estimated to be mostly male and white. The case of Amazon can be stated as another example of deployment bias caused by data bias. In order to improve their working operations and productivity, the company determined whether a specific postal address had enough paid subscribers, the presence of neighboring warehouses, and the number of qualified personnel capable of delivering to those locations (O'Donnellan, 2020). Even though it was motivated by financial gain, this led to the deployment bias in that segregated areas with low socioeconomic characteristics, primarily in Afro-American communities.

Since data and model biases originate from "how the software is designed, developed, deployed and the quality, integrity, and representativeness of the underlying data sources" (Pandya, 2019, p.9), mitigating such biases would help develop dynamic deployment bias management capability. As such, firms must ensure the quality of data in order to thoroughly train the system, which will support model development and deployment (Davenport & Malone, 2021). Firms should also build the dynamic capability to accomplish diversity while developing ML design and deployment teams (Shellenbarger, 2019), who will periodically conduct algorithm monitoring activities (Srinivasan & de Boer, 2020). For example, at Apple, special project engineers having dynamic AI and ML application capabilities are responsible for deploying system integration for robotic technologies (Marr, 2019). Simultaneously, the developed AI systems must go under a full-scale test before being deployed in a real-time environment so that potential weaknesses can be identified (Sipior, 2020). Overall, while developing dynamic capabilities for managing data bias, firms ought to manage data ethics and regulations in order to protect the end users' rights. Per se, accomplishing such capabilities would help an analytics practitioner to manage deployment bias and, thus, lead to the following hypothesis:

H2. Perception of data bias management capability influences deployment bias management capability.

When a model is developed, interpreted, and used differently than it is intended to be, it creates deployment bias (Suresh & Guttag, 2021). As marketing algorithms are not autonomous and fed by human input, such bias is inevitable (Bellamy et al., 2019). Bias in marketing models can result in poor model efficiency and organizational judgments, which can have disastrous effects on finances, society, and image (Fahse, Huber, & Giffen, 2021). While developed and deployed, marketing algorithms can represent past and present prejudices based on information gathered from the community and may have the potential to increase any preconceived views caused by human judgment (Huang, Ma, & Hu, 2018). For instance, the insurance authority in New York investigated United Health Group using radicalized algorithm models that preferred healthy white customers to ill black patients (Slaughter et al., 2020). This happened as the algorithmic model was trained based on the information that black patients pay lesser for healthcare (Takshi, 2020). It is also noteworthy that marketers usually tailor and deploy their services by taking their clients' gadgets and geo-location information into account. For instance, it was discovered that Mac users were charged more for accommodation on the Orbitz reservation service than standard PC consumers (Israeli & Ascazra, 2020). A similar case from the banking industry was also reported, where banks' algorithms favored more affluent, white customers than others. Hence, building dynamic capabilities for managing model biases would significantly lessen the risk of deployment biases (Rajkomar, Hardt, Howell, Corrado, & Chin, 2018). Firms can develop dynamic capability by ensuring the algorithmic model's explainability, transparency and fairness in terms of its actual feasibility (Srinivasan & de Boer, 2020). Diversity in talent team can help in detecting biases, identifying the representative population, as well as predicting unique usage circumstances of such models (Barocas & Boyd, 2017). For example, the Google applications developer whose algorithm led to the misidentification of African–Americans as "gorillas" pointed out that they could not anticipate the technology's faulty translation of darker-skinned faces (Miller, 2017). It could have been averted with a more diverse work team who would have become proactive to these issues. As such, developing dynamic capabilities would help undertake necessary interventions during the real-time deployment of marketing models (van Giffen et al., 2022). It is always critical to envisage the social and technical impacts of model bias to manage deployment-related concerns (Martin, 2019). Hence, we posit the following hypothesis:

H3. Perception of model bias management capability influences deployment bias management capability.

4.2. The impact of data bias, model bias, and deployment bias management capabilities on customer equity

To increase both revenue and client equity, data-driven firms are beginning to integrate AI and ML-based algorithms into various aspects of the marketing process (Libai et al., 2020). In order to provide services and products that are subject to cultural differences, businesses target not just the bigger market sectors but also subcultures like Asian Americans and Hispanics when developing and deploying algorithms (Salvato et al., 2018). Even though algorithmic patterns are employed to better serve current and potential customers (Guha, Rastogi, & Shim, 2000), data bias due to cultural preconceptions is still prevalent and has a detrimental influence on the market (Galdon Clavell, Martín Zamorano, Castillo, Smith, & Matic, 2020). According to Gartner (2020, p. 12), bias in AI systems may "impact the brand value of the firm" and prohibit a certain customer category from receiving enough exposure to advertising possibilities (Davenport et al., 2020; Hagen et al., 2020). For instance, Facebook prevented some advertisements from reaching younger girls due to using a cost-saving analytics model (Israeli & Ascazra, 2020). By utilizing their characteristics of race, sexual orientation, and religion, Facebook was allegedly altering advertisements for the United States-protected groups (Ali et al., 2019). Additionally, Simonite (2015) found that Google's discriminatory advertisement personalization was based on the fact that more men than women were granted access to highly remunerative careers. Hence, controlling such bias can increase brand as well as customer equity. Libai et al. (2020) assert that a substantial source of competitive advantage in algorithmic models might come from obtaining and keeping more diversified data sets. Thereby, it is essential to comprehend data properties, underlying parameters, and machine languages utilized to construct a responsible and ethical AI model that convinces clients to keep faith and trust in AI-generated services (Sivarajah, Kamal, Irani, & Weerakkody, 2017). For instance, when taking pictures of persons of Asian heritage in 2010, Nikon's S630 model digital camera flashed a warning message asking, "Did someone blink?" Later, it was discovered that the employment of faulty image-recognition algorithms was a factor in such unintended bias that damaged Nikon's brand equity. In such circumstances, some scholars have emphasized working closely with customers to ascertain how and when the data can be utilized effectively can lead to greater customer engagement (Akter et al., 2022; Anshari, Almunawar, Lim, & Al-Mudimigh, 2019; Sathi, 2017). Thus, we posit that:

