



**HAL**  
open science

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

Shahriar Akter, Saida Sultana, Marcello Mariani, Samuel Fosso Wamba,  
Konstantina Spanaki, Yogesh Dwivedi

► **To cite this version:**

Shahriar Akter, Saida Sultana, Marcello Mariani, Samuel Fosso Wamba, Konstantina Spanaki, et al.. Advancing algorithmic bias management capabilities in AI-driven marketing analytics research. *Industrial Marketing Management*, 2023, 114, pp.243-261. 10.1016/j.indmarman.2023.08.013 . hal-04194438

**HAL Id: hal-04194438**

**<https://audencia.hal.science/hal-04194438>**

Submitted on 2 Sep 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Advancing algorithmic bias management capabilities in AI-driven Marketing Analytics Research

**Shahriar Akter**

School of Business  
University of Wollongong, NSW 2522, Australia  
Email: [sakter@uow.edu.au](mailto:sakter@uow.edu.au)

**Saida Sultana**

School of Business  
University of Wollongong, NSW 2522, Australia  
Email: [ss089@uowmail.edu.au](mailto:ss089@uowmail.edu.au)

**Marcello Mariani**

Henley Business School  
University of Reading, Greenlands, Henley on Thames Oxfordshire, UK RG9 3AU  
Email: [m.mariani@henley.ac.uk](mailto:m.mariani@henley.ac.uk)

**Samuel Fosso Wamba**

Toulouse Business School  
Toulouse University, 20 Boulevard Lascrosses, 31068 Toulouse, France  
Email: [s.fosso-wamba@tbs-education.fr](mailto:s.fosso-wamba@tbs-education.fr)

**Konstantina Spanaki**

Audencia Business School, Nantes, France  
email: [kspanaki@audencia.com](mailto:kspanaki@audencia.com)  
ORCID: <https://orcid.org/0000-0001-6332-1731>

**Yogesh K Dwivedi**<sup>a, b</sup>  
(Corresponding author)

<sup>a</sup> Digital Futures for Sustainable Business & Society Research Group, School of Management, Swansea University, Bay Campus, Fabian Bay, Swansea, Wales, UK  
Email: [y.k.dwivedi@swansea.ac.uk](mailto:y.k.dwivedi@swansea.ac.uk)

<sup>b</sup> Department of Management, Symbiosis Institute of Business Management, Pune & Symbiosis International (Deemed University), Pune, Maharashtra, India

## **Highlights**

- This study identifies the sources of algorithmic biases in industrial marketing;
- The study frames the effects of algorithmic bias management capabilities on customer equity;
- The findings identify data bias as the antecedent of model and deployment bias management capabilities;
- The findings highlight the roles of model and deployment bias as partial mediators between data bias and customer equity.
- The study uses algorithmic bias management concepts through the dynamic capability lens.

# **Advancing algorithmic bias management capabilities in AI-driven Marketing Analytics Research**

## **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.

**Keywords:** Algorithms; Algorithmic bias; AI-driven Marketing Analytics; Artificial Intelligence

## **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 (Columbus 2020; Davenport et al., 2020; Kumar et al., 2020; Mariani and 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 et al., 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, Guha, Grewal, & Bressgott, 2020). AI-based marketing analytics methods and recommendation systems accelerate the growth of customer equity (Hagen et al., 2020; Ma & Sun, 2020; Vermeer et al., 2019). As such, firms develop marketing offerings in industrial markets by monitoring post-purchase behaviour and analysing real-time data (Huang & Rust, 2018; Mariani et al., 2022). However, there is widespread evidence of unethical marketing practices due to discriminatory marketing models (e.g., Akter et al., 2021a,b; 2022; Dwivedi et al., 2021a,b). This results in negative customer equity since many customers are restricted equitable access to various marketing offerings (Hartmann et al., 2021; Israeli & Ascarza, 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 specific business groups based on particular gender profiles (Smionite 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 et al., 2021; Coombs et al., 2021; Dalenberg, 2018; Duan et al., 2019; Israeli and Ascazra, 2020; Kumar et al., 2021; 2023; Lambrecht and Tucker, 2018; Sun et al., 2020; Ng 2018; 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 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 et al. 2017). An unrepresentative training dataset, weak model design, or prejudiced deployment results in unfair customer equity in terms of value, brand, or relationship (Hartmann et al., 2021; Israeli & Ascarza, 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 (Teece, 2007; Helfat & Peteraf, 2003; Helfat & Martin, 2015; Martin, 2011), 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 and Ascazra, 2020). Furthermore, managers can mitigate the risk of potential bias and reduce the adverse effects on stakeholders by carefully managing algorithms while applying AI in various marketing programs ranging from data products to promotion decisions (Israeli and 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 et al., 2021; Durach et al., 2017; Tranfield et al., 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 and 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 (Lemon et al., 2001; Kim, Kim, & Hwang, 2020; Razzaq et al., 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 et al., 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, Kim & Hwang, 2020), customer equity (CE) has been widely researched in the marketing management literature (i.e., Sun et al., 2020; Yu and Yuan, 2019). Researchers have consistently emphasized the significance of CE in industries like service (Hussain et al., 2020; Ou et al., 2017), manufacturing (Ho and 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 et al., 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 et al., 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 et al., 2018). Ramaseshan et al. (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 Rehman & Johnston (2019) and Petzer, Verster, & 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 et al., 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 et al., 2023; Xu et al., 2022). For instance, Dash et al. (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 et al., 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 and 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 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.

**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 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, T. 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 (2019)	Review	The research put forwards that any problems related to data sampling and model training in ML 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 et al. (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 Giffenet al. (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, A. 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 et al. (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.
Ntoutsis 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 et al. (2021a)	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 et al. (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.
<u>Israeli and Ascazra (2020)</u>	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, Nasraoui, Shafto (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.

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 et al., 2021), healthcare (Panch, Mattie, & Atun, 2019; Seyyed-Kalantari et al., 2021), human resource management (Newman, Fast, and Harmon, 2020; Raghavan et al., 2020), economics (Cowgill & Tucker, 2020), data-driven innovation (Akter et al., 2021), computational linguistics (Markl, 2022), public administration (Wirtz et al., 2020), social research (Thiem et al., 2020) and many others. However, though the extant literature on marketing management has recognized the multiple benefits of AI (Schweidel et al., 2023; Varsha et al., 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 et al., 2021a; van Giffen, Herhausen, & Fahse, 2022; Wan et al., 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 et al. (2021a) 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 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 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, Denyer, & Smart (2003) and Watson, Wilson, Smart, & 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 (Snyder 2019; Palmatier et al., 2018). 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 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.

