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Guest Editorial

Algorithmic bias in data-driven innovation in the age of AI

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ABSTRACT

Data-driven innovation (DDI) gains its prominence due to its potential to transform innovation in the age of AI. Digital giants Amazon, Alibaba, Google, Apple, and Facebook, enjoy sustainable competitive advantages from DDI. However, little is known about algorithmic biases that may present in the DDI process, and result in unjust, unfair, or prejudicial data product developments. Thus, this guest editorial aims to explore the sources of algorithmic biases across the DDI process using a systematic literature review, thematic analysis and a case study on the Robo-Debt scheme in Australia. The findings show that there are three major sources of algorithmic bias: data bias, method bias and societal bias. Theoretically, the findings of our study illuminate the role of the dynamic managerial capability to address various biases. Practically, we provide guidelines on addressing algorithmic biases focusing on data, method and managerial capabilities.

1. Introduction

"Surely, nothing can be more plain or even more trite common sense than the proposition that innovation [.] is at the center of practically all the phenomena, difficulties, and problems of economic life in capitalist society." (Schumpeter, 1939, 87)

Data-driven innovation (DDI) research has gained momentum recently as we increasingly identify it as the new source of "creative destruction" (Schumpeter, 1950, p. 83) in the age of Artificial Intelligence (AI). In a similar spirit, scholars illuminate the emergence of the DDI phenomenon as the next management revolution (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012), the fourth paradigm of science (Strawn, 2012), a new paradigm of knowledge assets (Hagstrom, 2012), or the next frontier for innovation, competition, and productivity (Manyika et al., 2011). While DDI has enabled managers to develop various strategic innovations leveraging a range of descriptive, diagnostic, predictive and prescriptive algorithm-based methods (Davenport, Guha, Grewal, & Bressgott, 2020a; Sheng, Amankwah-Amoah, Khan, & Wang, 2020), scholars increasingly caution that emerging DDI research is grappling with many algorithmic biases emanating from training data, analytics models and socio-cultural sources (Israeli & Ascazra, 2020; Tsamados et al., 2021). As such, biased algorithmic decision making may result in unjust, unfair, or prejudicial treatment of people related to race, income, sexual orientation, religion, gender, and other characteristics historically associated with discrimination and marginalization (Mitchell et al., 2020).

Algorithms have become a critical foundation of the digital economy, underpinning data-driven innovation to transform our lives (Floridi & Taddeo, 2016). But algorithms are also beset with significant ethical risks with respect to fairness, accountability, and transparency (Hoffmann, 2019; Lee, Davari, Singh, & Pandhare, 2018; Shin & Park, 2019). Recent literature demonstrates that the datasets used in algorithms often reflect long-standing structural inequalities in our society (Abebe et al., 2020; Benjamin, 2019; Hu, 2017). Examples include Uber's and Lyft's discriminatory dynamic pricing for destinations with predominantly African-American populations (Pandey & Caliskan, 2020), Facebook's career advertisements related to science, technology, engineering, and math (STEM) focusing only on males (Lambrecht & Tucker, 2015), or Optum's racially biased medical algorithms being biased against black consumers (Blier, 2019). We define an algorithm as a "finite, abstract, effective, compound control structure, imperatively given, accomplishing a given purpose under given provisions" (Hill, 2016, 47). This definition is applied in DDI with the help of a training dataset and a model to achieve specific organizational objectives. In the context of DDI, we define bias as a "deviation from standard" (Danks & London, 2017, 4692) that can originate at any stage of the DDI process ranging from data product conceptualization to market feedback (see Section 2.1). Although algorithmic bias is predominantly rooted in unrepresentative datasets (Shah, 2018; Israeli & Ascazra, 2020), it can be embedded in biased methods (Binns, 2018; Diakopoulos & Koliska, 2017) or societal biases (Angwin, Tobin, & Varner, 2017; Bartlett, Morse, Stanton, & Wallace, 2019; Danks & London, 2017).

In the age of AI, DDI has gained further momentum due to innovations in the areas of speech recognition, web search, analytics, sensors and biodata, facial recognition or recommendation engines (Akter, Michael, Uddin, McCarthy, & Rahman, 2020; Ng, 2018). As the two crucial organs of AI, both machine learning (ML) or deep learning (DL) algorithms, have gained far more prominence due to their ability to process high volumes of data (Syam & Sharma, 2018). However, these algorithms cannot identify causality. Rather they identify correlations between variables in probabilistic terms, which often identify meaningless patterns or correlations that result in inconclusive evidence