H4. Perception of data bias management capability influences customer equity.

Manipulating marketing models using a non-representative classification model may result in societal unfairness that can affect both customers and professional brands, which can endanger firms' long-term sustainability (Stahl, 2022). Once Facebook allowed advertisers to focus on a particular demographic category known as "Jew-haters" (Angwin et al., 2017), the company stated that the occurrence was an unintended result of algorithms. In some cases, bias in marketing models due to misrepresentative or biased data, poor algorithmic implementations, or past human inclinations can bring undesirable results in terms of profitability, customer satisfaction, or cost control (Hartmann & Wenzelburger, 2021). For example, because of its use of ML algorithms to set prices depending on the passengers' suburban background, Uber and Lyft came under fire for discriminating against customers of race (Whitney, 2017). Thus, we posit that:

H5. Perception of model bias management capability influences customer equity.

Understanding information sets, embedded variables, and machine languages is vital for developing and deploying reliable and moral artificial intelligence models (Zhou, Liu, Lei, Zhang, & Huang, 2021). For instance, AI-enabled chatbots are growing in popularity because of their natural language processing technology which is capable of identifying syntax format, translating meanings, and minimizing the response time for the users. Instead of depending upon a pre-programmed response, this system can start instant conversations with clients, respond to their inquiries immediately, and assist with every touch point throughout the customer's purchasing process (Adam, Wessel, & Benlian, 2021), which may reduce the chances of incurring deployment bias. Similarly, banking chatbot service is being employed in the financial sector to provide customers with financial advice on how to manage and invest their money, helping them in making wise financial decisions (Okuda & Shoda, 2018). In an effort to increase consumers' trust and confidence in AI-based services, IBM released AI Fairness 360, a complete open-source toolbox for assessing and mitigating unintentional biases in datasets and machine learning models. Overall, deploying robust and bias-free ML models would enable marketers to make sure that the products and services remain relevant during every touch point throughout the customer interactions while applying responsible and ethical AI would deliver the speed and scalability necessary to manage thousands of customer engagements in real-time (Akter et al., 2022). When used together, these applications may help an individual marketer to provide a seamless customer experience resulting in higher brand, relationship, and value equity. Hence, the discussion above generates the following hypothesis:

H6. Perception of deployment bias management capability influences customer equity.

4.3. The mediating effects of model bias and deployment bias management capabilities

Both model and deployment bias management capabilities have a direct and indirect influence on customer equity. First, model bias is argued to mediate between data bias management capability and customer equity because, without fitting the right marketing model, customer offerings might result in a low perception of value, brand, and relationship (Akter et al., 2022). For example, Services Australia has recently experienced a massive fall in customer equity due to a sub-standard machine learning model under its RoboDebt scheme, which unlawfully raised approx. $1.73 billion in debts from 433,000 people (ABC, 2020). However, a dynamic model management capability can result in higher customer equity, which has been experienced by Amazon through its 33% revenue generation through its machine learning-based robust recommendation engines (Davenport et al., 2020). Similarly, proper deployment of a marketing model with transparency, accountability, and explicability can increase customer equity by addressing various ethical and legal challenges (Davenport & Malone, 2021). For example, the Commonwealth Bank of Australia enhanced customer equity during the Covid-19 pandemic by deploying a three-month automatic loan repayment deferral program for its business customers to offset the adverse effects of lockdown and widespread disruptions in business operations. The extant literature on marketing analytics practice at an individual level identifies both the direct and indirect roles of model and deployment bias management capabilities to enhance customer equity (Israeli & Ascazra, 2020). Thus, we posit that:

H7.1. Model bias management capability mediates the relationship between data bias management capability and customer equity.

H7.2. Deployment bias management capability mediates the relationship between data bias management capability and customer equity.

5. Methods

5.1. Research setting

The research setting is based on one of the leading banks in Australia with more than 15.9 million customers and 48000 employees. The company has a partnership with H2O.ai, one of the leading AI giants in Silicon Valley, to analyse its vast amount of data efficiently with its cloud-based machine learning platform across its business for credit assessments, risk management, benefits and rebates, fraud detection,

Table 2
Operationalization of constructs.