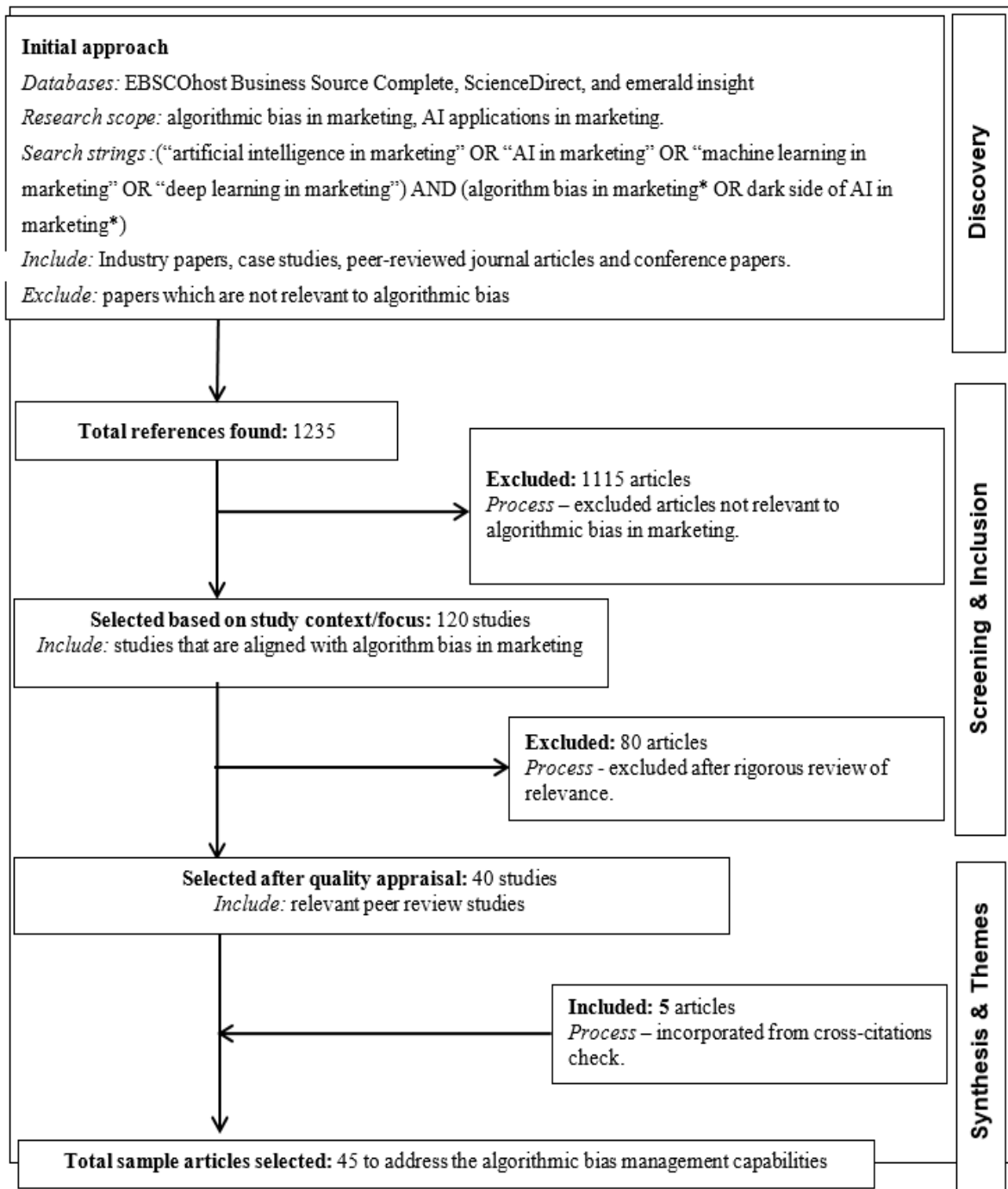


Figure 1: Literature review protocol

#### 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 (Geburu et al., 2020). Drawing on data quality literature (e.g., Nelson, Todd & Wixom 2005; Fosso Wamba, Akter & De Bourmont 2019), *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 and 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., Nelson et al., 2005; Fosso Wamba et al., 2019). For example, a recommendation engine may not work if the statistical principles or rules fail to associate the outcome variables and antecedents (Tsamadoset 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 et al., 2020). 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 et al., 2021a,b). *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 et al., 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 et al., 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 (CBA, 2020). Finally, *integrity* refers to the ability of the marketing analytics practitioners to uphold honesty, fairness, and justice (Colquitt 2007) or, fairness and moral character (Lind 2001) or value congruence (Sitkin and 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, Rust & Zeithaml, 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).

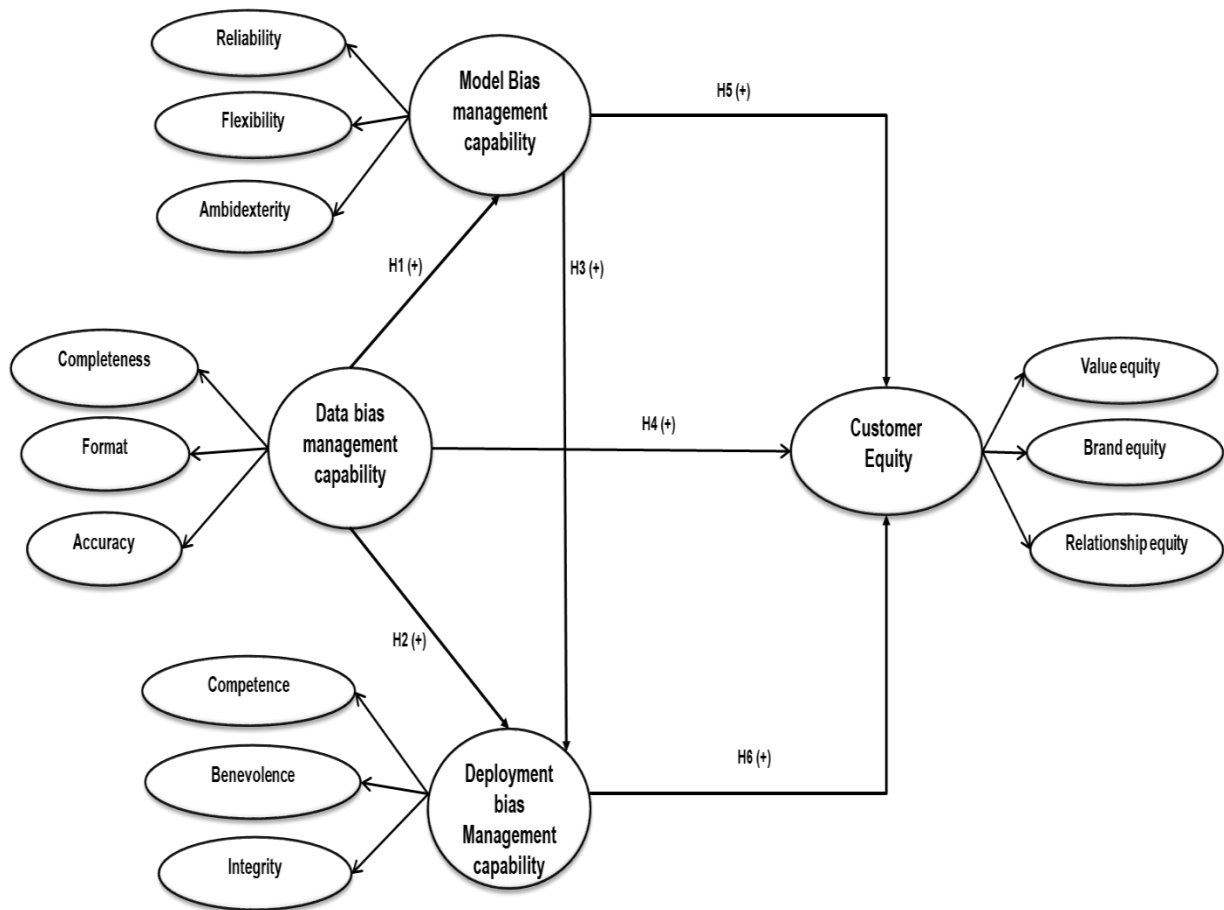


Figure 2: Research Model

#### 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 (Goretzko & Israel, 2022). Subsequently, such an incomplete model may exclude a specific group of people, which can also lead to incorrect forecasts for particular communities (Gianfrancesco et al., 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, Nasraoui, & Shafto, 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 et al., 2020), accuracy (Gudivada, Apon & Ding, 2017; Sengupta et al., 2018) and completeness (Rozado & David, 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, Teeple & Navathe, 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, 2019). 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, Tobin & Varner, 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 & Neil (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, 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., 2018). 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 and Ascarza, 2020). A similar case from the banking industry was also reported, where banks' algorithms favored more affluent, white customers than others (Will, 2021). Hence, building dynamic capabilities for managing model biases would significantly lessen the risk of deployment biases (Rajkomar et al., 2018). Firms can develop dynamic capability by ensuring the algorithmic model's explainability, transparency and fairness in terms of its actual feasibility (Srinivasan, 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, Herhausen & Fahse, 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 et al., 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 & Ascarza, 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 et al., 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 et al., 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 et al., 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 et al., 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 substandard machine learning model under its RoboDebt scheme, which unlawfully raised approx. \$1.73 billion in debts from 433,000 people (ABC, 2021).

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 & Ascarza, 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, 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, Todd, & Wixom, 2005), model bias management capability (Wixom & Todd, 2005), and deployment bias management capability (Akter et al., 2011). The study has also measured customer equity as the outcome constructs using value equity, brand equity, and relationship equity subdimensions (Ou, Verhoef, & Wiesel, 2017; Rust, Lemon, & Zeithaml, 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).



**Table 2 Operationalization of Constructs**

Constructs	Sub-constructs	Definitions	Item labels	Items
<b>Data bias management capability</b>	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.
<b>Model bias management capability</b>	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., 2020).	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.

<b>Deployment bias management capability</b>	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.
<b>Customer Equity</b>	Value Equity	It refers to the customer's subjective assessment of the benefits vs. cost of algorithmic services in a dynamic environment (Vogel et al., 2008; Ou, Verhoef, & Wiesel, 2017).	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; Rust et al. 2004; Ou, Verhoef, & Wiesel, 2017)	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, Verhoef, & Wiesel, 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.

## **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 et al., 2012; Sarstedt et al., 2019; Wetzels et al., 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 et al., 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 et al., 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 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, and Sarstedt's (2015) heterotrait-monotrait (HTMT) criterion (coefficients  $<0.90$ ) (see Appendix 3).