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(Tsamados et al., 2021). In a similar spirit, Boyd & Crawford (2012, 668) stated, "seeing patterns where none actually exist, simply because massive quantities of data can offer connections that radiate in all directions." The research on algorithmic biases in DDI has attracted attention as researchers increasingly aim to develop ethical and fair AI (Dwivedi et al., 2021; Floridi, 2019; Floridi & Taddeo, 2016; Shah, 2018; Tsamados et al., 2021) across organizations (Blier, 2019; Hunter, 2020; Johnson, 2019; Martin, 2019), financial institutions (Agarwal, 2019; Davenport, 2019) and national governments (ABC News, 2020; Hauer, 2019; Roberts et al., 2019; Taddeo, McCutcheon, & Floridi, 2019). Despite the unequal, unjust and unfair effects of algorithmic bias in DDI, there is a paucity of research in this domain (Kar & Dwivedi, 2020, 2021; Kumar, Dwivedi, & Anand, 2021; Vimalkumar, Gupta, Sharma, & Dwivedi, 2021). Against this backdrop, the purpose of this guest editorial is to review the sources of algorithmic bias in DDI processes and to provide guidelines on how such biases can be addressed using dynamic managerial capability as a theoretical foundation (Helfat & Peteraf, 2003; Helfat & Martin, 2014; Martin, 2011). As such, our guest editorial aims to address the following research question:

1.1. RQ: What are the sources of algorithmic bias in the DDI process?

To answer this research question, we have discussed the DDI innovation process with the impact of algorithmic biases in Section 2 and theoretical underpinnings in Section 3. Then we applied a systematic literature review (SLR) method and discussed the procedures of thematic analysis in Section 4. With regard to the findings of the thematic analysis, we discuss the sources of algorithmic bias in various phases of DDI in Section 5. We then discuss a case study of algorithmic bias on the Australian Robo-debt crisis in Section 6. Finally, we present future research directions in Section 7, papers in the special issue in Section 8 and conclusions in Section 9.

2. Literature review

2.1. Data driven innovation

Data-driven innovation (DDI) is the process of creating and capturing value through a business model by untangling the potential value of data (Davenport & Kudyba, 2016). DDI aims to deliver innovative applications that may result in strategic advantages. These applications are generated from data analytics that drive firm performance and decision making processes, through utilizing data of any kind (Davenport, 2013; Stone & Wang, 2014). Companies are already deploying advanced analytics driven by data-rich ecosystems to develop competitive advantages (Akter & Wamba, 2016). Data monetization through DDI can transform firm performance for companies with a plethora of data. Therefore, Wixom and Ross (2017) recommend embracing DDI to improve internal business processes and decisions and to transform core products and service offerings. The growth of DDI relies heavily on a creative and dynamic method of fulfilling changing customers' needs (Im et al., 2013) at a time when customer demand for novelty, e.g. fast fashion, has never been higher.

2.2. Data products

Business organizations have developed a vast array of data products in recent years. For example, Amazon's powerful recommendation engine makes use of predictive modeling in data products (Brynjolfsson & McElheran, 2019; Jagannathan & Udaykumar, 2020; Varghese & Gopan, 2019; Wang, Kung, Wang, & Cegielski, 2018). Similarly, Trifacta developed Cloud Dataprep, which offers a data preparation service for rapid capture, processing, and data modeling (Novet, 2017). Google Data Studio is an example of visual analytics-based data products that facilitate improved decision making through embedded visually insightful analytics to unlock potential value (Sultana, Akter, Kyriazis, & Wamba, 2021). Further, Bridgestone America uses analytics that combine internal data, automaker data, and software provider data to advise customers to visit repair shops in advance (Ransbotham et al., 2017). Leading technology companies such as Google, Facebook, LinkedIn, and Yahoo! build data products such as "People You May Know," "Groups You May Like," or "Jobs You May Be Interested In" by collating information on mutual friends, educational history, or employment history (Davenport, 2013). DDI has enhanced the customer experiences in many ways, as evident by Netflix's collaborative filtering algorithm that anticipates customer's movie ratings (Akter et al., 2019; Chen, Chiang, & Storey, 2012;). But it has also allowed for users' search behavior to be exploited, for example, by Google to deliver targeted advertising (Davenport & Patil, 2012; Hienz, 2014). The development of data-driven products features distinctive characteristics such as interactivity, continuity, and parallelism and thus relies heavily on customers' engagement with a company or platform and its products within a changing digital ecosystem (Sultana et al., 2021).