Constructs	Sub-constructs	Definitions	Item labels	Items
Data bias management capability	Completeness	It refers to the extent to which the dataset provides all the necessary information in a dynamic environment (Wixom & Todd, 2005).	COMP1	The dataset for a marketing algorithm provides a complete set of information.
			COMP2	The dataset for a marketing algorithm produces comprehensive information.
			COMP3	The dataset for a marketing algorithm provides all the information needed.
	Format	It refers to the perception of how well the data is laid out in a dynamic environment (Wixom & Todd, 2005).	FORM1	The dataset for a marketing algorithm is well formatted.
			FORM2	The dataset for a marketing algorithm is well laid out.
			FORM3	The dataset for the marketing algorithm is clearly presented on the screen.
	Accuracy	It refers to the perceived exactness of the dataset in a dynamic environment (Wixom & Todd, 2005).	ACCU1	The dataset for a marketing algorithm produces correct information.
			ACCU2	The dataset for a marketing algorithm provides few errors in the information.
			ACCU3	The dataset for a marketing algorithm provides accurate information.
Model bias management capability	Model Reliability	It refers to the degree to which the model is dependable in a dynamic environment (Nelson et al., 2005).	RELI1	The algorithmic model operates reliably for marketing analytics.
			RELI2	The algorithmic model performs reliably for marketing analytics.
			RELI3	The operation of the algorithmic model is dependable for marketing analytics.
	Model Flexibility	It refers to the ability of any marketing analytics model to adapt to a range of user needs and fluctuating conditions in a dynamic environment (Nelson et al., 2005).	ADAP1	The algorithmic model can be adapted to meet a variety of marketing analytics needs.
			ADAP2	The algorithmic model can flexibly adjust to new demands or conditions during marketing analytics.
			ADAP3	The algorithmic model is flexible in addressing needs as they arise during marketing analytics.
	Model Ambidexterity	It refers to the ability to exploit the current markets/customers while exploring new ones in a dynamic environment (De Luca et al., 2021).	AMBI1	The algorithmic model can explore synergies with our existing offerings.
			AMBI2	The algorithmic model can specify new strategic possibilities.
			AMBI3	The algorithmic model can imagine the association between our existing offerings and future ones.
Deployment bias management capability	Competence	The extent to which the bank is believed to have the necessary knowledge and skills to provide bias-free algorithmic services in a dynamic environment.	COMP1	The bank is competent in providing algorithmic service.
			COMP2	The bank performs its role very well.
			COMP3	The bank understands the needs of customers it serves.
	Benevolence	The extent to which the bank is believed to serve the customers with good intentions in a dynamic environment.	BENE1	The bank's algorithmic intentions are benevolent.
			BENE2	The bank has good intentions towards me.
			BENE3	The bank's algorithmic services are well meaning.
	Integrity	The extent to which the bank is believed to commit moral and ethical principles in a dynamic environment.	INTE1	Promises made by the bank are reliable.
			INTE2	The bank would keep its commitment.
			INTE3	Algorithmic services given by the bank is its best judgment.
Customer Equity	Value Equity	It refers to the customer's subjective assessment of the benefits vs. cost of algorithmic services in a dynamic environment (Ou et al., 2017; Vogel et al., 2008).	VAEQ1	The price-quality ratio of the service the bank is offering is good.
			VAEQ2	I can buy their services at places that are convenient for me.
			VAEQ3	I can make use of the service of this bank at any time and place I want.
	Brand Equity	It refers to a customer's subjective assessment of the brand on algorithmic services in a dynamic environment (Lemon et al., 2001; Ou et al., 2017; Rust et al., 2004)	BREQ1	The bank has an innovative brand.
			BREQ2	The bank is well known as a good corporate citizen.
			BREQ3	The bank has a strong brand.
	Relationship Equity	The extent to which customers intend to stay in a relationship with the brand over time (Lemon et al., 2001; Ou et al., 2017)	REEQ1	I have the feeling that the bank knows exactly what I want.
			REEQ2	I feel committed to this bank.
			REEQ3	I feel at home with this bank.

and app-based customer service. The AI-powered solutions help the bank to anticipate customer needs and reimagine produce and digital experiences to meet those needs.

5.2. Scale development

The study has adapted scales from past studies (see Table 2) to measure data-bias management capability (Nelson et al., 2005), model bias management capability (Wixom & Todd, 2005), and deployment bias management capability (Akter, D'Ambra, & Ray, 2011). The study has also measured customer equity as the outcome constructs using value equity, brand equity, and relationship equity subdimensions (Ou et al., 2017; Rust et al., 2004). We measured all the constructs from the firm's perspective except for customer equity. The customer equity construct was measured using cross-sectional survey data from customers of the bank who have used AI-powered solutions for the last three years at least. The pre-testing phase collected data from 25 respondents to check the structure and format of the questionnaire. As part of pilot testing, we collected data from 55 analytics practitioners from the bank as well as 55 customers to check the measurement properties and dimensionality of the research model. We have reported the definitions and measurement scales in Table 2. All the constructs were measured using a 7-point Likert Scale.