**Table 3: Assessment of First-Order, Reflective Model**

Dimensions	Reflective Constructs	Items	Loadings	CR	AVE
Data bias management capability (DABMC)	Completeness (COMP)	COMP1 COMP2 COMP3	0.898 0.907 0.897	0.928	0.811
	Format (FORM)	FORM1 FORM2 FORM3	0.810 0.865 0.859	0.882	0.714
	Accuracy (ACCU)	ACCU1 ACCU2 ACCU3	0.882 0.907 0.903	0.925	0.805
Model bias management capability (MOBMC)	Reliability (RELI)	RELI1 RELI2 RELI3	0.749 0.898 0.851	0.874	0.699
	Flexibility (FLEX)	FLEX1 FLEX2 FLEX3	0.820 0.851 0.809	0.866	0.684
	Ambidexterity (AMBI)	AMBI1 AMBI2 AMBI3	0.811 0.886 0.857	0.888	0.726
Deployment bias management capability (DPBMC)	Competence (COMP)	COMP1 COMP2 COMP3	0.880 0.858 0.870	0.902	0.755
	Benevolence (BENE)	BENE1 BENE2 BENE3	0.923 0.913 0.975	0.941	0.841
	Integrity (INTE)	INTE1 INTE2 INTE3	0.826 0.871 0.848	0.885	0.720
Customer Equity (CUEQ)	Value Equity (VAEQ)	VAEQ1 VAEQ2 VAEQ3	0.901 0.910 0.894	0.929	0.813
	Brand Equity (BREQ)	BREQ1 BREQ2 BREQ3	0.821 0.820 0.846	0.868	0.687
	Relationship Equity (REEQ)	REEQ1 REEQ2 REEQ3	0.841 0.858 0.841	0.884	0.717
Formative construct		Items	Weights	t-value	VIF
Control variables (Firm level) (COVA-F)		Age Gender Experience Job type	0.139 0.541 0.341 0.266	0.633 1.345 0.566 0.688	1.229 1.319 1.234 1.337
Control variables (Customers) (COVA-C)		Age Gender Income Service type	0.419 0.545 0.432 0.267	0.788 1.365 0.561 0.751	1.639 1.571 1.356 1.441

**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	<b>0.900</b>													
Format (FORM)	5.531	1.331	0.345	<b>0.845</b>												
Accuracy (ACCU)	5.322	1.314	0.419	0.432	<b>0.897</b>											
Reliability (RELI)	5.197	1.410	0.422	0.443	0.487	<b>0.836</b>										
Flexibility (FLEX)	5.228	1.135	0.391	0.461	0.461	0.496	<b>0.827</b>									
Ambidexterity (AMBI)	5.456	1.195	0.375	0.519	0.471	0.511	0.419	<b>0.852</b>								
Competence (COMP)	5.524	1.234	0.421	0.421	0.331	0.375	0.365	0.421	<b>0.869</b>							
Benevolence (BENE)	5.364	1.109	0.356	0.485	0.425	0.435	0.4220	0.335	0.384	<b>0.917</b>						
Integrity (INTE)	5.489	1.258	0.398	0.531	0.485	0.521	0.524	0.421	0.332	0.421	<b>0.849</b>					
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	<b>0.902</b>				
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	<b>0.828</b>			
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	<b>0.847</b>		
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	<b>n.a.</b>	
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	<b>n.a.</b>

\*square root of AVE on the diagonal

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 ( $\beta=0.853$ ), FORM ( $\beta=0.900$ ) and ACCU ( $\beta=0.891$ ) are significant subdimensions of DABMC as the path coefficients are significant at  $p<0.001$ . Similarly, RELI ( $\beta=0.848$ ), FLEX ( $\beta=0.872$ ), and AMBI ( $\beta=0.891$ ) have significant relationships with MOMBC dimension and COMP ( $\beta=0.930$ ), BENE ( $\beta=0.929$ ), and INTE ( $\beta=0.720$ ) 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.

**Table 5: Assessment of the higher-order model**

Model	Second-order	First-order	$\beta$	$R^2$	$t$ -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
(Antecedents)	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
(Antecedents)	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) Brand Equity (BREQ) Relationship Equity (REEQ)	0.878 0.906 0.850	0.813 0.687 0.717	56.085 76.040 42.378

## 5.6 Structural Model

The findings of the structural model (Table 6) show the significance of the hypothetical associations using path coefficients ( $\beta$ ), coefficient of determination ( $R^2$ ), and the effect size ( $f^2$ ). The findings confirm that DABMC has a significant, positive impact on MOBMC ( $\beta=0.595$ ,  $p<0.001$ ) and DPBMC ( $\beta=0.565$ ,  $p<0.001$ ). MOBMC significantly influences DPBMC ( $\beta=0.376$ ,  $p<0.001$ ), and both DABMC and MOBMC explain 66% variance of DPBMC. Thus, we confirm H1, H2 and H3. The findings also confirm that DABMC ( $\beta=0.396$ ,  $p<0.001$ ), MOBMC ( $\beta=0.218$ ,  $p<0.001$ ) and DPBMC ( $\beta=0.298$ ,  $p<0.001$ ) 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 (Barron & 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 ( $\beta=0.130$ ,  $p<0.001$ ) and DPBMC ( $\beta=0.153$ ,  $p<0.001$ ) following the guidelines of Hayes, Preacher, and Myers (2011) 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 6: Results of the structural model**

Hypotheses	Main Model	Path coefficients	f <sup>2</sup>	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)
<b>H7a</b>	DABMC-MOBMC-CUSEQ	0.130	3.732	0.000
<b>H7b</b>	DABMC-DPBMC-CUSEQ	0.153	3.636	0.000

## 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 and 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, 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 ( $\beta=0.595$ ) and deployment bias management capability ( $\beta=0.565$ ). 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 ( $\beta=0.376$ ), 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 ( $\beta=0.396$ , H4), model ( $\beta=0.218$ , H5) and deployment ( $\beta=0.298$ , 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, 2021a,b; 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 & Ascarza, 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 et al., 1997; Teece, 2007) 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 2020) and algorithmic biases (Kordzadeh & Ghasemaghaei, 2022; Jones-Jang & Park, 2023), 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 et al., 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 et al., 2021; Gurbaxani & Dunkle, 2019), suggesting that in today's digital and data-rich environments (Wedel and 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., 2023a; 2023b). 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.

## References

- Adam, M., Wessel, M. & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31(2), 427-445. <https://doi.org/10.1007/s12525-020-00414-7>
- Adomavicius, G., Bockstedt, J., Curley, S.P., Zhang, J. & Ransbotham, S. (2019). The hidden side effects of recommendation systems. *MIT Sloan Management Review*, 60(2), 1. <https://sloanreview.mit.edu/article/the-hidden-side-effects-of-recommendation-systems/>
- Akter, S., Dwivedi, Y.K., Biswas, K., Michael, K., Bandara, R.J. & Sajib, S. (2021a). Addressing algorithmic bias in AI-driven customer management. *Journal of Global Information Management (JGIM)*, 29(6), 1-27. DOI: 10.4018/JGIM.20211101.0a3
- Akter, S., Dwivedi, Y.K., Sajib, S., Biswas, K., Bandara, R.J. & Michael, K. (2022). Algorithmic bias in machine learning-based marketing models. *Journal of Business Research*, 144, 201-216. <https://doi.org/10.1016/j.jbusres.2022.01.083>
- Akter, S., D'Ambra, J. & Ray, P. (2011). Trustworthiness in mHealth information services: an assessment of a hierarchical model with mediating and moderating effects using partial least squares (PLS). *Journal of the American Society for Information Science and Technology*, 62(1), 100-116. DOI: 10.1002/asi.21442
- Akter, S., Fosso Wamba, S. & Dewan, S. (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. *Production Planning & Control*, 28(11-12), 1011-1021. <https://doi.org/10.1080/09537287.2016.1267411>
- Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y. K., D'Ambra, J., & Shen, K. N. (2021b). Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management*, 60, 102387. <https://doi.org/10.1016/j.ijinfomgt.2021.102387>
- Ali, M., Sapiezynski, P., Bogen, M., Korolova, A., Mislove, A. & Rieke, A. (2019). Discrimination through optimization: How Facebook's Ad delivery can lead to biased outcomes. *Proceedings of the ACM on human-computer interaction*, 3(CSCW), 1-30. <https://doi.org/10.1145/3359301>
- Almquist, E., Cleghorn, J., & Sherer, L. (2018). The B2B elements of value. *Harvard Business Review*, 96(3), 18. Accessed from <https://ellisonchair.tamu.edu/files/2020/06/The-B2B-Elements-of-Value.pdf>
- Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic management journal*, 14(1), 33-46. <https://doi.org/10.1002/smj.4250140105>
- Angwin, J., Tobin, A., & Varner, M. (2017, Nov.21). Facebook (still) letting housing advertisers exclude users by race. ProPublica. <https://www.propublica.org/article/facebook-advertising-discrimination-housing-race-sex-national-origin>
- Anees-ur-Rehman, M., & Johnston, W. J. (2019). How multiple strategic orientations impact brand equity of B2B SMEs. *Journal of Strategic Marketing*, 27(8), 730-750. <https://doi.org/10.1080/0965254X.2018.1482943>
- Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2019). Customer relationship management and big data enabled: Personalization & customization of services. *Applied Computing and Informatics*, 15(2), 94-101. <https://doi.org/10.1016/j.aci.2018.05.004>