2.3. Data-driven innovation process

Following the approach of the product innovation process, scholars have investigated critical steps of DDI as a closed-loop process (Jin, Liu, Ji, & Liu, 2016; Tao et al., 2018). In Fig. 1, the key steps of DDI are identified as product conceptualization, data acquisition, data refinement, storage and retrieval, distribution, presentation, and market feedback (Akter, Hossain, Lu, & Shams, 2021; Davenport & Kudyba, 2016). DDI starts with conceptualizing the needs of the market, and then develops foundations for further steps. To generate high customer satisfaction, firms need to pay detailed attention, to learn, and then to deliver novel data products focusing on their customers' needs (Chen, 2015). Data acquisition is the next step that focuses on capturing structured and unstructured data from all possible internal and external data sources (Cohen, Dolan, Dunlap, Hellerstein, & Welton, 2009; Dwoskin, 2015; Michael & Miller, 2013). In utilizing the advantages of big data, and to produce results that include successful innovation, data refinement has great importance (Boiten, 2016). At this stage, through refinement of structured and unstructured raw data, an abstract model leading to an implementable data structure is produced (Chen & Udding, 1989; Wirth, 2001). All entities within the abstract dataset should resemble practical, real-life events (Sultana et al., 2021). Data modeling techniques such as the Entity-Relationship Model can be applied to define the type of data required for efficient storage and management (Pandey & Pandey, 2019; Storey & Song, 2017). Next, DDI focuses on the storage, distribution, presentation, and market feedback stages, in order to deliver data products.

Storage and retrieval of data necessitates a robust data management platform to effectively deal with the variety, velocity and volume of unpolished data (Koulouzis et al., 2019; Wang et al., 2018; OMara, Meredig, & Michel, 2016). Retrieval ensures the integration of cutting-edge search processing, set up to align with the organization's data-driven products and storage infrastructure (Davenport & Kudyba, 2016). The data distribution model should foster rapid learning and problem resolution through collaborative problem solving (Sultana et al., 2021). The increased accessibility of smartphones and digital devices (e.g. edge devices) has forced data product innovators to reconfigure content design, and to configure mechanisms that are enabled by new generations of tools and technologies, in order to attain increased automation and reach (Davenport & Kudyba, 2016; Saldanha, 2019). Organizations need to integrate unique operational and business models, supported by analytic capabilities in order to facilitate the presentation and monetization of data for the designated stakeholders (Wixom & Ross, 2017). A unified data platform with data sharing across organizational boundaries is very useful for the effective presentation of data products to target stakeholder groups (Sultana et al., 2021).

The final step of DDI is engaging with the market through the interaction of the data products with the target customer segment, either

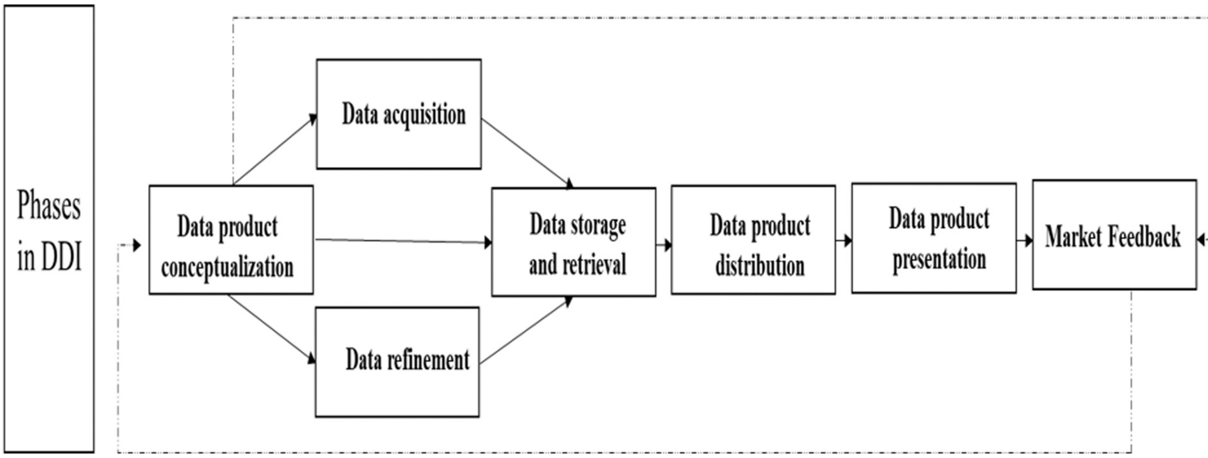

Fig. 1. Phases in data-driven innovation.

as a group or as an individual. Companies need to appropriately harness diverse methods and channels to gather valuable insights about their data products on a continuous basis. These appraisals might be accomplished through customer feedback platforms (Hasson, Piorkowski, & McCulloh, 2019; Wei, Shi, Li, & Chen, 2020), social media ratings, polling tools (Grewal, Hulland, Kopalle, & Karaha, 2020), interactive blogs (Zeidler, 2015), or by the utilization of on-site widgets such as Beacon (Sultana et al., 2021). The application of artificial intelligence-enabled machine learning technologies and the Internet of Things (IoT) has allowed the optimization of customer feedback through continuous interaction data (Akter et al., 2020). At present, with advances in machine learning and deep learning, algorithm processing technologies can deliver significant value to customers through classifying, coordinating, and categorizing customer profiles using a range of features data products (Davenport & Ronanki, 2018; Kiron, Prentice, & Ferguson, 2014). Table 1 shows seminal studies on DDI across different industries.