5.3. Main study

We used two sources of cross-sectional survey data: analytics practitioners (marketing managers, CRM managers, data analysts, IT professionals, machine learning experts, etc.) who are part of the algorithmic bias management team as well as the actual customers of the bank who received AI-powered service solutions. Using a professional market research firm, we approached a panel of 781 respondents in the bank who met the screening criteria of at least three years' analytics/algorithmic decision-making experience and 18+ years old. 233 respondents filled out the complete survey, and after excluding spurious responses, we finally analysed 200 responses from analytics practitioners in the bank. The spurious responses refer to straight-lining responses, missing values, quick response time, and abnormal response patterns (e.g., inattentive or careless responses) (Meade & Craig, 2012). Similarly, using a simple random sampling technique, we approached a panel of 678 actual customers, collected 241 complete responses, and after checking all the quality criteria, we finally analysed 200 responses. Appendices 1 and 2 show the demographic profiles of both samples and confirm their diversity in terms of gender, age, experience, job types (analytics practitioners) and location (customers).

5.4. Data analysis

Due to the hierarchical nature of the constructs in the research model, we used the repeated indicator approach using Partial Least Squares (PLS) based Structural Equation Modeling (SEM) to estimate the measurement properties of the model since it ensures theoretical parsimony and model simplicity (Becker, Klein, & Wetzels, 2012; Sarstedt, Hair Jr, Cheah, Becker, & Ringle, 2019; Wetzels, Odekerken-Schröder, & Van Oppen, 2009). Using SmartPLS 4.0, the study has applied PLS-SEM using a nonparametric bootstrapping with 5000 replications for inside approximation, applying the path weighting scheme (Ringle, Wende, & Becker, 2022). The algorithmic advantages of PLS-SEM contribute to robust prediction, factor identification, and factor determinacy in estimating our proposed hierarchical model (Akter, Fosso Wamba, & Dewan, 2017). Following the guidelines of Hulland, Baumgartner, and Smith (2018), we applied a priori and post-hoc methods to address common method variance (CMV) issues. As part of the priori method, we separated the three algorithmic bias management capability constructs from the customer equity construct as data were collected from two different sample units (analytics practitioners vs. actual customers). As part of the post-hoc method, we collected data using theoretically unrelated variables as marker variables (e.g., I have never heard of blockchain technology) (Simmering, Fuller, Richardson, Ocal, & Atinc, 2015). The findings of the correlation coefficients show a non-significant relationship ($r = 0.063 - 0.071$, $p > 0.05$) between marker variables and three antecedents (data bias, model bias and deployment bias management capabilities).

5.5. Measurement model

The study estimates the measurement properties of all the nine reflective first-order constructs: completeness, format, accuracy, competence, benevolence, integrity, value equity, brand equity, and relationship equity (see Table 3). The findings of the measurement model confirm the reliability of the scales through significant loading of each item (0.70, $p < 0.001$) and composite reliability (CR) scores exceeding 0.80 (Fornell & Larcker, 1981). Whereas composite reliability indicates scale reliability by measuring the internal consistency of items of a construct, average variance extracted (AVE) scores indicate convergent validity by measuring the convergence of items through sharing the proportion of variance of a construct against its

Table 3
Assessment of first-order, reflective model.

Dimensions	Reflective constructs	Items	Loadings	CR	AVE
Data bias management capability (DABMC)	Completeness (COMP)	COMP1	0.898	0.928	0.811
		COMP2	0.907		
		COMP3	0.897		
	Format (FORM)	FORM1	0.810	0.882	0.714
		FORM2	0.865		
		FORM3	0.859		
	Accuracy (ACCU)	ACCU1	0.882	0.925	0.805
		ACCU2	0.907		
		ACCU3	0.903		
Model bias management capability (MOBMC)	Reliability (RELI)	RELI1	0.749	0.874	0.699
		RELI2	0.898		
		RELI3	0.851		
	Flexibility (FLEX)	FLEX1	0.820	0.866	0.684
		FLEX2	0.851		
		FLEX3	0.809		
	Ambidexterity (AMBI)	AMBI1	0.811	0.888	0.726
		AMBI2	0.886		
		AMBI3	0.857		
Deployment bias management capability (DPBMC)	Competence (COMP)	COMP1	0.880	0.902	0.755
		COMP2	0.858		
		COMP3	0.870		
	Benevolence (BENE)	BENE1	0.923	0.941	0.841
		BENE2	0.913		
		BENE3	0.975		
	Integrity (INTE)	INTE1	0.826	0.885	0.720
		INTE2	0.871		
		INTE3	0.848		
		VAEQ1	0.901		
	Value Equity (VAEQ)	VAEQ2	0.910	0.929	0.813
		VAEQ3	0.894		
Customer Equity (CUEQ)	Brand Equity (BREQ)	BREQ1	0.821		
		BREQ2	0.820	0.868	0.687
		BREQ3	0.846		
		REEQ1	0.841		
	Relationship Equity (REEQ)	REEQ2	0.858	0.884	0.717
		REEQ3	0.841		
Formative construct		Items	Weights	t-value	VIF
Control variables (Firm level) (COVA-F)		Age	0.139	0.633	1.230
		Gender	0.541	1.345	1.320
		Experience	0.341	0.566	1.325
		Job type	0.266	0.688	1.473
Control variables (Customers) (COVA-C)		Age	0.419	0.788	1.639
		Gender	0.545	1.365	1.571
		Income	0.432	0.561	1.356
		Service type	0.267	0.751	1.441

measurement error. The findings confirm that average variance extracted (AVE) scores meet the minimum threshold level of 0.50. We assessed the formative control variables at both the firm and customer levels by applying the variance inflation factors (VIF) and weights. The findings did not report any collinearity, as VIF values were between 1.062 to 1.278 ($\leq$ 5). The findings of the study also report the square root of the AVEs in the diagonals of Table 4, which evidence the discriminant validity of the first-order constructs (Fornell & Larcker, 1981). We have also undertaken an investigation of the cross-loading of items across the constructs, and the findings confirm that items of respective constructs have significantly higher loadings than other constructs. A further examination of discriminant validity was confirmed using Henseler, Ringle, & Sarstedt's (2015) heterotrait-monotrait (HTMT) criterion (coefficients <0.90) (see Appendix 3).