- Baker, R. S., & Hawn, A. (2021). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, 1-41. <https://doi.org/10.1007/s40593-021-00285-9>
- Balayn, A., Lofi, C. & Houben, G.J. (2021). Managing bias and unfairness in data for decision support: a survey of machine learning and data engineering approaches to identify and mitigate bias and unfairness within data management and analytics systems. *The VLDB Journal*, 30(5), 739-768. <https://doi.org/10.1007/s00778-021-00671-8>
- Barocas, S. & Boyd, D. (2017). Engaging the ethics of data science in practice. *Communications of the ACM*, 60(11), 23-25. <https://doi.org/10.1145/3144172>
- Baron, R.M. & Kenny, D.A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, 51(6), 1173. DOI: 10.1037//0022-3514.51.6.1173
- Batra, M. M. (2017). Customer experience-an emerging frontier in customer service excellence. In *Competition Forum* (Vol. 15, No. 1, pp. 198-207). American Society for Competitiveness. [https://www.researchgate.net/profile/MadanBatra/publication/341667795\\_Customer\\_Experience\\_An\\_Emerging\\_Frontier\\_in\\_Customer\\_Service\\_Excellence\\_In\\_Competition\\_Forum/links/5ecdd75392851c9c5e5f61e8/Customer-Experience--An-Emerging-Frontier-in-Customer-Service-Excellence-In-Competition-Forum.pdf](https://www.researchgate.net/profile/MadanBatra/publication/341667795_Customer_Experience_An_Emerging_Frontier_in_Customer_Service_Excellence_In_Competition_Forum/links/5ecdd75392851c9c5e5f61e8/Customer-Experience--An-Emerging-Frontier-in-Customer-Service-Excellence-In-Competition-Forum.pdf)
- Becker, J.M., Klein, K. & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models. *Long range planning*, 45(5-6), 359-394. <https://doi.org/10.1016/j.lrp.2012.10.001>
- Bellamy, R.K., Dey, K., Hind, M., Hoffman, S.C., Houde, S., Kannan, K., Lohia, P., Martino, J., Mehta, S., Mojsilović, A. & Nagar, S. (2019). AI Fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias. *IBM Journal of Research and Development*, 63(4/5), 4-1. DOI: 10.1147/JRD.2019.2942287
- Bhutta, N., Chang, A.C. & Dettling, L.J. (2020). Disparities in wealth by race and ethnicity in the 2019 Survey of Consumer Finances. FEDS Notes 2020-09-28-2, Board of Governors of the Federal Reserve System (U.S.), DOI: 10.17016/2380-7172.2797
- Blier, N. (2019, August 15). Bias in AI and machine learning: Sources and solutions. *Lexalytics*. <https://www.lexalytics.com/lexablog/bias-in-ai-machine-learning>.
- Braun, V. & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, 3(2), 77-101. DOI:10.1191/1478088706qp063oa
- Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. <https://www.mckinsey.com/featured-insights/artificialintelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy>
- Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, 106, 102312. <https://doi.org/10.1016/j.technovation.2021.102312>
- Cartwright, S., Liu, H., & Raddats, C. (2021). Strategic use of social media within business-to-business (B2B) marketing: A systematic literature review. *Industrial Marketing Management*, 97, 35-58. <https://doi.org/10.1016/j.indmarman.2021.06.005>
- Castaneda, J., Jover, A., Calvet, L., Yanes, S., Juan, A. A., & Sainz, M. (2022). Dealing with Gender Bias Issues in Data-Algorithmic Processes: A Social-Statistical Perspective. *Algorithms*, 15(9), 303. <https://doi.org/10.3390/a15090303>
- Chang, W., Park, J. E., & Chaiy, S. (2010). How does CRM technology transform into organizational performance? A mediating role of marketing capability. *Journal of Business Research*, 63(8), 849–855. <https://doi.org/10.1016/j.jbusres.2009.07.003>
- Christofi, M., Vrontis, D. & Cadogan, J.W. (2021). Micro-foundational ambidexterity and multinational enterprises: a systematic review and a conceptual framework. *International Business Review*, 30(1), 101625. <https://doi.org/10.1016/j.ibusrev.2019.101625>
- Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018). Notes from the AI frontier: Insights from hundreds of use cases. *McKinsey Global Institute*, 2.
- Colquitt, A.J., Scott, B.A., & LePine, J. (2007). Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology*, 92(4), 909–927. <https://psycnet.apa.org/doi/10.1037/0021-9010.92.4.909>

- Commonwealth Bank Australia (2020), “Helping our customers understand the options available to them”, available at: <https://www.commbank.com.au/latest/coronavirus.html#:~:text=Loan%20repayment%20deferrals%203A,months%20through%20to%20September%202020>
- Coombs, C., Stacey, P., Kawalek, P., Simeonova, B., Becker, J., Bergener, K., Trautmann, H. (2021). What is it about humanity that we can't give away to intelligent machines? A European perspective. *International Journal of Information Management*, 58, 102311. <https://doi.org/10.1016/j.ijinfomgt.2021.102311>
- Cowgill, B., & Tucker, C. E. (2020). Algorithmic fairness and economics. *Columbia Business School Research Paper*. <https://dx.doi.org/10.2139/ssrn.3361280>
- Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability*, 14(3), 43-53.
- Dalenberg, D. J. (2018). Preventing discrimination in the automated targeting of job advertisements. *Computer Law & Security Review*, 34(3), 615-627. <https://doi.org/10.1016/j.clsr.2017.11.009>
- Danks, D., & London, A. J. (2017, August). Algorithmic Bias in Autonomous Systems. In *IJCAI*, 17, 4691–4697. DOI:10.24963/ijcai.2017/654
- Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. In *Ethics of Data and Analytics* (pp. 296-299). Auerbach Publications.
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48, 24-42. <https://doi.org/10.1007/s11747-019-00696-0>
- Davenport, T. & Malone, K. (2021). Deployment as a critical business data science discipline. *Harvard Data Science Review*, 3.1, 1-11, DOI: <https://doi.org/10.1162/99608f92.90814c32>.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108-116. <http://blockqai.com/wp-content/uploads/2021/01/analytics-hbr-ai-for-the-real-world.pdf>
- Deloitte and Salesforce (2018), ‘Consumer experience in the retail renaissance’ available at: <https://www.deloittedigital.com/us/en/blog-list/2018/consumer-experience-in-the-retail-renaissance-how-leading-brand.html>
- De Luca, L.M., Herhausen, D., Troilo, G. & Rossi, A. (2021). How and when do big data investments pay off? The role of marketing affordances and service innovation. *Journal of the Academy of Marketing Science*, 49(4), 790-810. <https://doi.org/10.1007/s11747-020-00739-x>
- De Visser, E. J., Peeters, M. M., Jung, M. F., Kohn, S., Shaw, T. H., Pak, R., & Neerinx, M. A. (2020). Towards a theory of longitudinal trust calibration in human–robot teams. *International journal of social robotics*, 12(2), 459-478. <https://doi.org/10.1007/s12369-019-00596-x>
- Dilmegani, C. (2022, October 27). *Bias in AI: What it is, Types, Examples & 6 Ways to Fix it in 2022*. AIMultiple; AIMultiple. <https://research.aimultiple.com/ai-bias/>
- Doney, P. M., & Cannon, J. P. (1997). An examination of the nature of trust in buyer–seller relationships. *Journal of marketing*, 61(2), 35-51. <https://doi.org/10.1177/002224299706100203>
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data—evolution, challenges and research agenda. *International journal of information management*, 48, 63-71.
- Durach, C.F., Kembro, J. & Wieland, A. (2017). A new paradigm for systematic literature reviews in supply chain management. *Journal of Supply Chain Management*, 53(4), 67-85. <https://doi.org/10.1111/jscm.12145>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023a). “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.
- Dwivedi, Y. K., Pandey, N., Currie, W., & Micu, A. (2023). Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda. *International Journal of Contemporary Hospitality Management*. Available at <https://doi.org/10.1108/IJCHM-05-2023-0686>

- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021a). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ... & Wang, Y. (2021b). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59, 102168. <https://doi.org/10.1016/j.ijinfomgt.2020.102168>
- Elia, S., Giuffrida, M., Mariani, M. M., & Bresciani, S. (2021). Resources and digital export: An RBV perspective on the role of digital technologies and capabilities in cross-border e-commerce. *Journal of Business Research*, 132, 158-169. <https://doi.org/10.1016/j.jbusres.2021.04.010>
- Eyers (2020). CommBank using AI to help triage loan deferral customers. Retrieved on January 14, 2023 from <https://www.afr.com/companies/financial-services/commbank-using-ai-to-help-triage-loan-deferral-customers-20200629-p5578e>
- Fahse, T., Huber, V., & Giffen, B. V. (2021, March). Managing bias in machine learning projects. In *International Conference on Wirtschaftsinformatik* (pp. 94-109). Springer, Cham.
- Fairlie, R., Robb, A. & Robinson, D.T. (2022). Black and white: Access to capital among minority-owned start-ups. *Management Science*, 68(4), 2377-2400. <https://doi.org/10.1287/mnsc.2021.3998>
- Fosso Wamba, S., Akter, S., & De Bourmont, M. (2019). Quality dominant logic in big data analytics and firm performance. *Business Process Management Journal*, 25(3), 512-532.
- Fornell, C. & Larcker, D.F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 18(3), <https://doi.org/10.1177/002224378101800313>
- Galdon Clavell, G., Martín Zamorano, M., Castillo, C., Smith, O. & Matic, A. (2020), February. Auditing algorithms: On lessons learned and the risks of data minimization. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 265-271). <https://doi.org/10.1145/3375627.3375852>
- Gartner, 2020. Healthcare technology innovations for identifying and managing COVID-19 patients. (Accessed 22 October, 2022) <https://www.gartner.com/document/3983039?ref=solrAll&refval=251329959/>
- Gebri, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., & Wallach, H. (2020). Hal Daumé III au2, and Kate Crawford. *Datasheets for datasets*, 2.
- Gianfrancesco, M. A., Tamang, S., Yazdany, J., & Schmajuk, G. (2018). Potential biases in machine learning algorithms using electronic health record data. *JAMA internal medicine*, 178(11), 1544-1547. doi: 10.1001/jamainternmed.2018.3763
- Gkikas, D. C., & Theodoridis, P. K. (2022). AI in Consumer Behavior. *Advances in Artificial Intelligence-based Technologies: Selected Papers in Honour of Professor Nikolaos G. Bourbakis—Vol. 1*, 147-176. [https://doi.org/10.1007/978-3-030-80571-5\\_10](https://doi.org/10.1007/978-3-030-80571-5_10)
- Goretzko, D., & Finja Israel, L. S. (2022). Pitfalls of machine learning-based personnel selection: Fairness, transparency, and data quality. *Journal of Personnel Psychology*, 21(1), 37. <https://doi.org/10.1027/1866-5888/a000287>
- Grewal, R., Lilien, G. L., Petersen, J. A., & Wuyts, S. (2022). Business-to-business marketing: Looking back, looking forward. In *Handbook of business-to-business marketing* (pp. 2-11). Edward Elgar Publishing. <https://doi.org/10.4337/9781800376878.00008>
- Grote, T. & Keeling, G. (2022). On algorithmic fairness in medical practice. *Cambridge Quarterly of Healthcare Ethics*, 31(1), 83-94. DOI: 10.1017/S0963180121000839
- Gudivada, V., Apon, A., & Ding, J. (2017). Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations. *International Journal on Advances in Software*, 10(1), 1-20. <http://www.ariajournals.org/software/>
- Guha, S., Rastogi, R. & Shim, K. (2000). ROCK: A robust clustering algorithm for categorical attributes. *Information systems*, 25(5), 345-366. [https://doi.org/10.1016/S0306-4379\(00\)00022-3](https://doi.org/10.1016/S0306-4379(00)00022-3)
- Gurbaxani, V., & Dunkle, D. (2019). Gearing up for successful digital transformation. *MIS Q. Executive*, 18(3), 6.
- Hawkins, D., & Hoon, S. (2019). The impact of customer retention strategies and the survival of small service-based businesses. *Stephanie, The Impact of Customer Retention Strategies and the Survival of Small Service-Based Businesses* (August 29, 2019). <https://dx.doi.org/10.2139/ssrn.3445173>



- Hagen, L., Uetake, K., Yang, N., Bollinger, B., Chaney, A.J., Dzyabura, D., Etkin, J., Goldfarb, A., Liu, L., Sudhir, K. & Wang, Y. (2020). How can machine learning aid behavioral marketing research? *Marketing Letters*, 31(4), 361-370. <https://doi.org/10.1007/s11002-020-09535-7>
- Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P. & Ray, S. (2021). Mediation analysis. In *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R* (pp. 139-153). Springer, Cham.
- Hardesty, Larry. "Study Finds Gender and Skin-Type Bias in Commercial Artificial-Intelligence Systems." MIT News, February 11, 2018. Available at <http://news.mit.edu/2018/study-finds-gender-skin-type-bias-artificial-intelligence-systems-0212> (accessed February 19, 2023).
- Hartmann, J., Heitmann, M., Schamp, C., & Netzer, O. (2021). The power of brand selfies. *Journal of Marketing Research*, 00222437211037258.
- Hartmann, K. & Wenzelburger, G. (2021). Uncertainty, risk and the use of algorithms in policy decisions: a case study on criminal justice in the USA. *Policy Sciences*, 54(2), 269-287. <https://doi.org/10.1007/s11077-020-09414-y>
- Hassani, B.K. (2021). Societal bias reinforcement through machine learning: a credit scoring perspective. *AI and Ethics*, 1(3), 239-247. <https://doi.org/10.1007/s43681-020-00026-z>
- Hayes, A.F., Preacher, K.J. & Myers, T.A. (2010). Mediation and the estimation of indirect effects in political communication research. *Sourcebook for political communication research: Methods, measures, and analytical techniques* (pp. 434-65). Routledge.
- Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D. & Winter, S.G. (2007). *Dynamic capabilities: Understanding strategic change in organizations*. Malden, MA: Blackwell Publishing.
- Helfat, C. E., & Lieberman, M. B. (2002). The birth of capabilities: market entry and the importance of pre- history. *Industrial and corporate change*, 11(4), 725-760. <https://doi.org/10.1093/icc/11.4.725>
- Helfat, C.E. & Martin, J.A. (2015). Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. *Journal of Management*, 41(5), 1281-1312. <https://doi.org/10.1177/0149206314561301>
- Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource- based view: Capability lifecycles. *Strategic management journal*, 24(10), 997-1010. <https://doi.org/10.1002/smj.332>
- Hooker, S. (2021). Moving beyond "algorithmic bias is a data problem". *Patterns*, 2(4), 100241. <https://doi.org/10.1016/j.patter.2021.100241>
- Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155-172. <https://doi.org/10.1177/1094670517752459>
- Huang, X.L., Ma, X. and Hu, F., 2018. Machine learning and intelligent communications. *Mobile Networks and Applications*, 23(1), pp.68-70.
- Hulland, J., Baumgartner, H. & Smith, K.M. (2018). Marketing survey research best practices: evidence and recommendations from a review of JAMS articles. *Journal of the Academy of Marketing Science*, 46(1), 92-108. <https://doi.org/10.1007/s11747-017-0532-y>
- Hussain, I., Mu, S., Mohiuddin, M., Danish, R. Q., & Sair, S. A. (2020). Effects of sustainable brand equity and marketing innovation on market performance in hospitality industry: Mediating effects of sustainable competitive advantage. *Sustainability*, 12(7), 2939. <https://doi.org/10.3390/su12072939>
- Indriasari, E., Gaol, F. L., & Matsuo, T. (2019, July). Digital banking transformation: Application of artificial intelligence and big data analytics for leveraging customer experience in the Indonesia banking sector. In *2019 8th International Congress on Advanced Applied Informatics (IIAI-AAI)* (pp. 863-868). IEEE. <https://doi.org/10.1109/IIAI-AAI.2019.00175>
- Israeli, A. & Asczra, E. (2020). Algorithmic Bias in Marketing (Reference no. 9-521-020). *Harvard Business Publishing*. <https://store.hbr.org/product/algorithmic-bias-in-marketing/521020>
- Janssen, M., Brous, P., Estevez, E., Barbosa, L.S. & Janowski, T. (2020). Data governance: Organizing data for trustworthy Artificial Intelligence. *Government Information Quarterly*, 37(3), 101493. <https://doi.org/10.1016/j.giq.2020.101493>
- Jones-Jang, S. M., & Park, Y. J. (2023). How do people react to AI failure? Automation bias, algorithmic aversion, and perceived controllability. *Journal of Computer-Mediated Communication*, 28(1), zmac029. <https://doi.org/10.1093/jcmc/zmac029>
- Keller, K.L. (2003). Understanding brands, branding and brand equity. *Interactive marketing*, 5(1), 7-20. <https://doi.org/10.1057/palgrave.im.4340213>
- Kenny, D. A. (2015). Moderation. available at: <http://davidakenny.net/cm/moderation.htm>.

- Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *Journal of Business research*, 65(10), 1480-1486. <https://doi.org/10.1016/j.jbusres.2011.10.014>
- Kim, W., Kim, H. & Hwang, J. (2020). Sustainable growth for the self-employed in the retail industry based on customer equity, customer satisfaction, and loyalty. *Journal of Retailing and Consumer Services*, 53, 101963. <https://doi.org/10.1016/j.jretconser.2019.101963>
- Kitchens, B., Dobolyi, D., Li, J., & Abbasi, A. (2018). Advanced customer analytics: Strategic value through integration of relationship-oriented big data. *Journal of Management Information Systems*, 35(2), 540-574. <https://doi.org/10.1080/07421222.2018.1451957>
- Kordzadeh, N. & Ghasemaghaei, M. (2022). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, 31(3), 388-409. <https://doi.org/10.1080/0960085X.2021.1927212>
- Kumar, V. & George, M. (2007). Measuring and maximising customer equity: A critical analysis. *Journal of Academy of Marketing Science*, 35, 157-171. <https://doi.org/10.1007/s11747-007-0028-2>
- Kumar, A., Ramachandran, A., De Unanue, A., Sung, C., Walsh, J., Schneider, J., Ridgway, J., Schuette, S.M., Lauritsen, J. & Ghani, R. (2020). A Machine Learning System for Retaining Patients in HIV Care. *arXiv*. <https://doi.org/10.48550/arXiv.2006.04944>
- Kumar, A., Shankar, R. & Aljohani, N.R. (2020). A big data driven framework for demand-driven forecasting with effects of marketing-mix variables. *Industrial marketing management*, 90, 493-507. <https://doi.org/10.1016/j.indmarman.2019.05.003>
- Kumar, P., Dwivedi, Y. K., & Anand, A. (2021). Responsible artificial intelligence (AI) for value formation and market performance in healthcare: The mediating role of patient's cognitive engagement. *Information Systems Frontiers*, 1-24, doi: <https://doi.org/10.1007/s10796-021-10136-6>
- Kumar, P., Sharma, S. K., & Dutot, V. (2023). Artificial intelligence (AI)-enabled CRM capability in healthcare: The impact on service innovation. *International Journal of Information Management*, 69, 102598.
- Lambrecht, A. & Tucker, C.E. (2018). Algorithmic bias? An empirical study into apparent gender-based discrimination in the display of STEM career ads. *An Empirical Study into Apparent Gender-Based Discrimination in the Display of STEM Career Ad*. 1-40. <http://dx.doi.org/10.2139/ssrn.2852260>
- Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of stem career ads. *Management Science*, 65(7), 2966-2981. <https://doi.org/10.1287/mnsc.2018.3093>
- Lee, N.T. (2018). Detecting racial bias in algorithms and machine learning. *Journal of Information Communication and Ethics in Society*, 16(3), 252-260. <https://doi.org/10.1108/JICES-06-2018-0056>
- Lee, S. M., & Lee, D. (2020). "Untact": a new customer service strategy in the digital age. *Service Business*, 14(1), 1-22. <https://doi.org/10.1007/s11628-019-00408-2>
- Lemon, K.N., Rust, R.T. & Zeithaml, V.A. (2001). What drives customer equity? *Marketing management*, 10(1), 20-25.
- Libai, B., Bart, Y., Gensler, S., Hofacker, C.F., Kaplan, A., Kötterheinrich, K. & Kroll, E.B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing*, 51, 44-56. <https://doi.org/10.1016/j.intmar.2020.04.002>
- Lind, E.A. (2001). Fairness heuristic theory: Justice judgments as pivotal cognitions in organizational relations. In J. Greenberg & R. Cropanzano (Eds.), *Advances in organizational justice* (pp. 56–88). Stanford, CA: Stanford University Press.
- Ma, L., & Sun, B. (2020). Machine learning and AI in marketing—Connecting computing power to human insights. *International Journal of Research in Marketing*, 37(3), 481-504. <https://doi.org/10.1016/j.ijresmar.2020.04.005>
- Majhi, S.G., Anand, A., Mukherjee, A. & Rana, N.P. (2021). The optimal configuration of IT-enabled dynamic capabilities in a firm's capabilities portfolio: A strategic alignment perspective. *Information Systems Frontiers*, 1-16. <https://doi.org/10.1007/s10796-021-10145-5>
- Mariani, M. M., & Wamba, S. F. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, 121, 338-352. <https://doi.org/10.1016/j.jbusres.2020.09.012>

- Mariani, M. M., & Nambisan, S. (2021). Innovation analytics and digital innovation experimentation: the rise of research-driven online review platforms. *Technological Forecasting and Social Change*, 172, 121009. <https://doi.org/10.1016/j.techfore.2021.121009>
- Mariani, M. M., Perez- Vega, R., & Wirtz, J. (2022). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. *Psychology & Marketing*, 39(4), 755-776. <https://doi.org/10.1002/mar.21619>
- Markl, N. (2022, June). Language variation and algorithmic bias: understanding algorithmic bias in British English automatic speech recognition. In *2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 521-534). <https://doi.org/10.1145/3531146.3533117>
- Marr, B. (2019). *Artificial intelligence in practice: how 50 successful companies used AI and machine learning to solve problems*. John Wiley & Sons.
- Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of business ethics*, 160, 835-850. <https://doi.org/10.1007/s10551-018-3921-3>
- Mayer, R.C., Davis, J.H., & Schoorman, F.D. (1995). An integration model of organizational trust. *Academy of Management Review*, 20(3), 709–734. <https://doi.org/10.5465/amr.1995.9508080335>
- Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological methods*, 17(3), 437.
- Mikalef, P., Conboy, K. and Krogstie, J., 2021. Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. *Industrial Marketing Management*, 98, pp.80-92. <https://doi.org/10.1016/j.indmarman.2021.08.003>
- Miller, B.D. (2017). *Cultural anthropology*. Pearson.
- Moon, S., & Iacobucci, D. (2022). Social media analytics and its applications in marketing. *Foundations and Trends® in Marketing*, 15(4), 213-292. <http://dx.doi.org/10.1561/17000000073>
- Moradi, A., & Vazifehdust, H. (2022). Brand equity and brand image with customer loyalty in pharmaceutical companies. *Entrepreneurship Knowledge*, 2(4).
- Nelson, R.R., Todd, P.A. & Wixom, B.H. (2005). Antecedents of information and system quality: an empirical examination within the context of data warehousing. *Journal of management information systems*, 21(4), 199-235. <https://doi.org/10.1080/07421222.2005.11045823>
- Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes*, 160, 149-167. <https://doi.org/10.1016/j.obhdp.2020.03.008>
- Ntoutsis, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdil, W., Vidal, M.E., Ruggieri, S., Turini, F., Papadopoulos, S., Krasanakis, E. & Kompatsiaris, I. (2020). Bias in data- driven artificial intelligence systems-An introductory survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 10(3), e1356. <https://doi.org/10.1002/widm.1356>
- O'Donnellan, R. (2020). Racist robots? How AI bias may put financial firms at risk. Intuition; Intuition. <https://www.intuition.com/disruption-in-financial-services-racist-robots-how-ai-bias-may-put-financial-firms-at-risk/>
- Okuda, T. & Shoda, S. (2018). AI-based chatbot service for financial industry. *Fujitsu Scientific and Technical Journal*, 54(2), 4-8.
- Ou, Y.C., Verhoef, P.C. & Wiesel, T. (2017). The effects of customer equity drivers on loyalty across services industries and firms. *Journal of the Academy of Marketing Science*, 45(3), 336-356. <https://doi.org/10.1007/s11747-016-0477-6>
- Panch, T., Mattie, H., & Atun, R. (2019). Artificial intelligence and algorithmic bias: implications for health systems. *Journal of global health*, 9(2). <https://doi.org/10.7189%2Fjogh.09.020318>
- Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: Purpose, process, and structure. *Journal of the Academy of Marketing Science*, 46, 1–5. <https://doi.org/10.1007/s11747-017-0563-4>.
- Pandey, A. & Caliskan, A. (2020). Iterative effect-size bias in ridehailing: Measuring social bias in dynamic pricing of 100 million rides. *arXiv*, 1-16. <https://doi.org/10.1145/3461702.3462561>
- Pandya, J. (2019, January 20). Can artificial intelligence be biased? Forbes. <https://www.forbes.com/sites/cognitiveworld/2019/01/20/can-artificial-intelligence-be-biased/?sh=470c23747e7c>
- Parikh, R.B., Teeple, S. & Navathe, A.S. (2019). Addressing bias in artificial intelligence in health care. *Jama*, 322(24), 2377-2378. <https://doi:10.1001/jama.2019.18058>