The emergence of DDI exposes stakeholders to the risk of algorithmic bias. At different stages of DDI, sources of algorithmic bias can produce detrimental impacts on the outcomes of the data products. For example, societal factors and individual beliefs can adversely affect the adequate conceptualization of the data product offerings. Then at the data acquisition and refinement stage, training dataset related factors can cause algorithmic bias (Davenport, Guha, Grewal, & Bressgott, 2020). Sample size and observability can result in biased outcomes of data retrieval. Data presentation may suffer from generalization problems. Finally, the feedback loop and interactions with a human/machine can cause harmful polarization. Overall, algorithmic bias can result in discriminatory pricing, restricting access to resources for vulnerable customers or members of minority groups (Israeli & Ascazra, 2020), and promoting price discrimination (Payne, Wilkinson, & Young, 2011). Therefore, protecting customers from bias within the current data-driven innovation of data products enabled by algorithmic applications is an important research avenue (Carmon, Schrift, Wertenbroch, & Yang, 2019; Davenport, Brynjolfsson, McAfee, & Wilson, 2019). In the following section, we present our theoretical positioning of the dynamic managerial capability and its role in addressing algorithmic bias across DDI steps.

3. Theory: dynamic managerial capability

The theoretical view of dynamic managerial capability posits that managers leverage distinctive capabilities to effectively build, nurture and apply dynamic capabilities within and across organizational boundaries (Helfat & Peteraf, 2003). Dynamic managerial capabilities include managerial cognitive, social, and human capabilities that play critical roles in building dynamic capabilities at the organization level in sensing, seizing and reconfiguring capabilities (Helfat & Peteraf, 2003; Teece, 2009). Managerial cognitive ability refers to the cognitive capacity of managers to accomplish tasks requiring significant cognitive engagement such as problem-solving, reasoning and perception attention to detail (Helfat & Peteraf, 2015). Managerial social capability refers to the ability to develop contacts and connections through organizational and individual social networks, allowing effective connections with critical information channels, vital resources, and opportunities to produce competitive advantages for firms (Adler & Kwon, 2002). Finally, managerial human capability is the managerial capacity to apply skills, knowledge and innovative capabilities that have been developed through past experience and educational background (Castanias & Helfat, 2001). The dynamic capability view perceives dynamic managerial capabilities as essential for effectively transforming internal resources and capabilities in accordance with changes in the external environment, through the integration of new technologies and successful innovation (Adner & Helfat, 2003; Kor & Mesko, 2013; Sirmon & Hitt, 2009; Teece, 2009, 2007).

The DDI process necessitates a range of skills, including data refinement, to convert an abstract data model into an implementable data structure (Boiten, 2016; Wirth, 2001) that includes intense engagement with key stakeholders (Wixom & Ross, 2017) and effective integration of customer feedback and insights (Hasson et al., 2019; Wei et al., 2020). Within the context of DDI, managers need to pay close attention to detect and eliminate potential risks of bias that may pose serious adversarial impacts to stakeholders, including customers (Israeli & Ascazra, 2020; Rozado, 2020). As such, Israeli and Ascazra (2020) state the importance of diversity in developer teams in DDI applications. In a similar spirit, scholars suggest nurturing diversity in the workforce responsible for developing DDI, an environment that utilizes advanced technologies, such as AI (Davenport, 2020; Rozado, 2020).

Overall, DDI requires intimate cognitive engagement due to the data-intensive nature of new data product development to effectively deliver predictive performance (Paulus and Kent 2020). DDI is highly iterative and complex in nature; therefore, it requires excellent problem-solving skills to create, devise and apply innovative approaches to address novel problems (Ng, 2018). Moreover, an individual manager's human capital, such as experience and specialized expertize, can prove invaluable during data product development, as that development requires expert engagement for reliable labeling (Sun, Nasraoui, & Shafto, 2020). In a situation where very little training data is available, a significant amount of specialized knowledge within the team is critical. Rich managerial social capital can also encourage diversity and foster an inclusive, dynamic community (Eisenhardt & Martin, 2000; Salvato & Vassolo, 2018). Table 2 shows dynamic managerial capabilities

Table 1
Seminal studies on data driven innovation.