The findings of our higher-order, reflective measurement model, are reported in Table 5 following established guidelines (e.g., Becker et al., 2012; Sarstedt et al., 2019; Wetzels et al., 2009). The path coefficients between first-order and second-order constructs are significant. DABMC is comprised of 9 items (3+3+3) containing COMP, FORM and ACCU subdimensions. Similarly, MOBMC (=9 items) consists of RELI, FLEX and AMBI subdimensions and DPBMC (= 9 items) consists of COMP, BENE and INTE subdimensions. The findings in Table 5 show that COMP (β=0.853), FORM (β=0.900) and ACCU (β=0.891) are significant subdimensions of DABMC as the path coefficients are significant at $p<0.001$. Similarly, RELI (β=0.848), FLEX (β=0.872), and AMBI (β=0.891) have significant relationships with MOMBC dimension and COMP (β=0.930), BENE (β=0.929), and INTE (β=0.720) have significant associations with DPBMC dimension. Therefore, the findings of the study confirm the robustness of the second-order, reflective model by ensuring the significant associations between second-order and first-order constructs.

5.6. Structural model

The findings of the structural model (Table 6) show the significance of the hypothetical associations using path coefficients (β), coefficient of determination (R^2), and the effect size (f^2). The findings confirm that DABMC has a significant, positive impact on MOBMC (β=0.595, $p<0.001$) and DPBMC (β=0.565, $p<0.001$). MOBMC significantly influences DPBMC (β=0.376, $p<0.001$), and both DABMC and MOBMC explain 66% variance of DPBMC. Thus, we confirm H1, H2 and H3. The findings also confirm that DABMC (β=0.396, $p<0.001$), MOBMC (β=0.218, $p<0.001$) and DPBMC (β=0.298, $p<0.001$) have a significant positive influence on CUSEQ, explaining 57% of the variance. Hence, the findings confirm H4, H5 and H6.

In testing the mediating effects, we identify MOBMC and DPBMC as the partial mediators because DABMC has a significant direct impact CUSEQ (the outcome variable) without the influence of the mediators (Baron & Kenny, 1986). The findings on R^2 show that 53% of the variance in MOBMC, 66% of the variance in DPBMC and 57% of the variance in CUSEQ were explained by the research model. Table 7 shows the indirect effects of MOBMC (β=0.130, $p<0.001$) and DPBMC (β=0.153 $p<0.001$) following the guidelines of Hayes, Preacher, and Myers (2010) and Preacher and Hayes (2008) applying the bootstrapped sampling distribution with a 95% confidence interval. Hence, we further confirm MOBMC and DPBMC as partial mediators (Hair et al., 2021). The findings on control variables, both from firm and customer perspectives, show that they have an insignificant impact on CUSEQ ($p>0.05$). Following Shmueli et al. (2019), we applied PLSpredict to estimate predictive validity by using a training sample (n=200) and a holdout sample (n=20). The results ensure the predictive validity of the nomological network as it provided lower prediction errors in comparison with Linear Regression Model- root mean squared error (RMSE).

Table 4
Correlations of LVs, AVEs and descriptive statistics*.

Construct	Mean	SD	COMP	FORM	ACCU	RELI	FLEX	AMBI	COMP	BENE	INTE	VAEQ	BREQ	REEQ	COVA (F)	COVA (C)
Completeness (COMP)	5.451	1.342	**0.900**													
Format (FORM)	5.531	1.331	0.345	**0.845**												
Accuracy (ACCU)	5.322	1.314	0.419	0.432	**0.897**											
Reliability (RELI)	5.197	1.410	0.422	0.443	0.487	**0.836**										
Flexibility (FLEX)	5.228	1.135	0.391	0.461	0.461	0.496	**0.827**									
Ambidexterity (AMBI)	5.456	1.195	0.375	0.519	0.471	0.511	0.419	**0.852**								
Competence (COMP)	5.524	1.234	0.421	0.421	0.331	0.375	0.365	0.421	**0.869**							
Benevolence (BENE)	5.364	1.109	0.356	0.485	0.425	0.435	0.4220	0.335	0.384	**0.917**						
Integrity (INTE)	5.489	1.258	0.398	0.531	0.485	0.521	0.524	0.421	0.332	0.421	**0.849**					
Value equity (VAEQ)	5.454	1.253	0.386	0.391	0.411	0.399	0.534	0.473	0.425	0.448	0.495	**0.902**				
Brand equity (BREQ)	5.305	1.289	0.391	0.352	0.435	0.303	0.492	0.411	0.512	0.335	0.467	0.512	**0.828**			
Relationship equity (REEQ)	5.453	1.175	0.482	0.341	0.401	0.351	0.399	0.435	0.428	0.428	0.436	0.457	0.438	**0.847**		
Control Variables (COVA-F)	n.a.	n.a.	0.021	0.063	-0.072	0.045	0.046	0.028	0.011	0.042	0.035	0.033	0.055	0.066	**n.a.**	
Control Variables (COVA-C)	n.a.	n.a.	0.032	0.025	0.039	0.082	0.052	0.061	0.021	0.014	0.019	0.033	0.050	0.042	0.025	**n.a.**

* Square root of AVE on the diagonal

Table 5
Assessment of the higher-order model.