- Paulus, J.K. & Kent, D.M. (2020). Predictably unequal: understanding and addressing concerns that algorithmic clinical prediction may increase health disparities. *NPJ digital medicine*, 3(1),1-8. <https://doi.org/10.1038/s41746-020-0304-9>
- Petzer, D. J., Verster, A., & Cunningham, N. (2019). Using brand identity to build brand equity: A comparison between the South African and Dutch business-to-business architectural industry. *South African Journal of Business Management*, 50(1), 1-12. <https://hdl.handle.net/10520/EJC-15fa642ec8>
- Puspita, H., & Chae, H. (2021). An explorative study and comparison between companies' and customers' perspectives in the sustainable fashion industry. *Journal of Global Fashion Marketing*, 12(2), 133-145. <https://doi.org/10.1080/20932685.2020.1853584>
- Penrose, E.T. (1959). *The Theory of the Growth of the Firm*. New York: John Wiley.
- Peters, U. (2022). Algorithmic political bias in artificial intelligence systems. *Philosophy & Technology*, 35(2), 1-23. <https://doi.org/10.1007/s13347-022-00512-8>
- Preacher, K.J. & Hayes, A.F.(2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods*, 40(3), 879-891. <https://doi.org/10.3758/BRM.40.3.879>
- Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020, January). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency* (pp. 469-481). <https://doi.org/10.1145/3351095.3372828>
- Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science*, 48(1), 137-141. <https://doi.org/10.1007/s11747-019-00710-5>
- Rajkomar, A., Hardt, M., Howell, M.D., Corrado, G. & Chin, M.H.(2018). Ensuring fairness in machine learning to advance health equity. *Annals of internal medicine*, 169(12), 866-872. <https://doi.org/10.7326/M18-1990>
- Ramaseshan, B., Rabbanee, F. K., & Hui, L. T. H. (2013). Effects of customer equity drivers on customer loyalty in B2B context. *Journal of Business & Industrial Marketing*. <https://doi.org/10.1108/08858621311313929>
- Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. *MIT Sloan Management Review*, 59(1),1-24. <http://sloanreview.mit.edu/AI2017>
- Razaq, Z., Yousaf, S. & Hong, Z. (2017). The moderating impact of emotions on customer equity drivers and loyalty intentions: Evidence of within sector differences. *Asia Pacific Journal of Marketing and Logistics*. 29 (2), 239-264. <https://doi.org/10.1108/APJML-03-2016-0053>
- Rozado, D. (2020). Wide range screening of algorithmic bias in word embedding models using large sentiment lexicons reveals underreported bias types. *PloS one*, 15(4), e0231189. <https://doi.org/10.1371/journal.pone.0231189>
- Rust, R. T. (2020). The future of marketing. *International Journal of Research in Marketing*, 37(1), 15-26. <https://doi.org/10.1016/j.ijresmar.2019.08.002>
- Rust, R.T., Lemon, K.N. & Zeithaml, V.A., (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of marketing*, 68(1), 109-127. <https://doi.org/10.1509/jmkg.68.1.109.24030>
- Rust, R.T., Zeithaml, V.A. and Lemon, K.N. (2000), *Driving Customer Equity: How Customer Lifetime Value Is Reshaping Corporate Strategy*, The Free Press, New York, NY.
- Ryan, J., & Silvano, S. (2013). The critical role of corporate brand equity in B2B marketing: An example and analysis. *The Marketing Review*, 13(1), 38-49. <https://doi.org/10.1362/146934713X13590250137745>
- Salvato, M., Buchner, J., Budavári, T., Dwelly, T., Merloni, A., Brusa, M., ... & Nandra, K. (2018). Finding counterparts for all-sky X-ray surveys with NWAY: a Bayesian algorithm for cross-matching multiple catalogues. *Monthly Notices of the Royal Astronomical Society*, 473(4), 4937-4955. <https://doi.org/10.1093/mnras/stx2651>
- Sathi, A.(2017). *Engaging customers using big data: how Marketing analytics are transforming business*. Springer.
- Schweidel, D. A., Reisenbichler, M., Reutterer, T., & Zhang, K. (2023). Leveraging AI for content generation: A customer equity perspective. In *Artificial Intelligence in Marketing* (pp. 125-145). Emerald Publishing Limited. <https://doi.org/10.1108/S1548-643520230000020006>

- Sengupta, E., Garg, D., Choudhury, T., & Aggarwal, A. (2018, November). Techniques to eliminate human bias in machine learning. In *2018 International Conference on System Modeling & Advancement in Research Trends (SMART)* (pp. 226-230). <https://doi.org/10.1109/SYSMART.2018.8746946>
- Seo, H., Fu, L., & Song, T. H. (2023). Differential Impact of Customer Equity Drivers on Satisfaction: The Case of China's Telecommunications Industry. *Asia Marketing Journal*, 24(4), 178-189. <https://doi.org/10.53728/2765-6500.1600>
- Seyyed-Kalantari, L., Zhang, H., McDermott, M. B., Chen, I. Y., & Ghassemi, M. (2021). Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. *Nature medicine*, 27(12), 2176-2182. <https://doi.org/10.1038/s41591-021-01595-0>
- Shamma, H. & Hassan, S. (2013). Customer-driven benchmarking: A strategic approach toward a sustainable marketing performance. *Benchmarking: An International Journal*, 20(3), 377-395. <https://doi.org/10.1108/14635771311318144>
- Shellenbarger, S. (2019, February 13). A crucial step for averting AI disasters. *Wall Street Journal*, <https://www.wsj.com/articles/a-crucial-step-for-avoiding-ai-disasters-11550069865>
- Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.H., Ting, H., Vaithilingam, S. & Ringle, C.M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European journal of marketing*.53(11), 2322-2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Siala, H. & Wang, Y. (2022). SHIFTing artificial intelligence to be responsible in healthcare: A systematic review. *Social Science & Medicine*, 296, 114782. <https://doi.org/10.1016/j.socscimed.2022.114782>
- Silberg, J. & Manyika, J. (2019). Notes from the AI frontier: Tackling bias in AI (and in humans). *McKinsey Global Institute*, 1-6
- Simmering, M.J., Fuller, C.M., Richardson, H.A., Ocal, Y. and Atinc, G.M., 2015. Marker variable choice, reporting, and interpretation in the detection of common method variance: A review and demonstration. *Organizational Research Methods*, 18(3), 473-511. <https://doi.org/10.1177/1094428114560023>
- Simonite, T. (2018, November). When it comes to Gorillas, Google photos remain blind. *Quantstreams*; *Quantstreams*. <https://quantstreams.com/2018/01/11/when-it-comes-to-gorillas-google-photos-remains-blind/>
- Simonite, T. (2015). Probing the dark side of google's ad-targeting system. *MIT Technology Review*.
- Sipior, J.C. (2020). Considerations for development and use of AI in response to COVID-19. *International Journal of Information Management*, 55, 102170. <https://doi.org/10.1016/j.ijinfomgt.2020.102170>
- Sitkin, S.B., & Roth, N.L. (1993). Explaining the limited effectiveness of legalistic "remedies" for trust/distrust. *Organization Science*, 4(3), 367-392. <https://doi.org/10.1287/orsc.4.3.367>
- Sivarajah, U., Kamal, M.M., Irani, Z. & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of business research*, 70, 263-286. <https://doi.org/10.1016/j.jbusres.2016.08.001>
- Slaughter, R. K., Kopec, J., & Batal, M. (2020). Algorithms and Economic Justice: Taxonomy of Harms and a Path Forward for the Federal Trade Commission. *Yale JL & Tech.*, 23, 1-63.
- Smith, G., Rustagi, I., & Haas, B. (2020). *Mitigating bias in artificial intelligence: an equity fluent leadership playbook*. University of California (Berkeley), Center for Equity, Gender & Leadership
- Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of business research*, 104, 333-339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Srinivasan, A.V. & de Boer, M. (2020). Improving trust in data and algorithms in the medium of AI. *Maandblad voor Accountancy en Bedrijfseconomie*, 94, 147. <https://link.gale.com/apps/doc/A621598415/AONE?u=anon~767b6a57&sid=googleScholar&xid=22665248>
- Stahl, B.C. (2022). Responsible innovation ecosystems: Ethical implications of the application of the ecosystem concept to artificial intelligence. *International Journal of Information Management*, 62, 102441. <https://doi.org/10.1016/j.ijinfomgt.2021.102441>
- Sun, W., Nasraoui, O. & Shafto, P. (2020). Evolution and impact of bias in human and machine learning algorithm interaction. *Plos one*, 15(8), e0235502. <https://doi.org/10.1371/journal.pone.0235502>
- Suresh, H. & Gutttag, J. (2021). A framework for understanding sources of harm throughout the machine learning life cycle. In *Equity and access in algorithms, mechanisms, and optimization*, 1-9. <https://doi.org/10.1145/3465416.3483305>