Study type	Study	Main findings on data driven innovation
Empirical	Duan, Wang, and Zhou (2020)	Using absorptive capacity theory, the authors identify use of business analytics, environmental scanning, data-driven culture, innovation (new product newness and meaningfulness) as the antecedents to influence competitive advantage.
Empirical	Cappa, Oriani, Peruffo, and McCarthy (2020)	Applying the resource-based view, this study identifies three dimensions of big data (i.e., volume, variety, and veracity) to understand when the benefits outweigh the costs in the context of mobile device applications.
Technical	Xiao, Wang, Jiang, and Li (2018)	The authors outline the collaborative filtering engine (CFE) developed and deployed by Amazon that provides a personalized recommendation system to offer customized products to its customers through utilizing their interaction data and historical transactional data.
Theoretical	Balayan and Tomin (2020)	The authors outline the interest-based advertising developed and deployed by Google that offers users personalized advertisements to internet users by utilizing their interactions with Google products and platforms.
Theoretical	Trotman, Kallumadi, and Dagenhardt (2020)	The authors outline data driven innovation practices of eBay that adopted big data and artificial intelligence-based machine learning models to showcase recently viewed items and deliver tailored sales offers through articulating recent trends and purchase information of other users.
Conceptual	Zulaikha, Mohamed, Kurniawati, Rusgianto, and Rusmita (2020)	E-commerce company Brain analyzed real-time customer interactions and activities data through predictive analytics to produce recommendations for higher likelihood products for customers.
Conceptual	Gilmore (2020)	Netflix adopted a content affinity algorithm within its recommendation system to suggest relevant content to viewers based on their recently watched content.
Analysis	Guda and Subramanian (2019)	The authors outline the dynamic surge pricing adopted by Uber that utilizes a vast array of data of a specific location, including weather conditions, local events and recent news, to determine relative prices for the trip.
Conceptual	Rindfleisch, OHern, and Sachdev (2017)	The authors suggest processes to capture, analyze, and take appropriate action on data generated by consumers to strengthen new product innovation, leading to enhanced customer experience.
Theoretical model	Ylijoki (2019)	The authors highlight that for a given DDI to be considered successful, insights produced by the data either through human interpretation or automatically should lead to improvements.
Empirical	Johnson, Scott, and Hannah (2017)	The study validates 3Vs of big data usage—volume, variety, and velocity—in a new product development model identifying the antecedents of the multidimensional usage of big data.
Conceptual	Chandy, Hassan, and Mukherji (2017)	Big data for social innovation in emerging markets was shown through a series of case studies to solve pressing social and environmental problems.

identified in seminal studies that can be used in addressing algorithmic biases.

4. Methods

Based on a systematic literature review, this articles aims at explicating the sources of algorithmic bias in DDI. We have followed the established guidelines outlined by seminal review studies (e.g., Cranfield, Eales, Hertel, & Preckel, 2003; Durach, Kembro, & Wieland, 2017) to conduct the literature review and thematic analysis. In this study, we have identified several sources of algorithmic bias in DDI within the context of the digital ecosystem. To carry out a literature review, the following key sources for scholarly articles have been consulted: ScienceDirect, Business Source Complete, EBSCOhost and Emerald Insight. During the data collection process, a diverse set of search strings were employed to extract relevant literature encompassing the empirical inquiry (Dada, 2018; Vrontis & Christofi, 2019).

The search was conducted to explore publications available between January 2016 and December 2020. The search strings included “algorithms” “machine learning” “deep learning” “algorithmic bias”, “algorithmic bias in data products”, “algorithmic bias in data-driven innovation”, “algorithmic bias in machine learning model”, “ethical issues in AI”, “ethical concerns of AI, ”fairness in AI”, “bias in AI applications” and “dark side of AI”. Following initial screening using keywords, title, abstract, and the body of the article, a total of 89 papers were selected for further review. Further refinement based on relevance to the research question resulted in a list of 31 articles. A cross-reference checking of bibliographies produced 9 more papers. Finally, 40 publications were selected for thematic analysis to answer the research question on related to sources of algorithmic bias.

We have identified three primary themes following the process of thematic analysis (Braun & Clarke, 2006; Ezzy, 2002; Akter et al., 2020). The identified three primary themes were as follows: training data bias, method bias and societal bias. The themes were then validated and cross-checked by applying a reliability measure Krippendorff’s alpha (or Kalpha). Firstly, by analysing every article of the final 40 articles under three criteria, K alpha was measured. Then, we have calculated the interrater reliability of the identified themes through adopting the procedure outlined by other researchers (Hayes & Krippendorff, 2007; Swert, 2012; Hayes, 2012). Finally, the analysis findings holds a Kalpha value of 0.90, which is significantly higher than the threshold level of 0.80, thus providing sufficient evidence of reliability (Table 3).

5. Findings on algorithmic biases

Algorithmic bias can be viewed as a discriminatory case of algorithmic outcomes that may have an adversarial impact on protected or unprotected groups due to inaccurate modeling that misses associations between output variables and input features (Rozado, 2020; Tsamados et al., 2021). According to Floridi and Taddeo (2016, 4), “While they are distinct lines of research, the ethics of data, algorithms and practices are obviously intertwined … [Digital] ethics must address the whole conceptual space and hence all three axes of research together, even if with

Table 2
Seminal studies on dynamic managerial capability.