Model	Second-order	First-order	β	R^2	*t*-statistic
Algorithmic Bias Management Capabilities (Antecedents)	Data bias management capability (DABMC)	Completeness (COMP)	0.853	0.811	33.193
		Format (FORM)	0.900	0.714	42.933
		Accuracy (ACCU)	0.891	0.805	54.145
	Model bias management capability (MOBMC)	Model reliability (RELI)	0.848	0.699	37.092
		Model flexibility (FLEX)	0.872	0.684	41.384
		Model ambidexterity (AMBI)	0.891	0.726	49.124
	Deployment Bias Management Capability (DPBMC)	Competence (COMP)	0.930	0.755	93.364
		Benevolence (BENE)	0.929	0.841	91.992
		Integrity (INTE)	0.907	0.720	60.597
Outcome	Customer Equity (CUSEQ)	Value Equity (VAEQ)	0.878	0.813	56.085
		Brand Equity (BREQ)	0.906	0.687	76.040
		Relationship Equity (REEQ)	0.850	0.717	42.378

Table 6
Results of the structural model.

Hypotheses	Main model	Path coefficients	f^2	Stand. Error	*t*-stat.
H1	DABMC ➔ MOBMC	0.595	0.548	0.045	13.105
H2	DABMC ➔ DPBMC	0.565	0.716	0.052	10.877
H3	MOBMC ➔ DPBMC	0.376	0.317	0.050	7.520
H4	DABMC ➔ CUSEQ	0.396	0.181	0.066	5.995
H5	MOBMC ➔ CUSEQ	0.218	0.171	0.055	3.962
H6	DPBMC ➔ CUSEQ	0.298	0.178	0.076	3.918

Table 7
Results of the mediation testing.

Hypotheses	Mediating paths	Indirect effect	t-value	Significance ($p<0.001$)
H7a	DABMC-MOBMC-CUSEQ	0.130	3.732	0.000
H7b	DABMC-DPBMC-CUSEQ	0.153	3.636	0.000

6. Discussion

6.1. Summary of findings

The results of the study show that algorithmic bias management capability for marketing models consists of three second-order dimensions: data bias management capability, model bias management capability, and deployment bias management capability. The findings also confirm that each of these dimensions is reflected by three first-order subdimensions, respectively. For example, data bias management capability is reflected by completeness, format and accuracy of data in which the most important subdimension in terms of variance explained is completeness of data (R^2=0.811), followed by accuracy (R^2=0.805), and format (R^2=0.714). These findings concur with the past findings that training data bias is a critical source of algorithmic bias, which can be managed through proper data governance (Akter et al., 2022; Israeli & Ascazra, 2020). However, the findings advance this line of research by specifically identifying three sources of data bias: completeness, format and accuracy. Similarly, the findings on model bias management capability show that the most important subdimension is the ambidexterity of the model (R^2=0.726)), followed by reliability (R^2=0.699), and flexibility (R^2=0.684). These findings reflect a fundamental shift in marketing analytics literature by pinpointing the mediating role of model bias through reliability, flexibility and ambidexterity that might contribute to meaningless correlations/patterns, implausible causality, and inconclusive evidence. The final antecedent deployment bias management capability shows that the most important subdimension is benevolence (R^2=0.841) of the marketing model to serve customers, followed by the competence of the model reflecting its knowledge and skills (R^2=0.755) and integrity (R^2=0.720) of the model to commit moral and ethical principles. Moving away from the bright side of AI deployments in marketing models, these findings urge practitioners to carefully consider the dark side, such as inequity and discrimination as stated by Davenport & Malone (p.1, Davenport & Malone, 2021), "The entire domain of data science may lose favor within an organization if models are only rarely deployed. And for those industries where auditability and transparency are absolutely critical, such as banking, finance, and health care, a poorly deployed model is a legal, business, or health risk." The outcome construct customer equity is assessed from the customer's perspective showing that the most important subdimension is value equity (R^2=0.813) followed by relationship equity (R^2=0.717) and brand equity (R^2=0.687). Although there are differences in the degree of variances explained by each dimension to its respective subdimensions, the magnitude of differences is small and all the relationships are significant at $p<0.000$. The novelty of these findings lies in specific estimation of brand, value and relationship equity through algorithmic bias management capabilities. These findings broadly support the argument of Chui et al. (2018) who found the positive impact of AI applications in marketing and customer value through an analysis of 400 use cases across 19 industries in a McKinsey & Co. study.