- Thiem, A., Mkrtchyan, L., Haesebrouck, T., & Sanchez, D. (2020). Algorithmic bias in social research: A meta-analysis. *PloS one*, 15(6), e0233625. <http://doi.org/10.1371/journal.pone.0233625>
- Tsamados, A., Aggarwal, N., Cowls, J., Morley, J., Roberts, H., Taddeo, M., & Floridi, L. (2021). The ethics of algorithms: Key problems and solutions. *AI & SOCIETY*, 1–16. <https://doi.org/10.1007/s00146-021-01154-8>
- Salvato, C., & Vassolo, R. (2018). The sources of dynamism in dynamic capabilities. *Strategic Management Journal*, 39(6), 1728-1752. <https://doi.org/10.1002/smj.2703>
- Sarstedt, M., Hair Jr, J.F., Cheah, J.H., Becker, J.M. & Ringle, C.M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal (AMJ)*, 27(3), 197-211. <https://doi.org/10.1016/j.ausmj.2019.05.003>
- Takshi, S. (2020). Unexpected Inequality: Disparate-Impact from Artificial Intelligence in Healthcare Decisions. *JL & Health*, 34, 215. <https://engagedscholarship.csuohio.edu/jlh/vol34/iss2/6>
- Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic management journal*, 28(13), 1319-1350. <https://doi.org/10.1002/smj.640>
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, 18(7), 509-533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)
- Teece, D., & Pisano, G. (2003). *The dynamic capabilities of firms*. In Handbook on knowledge management (pp. 195-213). Springer, Berlin, Heidelberg.
- Thompson, J. (2021, July). Mental Models and Interpretability in AI Fairness Tools and Code Environments. In International Conference on Human-Computer Interaction (pp. 574-585). Springer, Cham.
- Trainor K. J., Andzulis J. M., Rapp A., & Agnihotri R. (2014). Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. *Journal of Business Research*, 67(6): 1201-1208.
- Tranfield, D., Denyer, D. & Smart, P. (2003). Towards a methodology for developing evidence- informed management knowledge by means of systematic review. *British journal of management*, 14(3), 207-222. <https://doi.org/10.1111/1467-8551.00375>
- Turner, R. (2021, Jun 11). Robodebt-condemned-by-federal-court-judge-as-shameful-chapter. ABC News. <https://www.abc.net.au/news/2021-06-11/robodebt-condemned-by-federal-court-judge-as-shameful-chapter/100207674>
- Valentine, S. (2019). Impoverished algorithms: Misguided governments, flawed technologies, and social control. *Fordham Urb. LJ*, 46, 364. <https://ir.lawnet.fordham.edu/ulj/vol46/iss2/4>
- van Giffen, B., Herhausen, D. & Fahse, T. (2022). Overcoming the pitfalls and perils of algorithms: A classification of machine learning biases and mitigation methods. *Journal of Business Research*, 144, 93-106. <https://doi.org/10.1016/j.jbusres.2022.01.076>
- Varsha, P. S., Akter, S., Kumar, A., Gochhait, S., & Patagundi, B. (2021). The impact of artificial intelligence on branding: a bibliometric analysis (1982-2019). *Journal of Global Information Management (JGIM)*, 29(4), 221-246. [10.4018/JGIM.20210701.oa10](https://doi.org/10.4018/JGIM.20210701.oa10)
- Venture Beat (Ed.). (2021). *Report: AI investments see largest year-over-year growth in 20 years*. <https://venturebeat.com/2021/12/06/report-ai-investments-see-largest-year-over-year-growth-in-20-years/>
- Vermeer, S. A., Araujo, T., Bernritter, S. F., & van Noort, G. (2019). Seeing the wood for the trees: How machine learning can help firms in identifying relevant electronic word-of-mouth in social media. *International Journal of Research in Marketing*, 36(3), 492-508. <https://doi.org/10.1016/j.ijresmar.2019.01.010>
- Vigdor, N. (2019, November 10). Apple card investigated after gender discrimination complaints. The New York Times, <https://www.nytimes.com/2019/11/10/business/apple-credit-card-investigation.html>
- Vogel, V., Evanschitzky, H. & Ramaseshan, B. (2008). Customer equity drivers and future sales. *Journal of marketing*, 72(6), 98-108. <https://doi.org/10.1509/jmkg.72.6.098>
- Walsh, C. G., Chaudhry, B., Dua, P., Goodman, K. W., Kaplan, B., Kavuluru, R., Solomonides, A. & Subbian, V. (2020). Stigma, biomarkers, and algorithmic bias: recommendations for precision behavioral health with artificial intelligence. *JAMIA open*, 3(1), 9-15. <https://doi.org/10.1093/jamiaopen/ooz054>

- Wan, M., Ni, J., Misra, R., & McAuley, J. (2020, January). Addressing marketing bias in product recommendations. In *Proceedings of the 13th international conference on web search and data mining* (pp. 618-626). <https://doi.org/10.1145/3336191.3371855>
- Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. *International journal of management reviews*, 9(1), 31-51. <https://doi.org/10.1111/j.1468-2370.2007.00201.x>
- Watson, R., Wilson, H.N., Smart, P. & Macdonald, E.K.( 2018). Harnessing difference: a capability- based framework for stakeholder engagement in environmental innovation. *Journal of Product Innovation Management*, 35(2), 254-279. <https://doi.org/10.1111/jpim.12394>
- Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of marketing*, 80(6), 97-121. <https://doi.org/10.1509/jm.15.0413>
- Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5, 795–815. <https://doi.org/10.1002/smj.4250050207>
- Wetzels, M., Odekerken-Schröder, G. & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS quarterly*, pp.177-195. <https://doi.org/10.2307/20650284>
- Whitney, H. M. (2017). The Regulation of Discrimination by Individuals in the Market. *U. Chi. Legal F.*, 537.
- Wirtz, B. W., Weyerer, J. C., & Sturm, B. J. (2020). The dark sides of artificial intelligence: An integrated AI governance framework for public administration. *International Journal of Public Administration*, 43(9), 818-829. <https://doi.org/10.1080/01900692.2020.1749851>
- Wixom, B.H. & Todd, P.A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information systems research*, 16(1), 85-102. <https://doi.org/10.1287/isre.1050.0042>
- Xu, Z., Zhu, G., Metawa, N., & Zhou, Q. (2022). Machine learning based customer meta-combination brand equity analysis for marketing behavior evaluation. *Information Processing & Management*, 59(1), 102800. <https://doi.org/10.1016/j.ipm.2021.102800>
- Yang, S. J., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Computers and Education: Artificial Intelligence*, 2, 100008. <https://doi.org/10.1016/j.caeai.2021.100008>
- Yu, X., & Yuan, C. (2019). How consumers' brand experience in social media can improve brand perception and customer equity. *Asia Pacific Journal of Marketing and Logistics*. <https://doi.org/10.1108/APJML-01-2018-0034>
- Zhang, J. & Qu, G., (2019). Physical unclonable function-based key sharing via machine learning for IoT security. *IEEE Transactions on Industrial Electronics*, 67(8), 7025-7033. <https://doi.org/10.1109/TIE.2019.2938462>
- Zhou, R., Liu, W., Lei, S., Zhang, W., & Huang, L. (2021, October). A Machine Learning Based Sameness Recognition Method for Power System Management Information. In *2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2)* (pp. 3318-3322). IEEE. <https://doi.org/10.1109/EI252483.2021.9713542>
- Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization science*, 13(3), 339-351. <https://doi.org/10.1287/orsc.13.3.339.2780>

## Appendices

### **Appendix 1: Demographic profile of analytics professionals**

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

### Appendix 2: Demographic profile of customers

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