Study type	Study	Main findings	Relevance to algorithmic bias
Theoretical	Helfat and Peteraf (2003)	The authors suggest that managerial cognition, human capital and social capital are three microfoundations of dynamic managerial capability.	Dynamic managerial capabilities can act as a critical change agent in adopting innovative technologies in a manner that ensures fairness through effectively leveraging managerial cognitive ability, human capital and social capital.
Theoretical	Augier and Teece (2021)	The authors emphasize the role of managers in the development of dynamic capabilities following evolutionary and behavioral theoretical perspectives.	Managers can play vital roles in the effective evolution of organizational activities that may resist discriminatory practices thus allowing sustainable adoption of next generation technologies.
Review	Helfat and Martin (2014)	The authors find empirical evidence that managerial cognition, social capital and human capital can play a pivotal role in strategic change and organizational performance.	Dynamic managerial capabilities can be instrumental in ensuring effective management of fairness and bias during strategic change to ensure superior organizational performance.
Empirical	Peteraf and Reed (2007)	The authors confirm the necessary roles of dynamic managerial capabilities for the adaptive change of organizations within the context of a changing external environment.	Dynamic managerial roles can be instrumental in navigating adaptive changes within organization necessitating effective governance and procedures needed to address issues of bias originating from diverse sources.
Theoretical	Ambrosini and Altintas (2019)	The authors highlight that the microfoundations of dynamic managerial capabilities for competitive advantage.	Managers may effectively transform their organizational resource base to ensure critical resources be assigned to detect, mitigate and address algorithmic bias related issues.
Theoretical	Helfat and Peteraf (2015)	The authors highlight the role of managerial cognitive ability in performing organizational dynamic capabilities.	Superior managerial cognitive ability can ensure perspective taking, accommodating multiple perspectives and constructing associations among variables that can overcome personal beliefs or assumptions.
Empirical	Sirmon and Hitt (2009)	The authors suggest that the key focus of dynamic managerial capabilities is on resource management through effective asset orchestration to obtain superior firm performance.	Managers can orchestrate organizational resources in a manner that foster superior management of algorithmic bias.
Theoretical	Martin and Bachrach (2018)	This study highlights that dynamic managerial capability is an important theoretical viewpoint to explain the relationship between quality of managerial decisions, strategic changes and firm performance.	Superior quality of managerial decisions is a critical factor to ensure adoption of robust lifecycle approaches for algorithmic application development.
Empirical	Eggers and Kaplan (2009)	The authors find that managerial cognition plays a positive role in organizational adaptation by established firms, and the authors further suggest managerial attention towards emerging technology is related to higher growth of the firm.	Managerial attention to new technologies may be beneficial during successful organizational adaptation, resulting in effective and safe adoption of technologies for stakeholders and firm performance.
Empirical	Widianto, Lestari, Adna, Sukoco, and Nasih (2021)	The authors confirm the role of middle managers' dynamic roles and capabilities for organizational capacity for change and superior performance.	Middle managers can be catalysts in building organizational capacity for change in adopting AI tools and technologies and addressing algorithmic bias for safe adoption of technologies.

different priorities and focus"). Indeed, algorithmic bias can originate from an underlying dataset, inadequate methodological approaches (Walsh et al., 2020), or embedded societal factors.

5.1. Data bias

> *"Data plays a critical role in machine learning. Every machine learning model is trained and evaluated using data, quite often in the form of a static dataset. The characteristics of these datasets will fundamentally influence a model's behavior: A model is unlikely to perform well in the wild if its deployment context does not match its training or evaluation datasets, or if these datasets reflect unwanted biases."* (Gebru et al., 2020).

Training datasets used to train AI applications can cause algorithmic bias (Davenport et al., 2020; Israeli & Ascazra, 2020; Martínez-Villaseñor, Batyrshin, & Marín-Hernández, 2019; Sun et al., 2020). For example, a training dataset may not be adequate or may not represent a random sample from the target population, thus resulting in either sample inadequacy or sample selection bias. Similarly, if sample elements are selected from an incorrect target population, out-group homogeneity bias can arise as developers tend to identify members from incorrect sample units as more like a target population with regard to attributes, traits, values, attitudes and personality. Due to these biases, Amazon has recently abandoned using an AI-based recruitment algorithm platform that treated female applicants unfairly due to the scarcity of female applicants' data incorporated into the training dataset (Davenport et al., 2020; Martínez-Villaseñor et al., 2019). Similarly, the Apple credit card exhibited similar discriminatory outcomes for female applicants (Israeli & Ascazra, 2020). An algorithm's inability to foresee counterfactual data may cause fairness issues within the context of reinforcement learning, as we cannot predict appropriately how a patient will react to a new drug or whether a loan applicant who is not actually granted a loan would repay it (Chouldechova & Roth, 2020).

The size of the training dataset, if inadequate, can result in bias;

Table 3
Seminal studies on algorithmic biases.