Overall, our findings show that data bias management capability has a significant positive impact on both model bias management capability (β=0.595) and deployment bias management capability (β=0.565). These findings confirm H1 and H2 and signify the critical role of complete, well-formatted, and accurate data in developing and deploying a robust model which is reliable, flexible and ambidextrous. Shifting our attention from the anecdotal and fragmented evidence in the past literature, these findings empirically prove that a biased model and its deployment are caused by incorrect input features in training data that result in unexpected outcomes. The quality of a marketing model plays a critical role in serving customers (β=0.376), confirming the ability and knowledge of the data scientists, good intentions, and due ethical standards (H3). These findings indicate the necessity of developing dynamic algorithmic capabilities that embed ethics and justice to address the concern of unfair and discriminatory practices (Tsamados et al., 2021). The dynamic roles of data (β=0.396, H4), model (β=0.218, H5) and deployment (β=0.298, H6) bias management capabilities in shaping customer equity are reflected through its overall variance explained (R^2=0.569). According to the guidelines by Kenny (2015), these are strong effect sizes (> 0.025) in terms of the goodness of fit criterion. Although the findings show that data bias management capability plays the most important role in determining customer equity, followed by deployment and model, all the antecedents are significant, with a small degree of differences. The findings also confirm the significant, partial mediating roles of model bias and deployment bias management capabilities in influencing customer equity, which explain respectively 25% and 28% of the overall variance following the VAF (Variance Accounted For) calculation criterion by Akter et al. (2011).

6.2. Theoretical implications

This study makes several theoretical contributions. First, it contributes to advancing and extending the algorithmic bias management research stream in the marketing literature (e.g., Akter et al., 2022, Akter, Dwivedi, et al., 2021,Akter, McCarthy, et al., 2021; Danks & London, 2017; Lambrecht & Tucker, 2019; Walsh et al., 2020) and big data analytics capabilities literature (e.g., Kitchens et al., 2018; Mariani & Wamba, 2020; Moon & Iacobucci, 2022), by detecting and illustrating the primary dimensions (e.g., data bias, model bias, and deployment bias) and nine subdimensions of algorithmic bias management capabilities in AI-based marketing models that are relevant in highly uncertain and dynamic environments within industrial markets. This contribution enriches the ongoing debate within the literature about algorithmic biases (Israeli & Ascazra, 2020; Kordzadeh & Ghasemaghaei, 2022) in industrial marketing.

Second, this is virtually the first study in the industrial marketing literature that bridges the conceptual nexus between algorithmic bias management capabilities and customer equity (CE) (in the form of brand, relationship and value equity). Accordingly, we move beyond a dichotomic approach focusing either on algorithmic bias management capabilities (Akter et al., 2022) or on CE (Kumar & George, 2007). Indeed, by combining the algorithmic bias management capabilities research stream with the CE research stream in industrial marketing, we develop a holistic and multi-disciplinary (i.e., relying on marketing and data science) understanding of how algorithmic bias management capabilities can influence CE in B2B settings that are increasingly permeated by new digital technologies, such as AI-driven marketing (Schweidel et al., 2023; Xu et al., 2022). The finding that data bias management capabilities are a building block of bias management capabilities to reduce unjust and unfair outcomes, we suggest that CE primarily depends on data bias management capabilities and secondarily on model bias and deployment bias management capabilities.

Third, we contribute to extending current conceptualisations of dynamic capabilities (Teece, 2007; Teece et al., 1997) by introducing or extending three different capabilities: *data bias management capability* (DABMC), *model bias management capability* (MOBMC), *deployment bias management capability* (DPBMC). These should be contemplated as a specific set of bias management capabilities that can be juxtaposed by the firms to other dynamic capabilities to address customer equity-related issues in a data-driven manner. Accordingly, we also extend recent algorithmic bias management capabilities that have used dynamic capabilities (Akter et al., 2022) to identify algorithmic biases in ML-based marketing decision-making, suggesting that algorithmic bias management capabilities are dynamic capabilities that can change swiftly to fit the shifting business environment and are conducive to adapting, integrating, and re-configuring resources (Teece & Pisano, 2003) and opportunities brought about by AI and analytics driven changes in dynamic B2B environments.

Fourth and related to the previous point, this work contributes to extend also the research stream revolving around the dark side of data-driven technologies in marketing (Kumar, Shankar, & Aljohani, 2020) and algorithmic biases (Jones-Jang & Park, 2023; Kordzadeh & Ghasemaghaei, 2022), suggesting that an ensemble of bias management capabilities (i.e., data bias, model bias deployment bias management capabilities) can act both on technological resources (e.g., data and models) and organizational resources (e.g., integrity) to develop algorithmic capabilities that enhance customer equity in a fair, transparent, and accountable way. This extends research on capabilities portfolios (e.g., Majhi, Anand, Mukherjee, & Rana, 2021) that suggest that organizations can leverage on a collection of capabilities rather than individual capabilities. In so doing, we also argue that in highly turbulent and dynamic industrial markets, a portfolio or mix of bias management capabilities (covering data bias, model bias, deployment bias) is superior to individual bias management capabilities (e.g., only covering mode bias).