Study type	Study	Main findings on algorithmic bias in business applications
Conceptual	Davenport et al. (2020)	This study confirms the positive aspects of machine learning-based AI applications in current business environments. The authors note that training dataset and opacity of the underlying algorithm can cause algorithmic bias.
Conceptual	Floridi and Taddeo (2016)	Data ethics include moral problems of data (e.g., collection, processing, distribution and sharing) and algorithms (in various applications of AI) and corresponding practices (including responsible innovation) to provide morally robust solutions.
Conceptual	Floridi and Cowls (2019)	The five ethical principles including beneficence, non-maleficence, autonomy, justice and explicability are the core foundations of ethical AI.
Conceptual	Abbasi-Yadkori et al. (2019)	Fairness in designing ML algorithms by mitigating sampling bias, confirmation bias, performance bias and anchoring bias. Suggestions come as good annotation, pairing data scientists with social scientists, sample representatives and de-biasing in mind.
Conceptual	Satell and Abdel-Magied (2020)	Explainable, auditable and transparent algorithms to mitigate biases and develop ethical AI.
Conceptual	Rai (2020)	The authors highlight the capacity of algorithmic bias to adversely affect vulnerable communities or customer segments. The authors emphasize that the highly complex nature of machine learning algorithms have caused a lack of trust in AI applications and systems.
Conceptual	Rust (2020)	The authors raise concern for algorithmic bias in AI applications and recommend business professionals address the challenges created by algorithmic bias through carefully embedding principles of diversity and inclusion in machine learning application development practices.
Review	Chouldechova and Roth (2020)	This study explicates findings suggesting the potential for integrating unfair and discriminatory practices as a result of DDI in ML applications, through embedding human bias, as well as introducing new bias in ML applications.
Technical report	Sun et al. (2020)	This research incorporates comprehensive discussion of the trade-offs within bias and variance in machine learning based applications, and the authors suggest adopting a systematic procedure to tackle algorithmic bias within business applications.
Review	Paulus and Kent (2019)	The authors highlight that machine learning based applications may contain sampling or data issues that may produce biased predictions that may result in unfair or harmful decisions across customer groups.
Empirical	Rozado (2020)	The author suggests that heavily adopted machine learning based applications such as language modeling or recidivism prediction may exhibit prejudices or societal biases.
Teaching note	Israeli and Ascazra (2020)	The authors suggest that in marketing practices algorithmic bias may privilege or disadvantage a specific group of customers considering personal characteristics such as gender, sexual orientation, religion or race.
Conceptual	Tsamados et al. (2021)	A conceptual model on six types of ethical concerns are discussed in terms of epistemic concerns (inconclusive evidence, inscrutable evidence and misguided evidence) and normative concerns (unfair outcomes, transformative effects and traceability).

therefore, a situation with the availability of only a small training dataset can increase bias (Sun et al., 2020; Ng, 2018). Moreover, the popularity of certain items over others can result in bias in the training dataset (Sun et al., 2020; Collins et al., 2010; Joachims, Swaminathan, & Schnabel, 2017). Contrarily, algorithms used in recommendation engines may experience blind spots that may adversely affect item discovery, making it difficult for some customers to find certain products or services (Sun et al., 2020). Furthermore, a content-based filter or personalized filter may generate inequality in estimating relevance that can adversely affect the human discovery of a specific item (Sun et al., 2020). Also, assimilation bias caused by a polarization impact on rating data derived through the continuous feedback loop can be generated by the interactions between recommendation engine and humans (Williams, Lopez, Shafto, & Lee, 2019).

5.2. Method bias

> *"As the use of machine learning technology has rapidly increased, so too have reports of errors and failures. Despite the potentially serious repercussions of these errors, those looking to use trained machine learning models in a particular context have no way of understanding the systematic impacts of these models before deploying them."* (Mitchell et al., 2019, p.2).

Methodological and procedural approaches that are adopted to design, develop and deploy machine learning-based application may have a significant impact on an algorithmic bias (Walsh et al., 2020). For example, the methods might result in a correlation fallacy, confusing correlation with causation. As Tsamados et al. (2021, 3) state, "These types of algorithms generally identify association and correlation between variables in the underlying data, but not causal connections." Similarly, the methods might result in overgeneralization of findings by providing generic insights, which may not be suitable for a specific context. Furthermore, with regard to hypotheses formulation or validation, studies have shown that humans tend to confirm or favor information that confirms a pre-existing belief or hypothesis. Indeed, personal belief can result in confirmation bias in individuals that resist any attempt to falsify a proposition emerging from evidence (Thiem, Mkrtchyan, Haesebrouck, & Sanchez, 2020). To avoid confirmation bias, scholars have advised adopting models with explanatory capacity that are supported by theoretical underpinnings allowing for empirical testing (Thiem et al., 2020). To address algorithmic bias in a systematic manner, different lifecycle approaches have recently been adopted within the AI community to design, build and deploy machine learning applications. Akkiraju et al. (2020) suggest that continuous improvement and a rich engagement with the stakeholders can address the underlying challenges of DDI to attain the highest quality outcomes. Garcia et al. (2018) advised paying attention to the context of the AI system, data and the person involved within the lifecycle of DDI to effectively tackle the challenges of harmful, unfair and discriminatory results.