Finally, we also extend the emerging research stream revolving around digital capabilities (Elia, Giuffrida, Mariani, & Bresciani, 2021; Gurbaxani & Dunkle, 2019), suggesting that in today's digital and data-rich environments (Wedel & Kannan, 2016), a portfolio of "bias management" capabilities is critical for firms willing to engage with digital marketing (and more specifically their business customers) in an unbiased and ethical manner. This is especially relevant given the increasing relevance of AI-enabled algorithmic decision-making (Akter et al., 2022) in marketing and impact of emerging generative AI tools such as ChatGPT on marketing related activities (Dwivedi et al., 2023; Dwivedi, Pandey, Currie, & Micu, 2023). This way, "bias management" capabilities can be considered as a specific type of dynamic capabilities that can upgrade and reconstruct core organizational capabilities (Wang & Ahmed, 2007) in response to the changing digital environment.

6.3. Practical implications

Our results offer several practical implications. First, all managers exploring the sources of algorithmic bias management capabilities in marketing models and their influence on customer equity could use our results to guide their AI journey in industrial marketing. Second, our study suggests that firms need to put a holistic effort into managing data, model, and deployment bias management capabilities to foster customer equity. The findings confirm both the direct and indirect effects of these three primary dimensions that shape customer equity, which have implications for all marketing programs exploring the potential of AI. Indeed, there are growing concerns about data bias used to train AI algorithms that could lead to unintended consequences (e.g., discriminatory profiling, bank loan rejection, and rental applicant rejection) (Siala & Wang, 2022). The findings confirm that completeness, accuracy, and format are the data qualities that require critical attention to establish data bias management capability (Dilmegani, 2022). Some analysts even went as far as suggesting that "an AI system can be as good as the quality of its input data" (p. 1) (Dilmegani, 2022). The findings of our study confirm that data bias management capability significantly contributes to model bias and deployment bias management capabilities in shaping customer equity. Therefore, the findings suggest focusing on all bias management capabilities in an integrated manner to foster customer equity. Our findings provide a diagnostic tool that can be used to detect the sources of bias in AI based industrial marketing programs. This tool can help practitioners gain a strategic balance between revenue opportunities and unfair effects on society through their algorithmic offerings. The findings will provide managers greater autonomy to avert risk and prepare for any uncertainty, which can strike the right balance between organisational performance and bias-free outcomes to customers. Overall, the findings will ensure equality and social justice and contribute to customer equity through responsible AI practices in industrial marketing.

6.4. Future research and conclusions

This study is not without limitations, which also represent motivations for future research. First, while we found that algorithmic bias management capabilities for marketing consist of three second-order dimensions (e.g., data bias management capability, model bias management capability and deployment bias management capability), there might be a few more capabilities that are not contemplated. Future research might dig in depth about this. Second, we have identified subdimensions for each dimension. Technology advancement and changes in customer needs and wants over time might make some of these subdimensions weigh differently over time. Therefore, more longitudinal studies will be needed in the future to understand if the weight of each dimension and its subdimensions changes over time. Third, while the model was tested empirically effectively in order to generalize, further empirical studies should be undertaken across different industries and different contexts. This would significantly increase the generalizability of the findings. Last, given that we live in a networked economy, it would be interesting to understand what algorithmic bias management capabilities are drivers of customer equity (Sawhney & Zabin, 2002) that is a critical marketing construct increasingly examined in diverse AI contexts. This might pave the way for future research on the topic.

Data availability

Data will be made available on request.

Appendix A. Appendices

Appendix 1
Demographic profile of analytics professionals.

Items	Categories	%	Items	Categories	%
Gender	Male	57		18-25	33
	Female	43	Age	26-33	12
				34-41	28
				42-49	13
				50+	14
Experience in the job	3 Years	31		Data scientists	28
	4-5 years	28	Job types	Marketing managers	17
	6-7 years	14		IT managers	15
	8-9 years	15		Service managers	15
	10-11 years	07		Service managers	15
	12 yeas+	05		Others	10

Appendix 2
Demographic profile of customers.

Items	Categories	%	Items	Categories	%
Gender	Male	52		18-25	21
	Female	48	Age	26-33	25
				34-41	28
				42-49	17
				50+	09
Experience (with the bank)	3 years	15		NSW	30
	3-5 years	30	Location	Victoria	23
	5-7 years	28		Queensland	15
	7 years +	27		Western Australia	12
				South Australia	11
				Tasmania	09

Appendix 3
HTMT.

	COMP	FORM	ACCU	RELI	FLEX	AMBI	COMP	BENE	INTE	VAEQ	BREQ	REEQ
COMP	————											
FORM	0.558											
ACCU	0.642	0.735										
RELI	0.623	0.754	0.665									
FLEX	0.641	0.783	0.699	0.836								
AMBI	0.519	0.673	0.780	0.815	0.772							
COMP	0.653	0.751	0.726	0.679	0.513	0.629						
BENE	0.567	0.779	0.638	0.731	0.772	0.628	0.825					
INTE	0.681	0.625	0.710	0.799	0.747	0.719	0.654	0.675				
VAEQ	0.780	0.647	0.701	0.705	0.612	0.720	0.676	0.762	0.549			
BREQ	0.665	0.617	0.772	0.681	0.616	0.620	0.691	0.635	0.585	0.538		
REEQ	0.775	0.677	0.781	0.658	0.669	0.739	0.778	0.675	0.602	0.676	0.683	

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