Interaction with humans can result in a harmful feedback loop that can adversely affect AI models, causing them to produce exacerbated disparities for certain vulnerable populations or segments with biased predictions (Walsh et al., 2020). Conducting a bias-variance trade-off can impact the performance of AI models in DDI, as reducing variance and bias may have a reciprocal impact on each other. Ng (2018) suggests modification of input features considering insights gathered through error analysis, increasing model size with additional nodes or layers in the neural network, as well as taking into consideration an alternative model architecture to tackle avoidable algorithmic high bias. Inadequate experience with AI methods can produce unintended discriminatory results due to an inappropriately devised problem definition (Lorenzoni, Alencar, Nascimento, & Cowan, 2021).

5.3. Societal biases

"In order to fully unleash the profitable opportunities of AI, we first need to understand where biases come from. There is often an assumption that technology is neutral, but the reality is far from it. Machine learning algorithms are created by people, who all have biases. They are never fully "objective"; rather they reflect the world view of those who build them and the data they're fed". (Satell & Abdel-Magied, 2020, p.3).

Socio-cultural and demographic factors can result in an adversarial impact on the outcomes of DDI. Social and historical biases embedded within the dataset can exaggerate harm to disadvantaged populations of different social status, religion, sexual orientation, subcultures, age groups, gender and other social groups. Crawford et al. (2016) notes that underlying algorithms that have been applied in digital platforms may contain historical, and social discrimination. Delivering tailored products and services to a subcultural social group such as African-Americans or Asian-Americans using algorithm-based applications may produce historical, social discrimination. For example, Angwin et al. (2017) note that Facebook's targeted marketing ad on credit, employment and housing cannot be viewed by certain individuals with African-American backgrounds. Further, findings also suggest that historical discrimination and disparities are found in algorithmic decisions in determining credit or loan approval (Bartlett et al., 2019). The extant literature also reveals that Latino and Black individuals experience more rejections and also pay higher interest rates (Akter et al., 2021).

Cultural factors can cause discriminatory outcomes in algorithm-driven applications. For example, Yapo and Weiss (2018) note that Flickr has been criticized for producing racially indicative results such as associating animals (e.g., apes) with dark skin people. Similarly, Google searches exhibit racially biased results (e.g., advertisements related to crimes) when searching names with Black ethnic backgrounds (Kasperkevic, 2015). Sweeney (2013) raised concern regarding the racial bias of Google's advertising technology and urged fairness in the search technologies. In digital platforms, algorithms exhibit discriminatory outcomes to customers with certain socio-cultural and demographic backgrounds, as evidence supports that African-American customers experienced higher cancellation rates or extended waiting time in receiving Uber/Lyft trips (Ge et al., 2020; Pandey & Caliskan, 2020). In another context, Amazon's delivery system has systematically excluded neighborhoods with lower-level socio-economic demographics (Lee, Resnick, & Barton, 2019). Algorithmic biases also restrict access to critical resources, such as financial resources or opportunities such as admission to educational institutes for certain socio-cultural groups due to historical discriminatory practices that have been perpetuated to algorithm decision making (Vigdor, 2019; ODonnellan, 2020; Lee et al., 2019).

6. The algorithmic failure of Robo-debt scheme in Australia: a case analysis

"Marginalized groups face higher levels of data collection when they accept public benefits, walk through highly policed neighborhoods, enter the health-care system, or cross national borders. The data acts to reinforce their marginality when it is used to target them for suspicion and extra scrutiny. These groups seen as undeserving are singled out for punitive public policy and more intense surveillance, and the cycle begins again. It is a kind of collective red-flagging, a feedback of loop on injustice". (Eubanks, 2018, 6–7).

In 1990 legislation was passed allowing the Australian Taxation Office to share data with the Department of Social Security (now Services Australia). The process of data matching was to verify the reported income levels of welfare recipients against social security claims and to determine their level of accuracy. This process of data matching was automated in 2011 when the Australian Taxation Office cross-checked the Centrelink system (belonging to Services Australia) to target individuals who should not have received welfare payments because their actual earnings went above the threshold of eligibility. This generated more than 20,000 debt notices annually. While all these notices were not considered "welfare fraud" for the greater part, the system was effective in the recovery of debts. In 2015 the Department of Human Services conducted a two-stage pilot to replace the more manual system that had been in operation since 2011, using data from 2011 to 2013 but with limited actual stakeholder consultation (Parliament of Australia, 2017, ch. 6). By September 2016, the new fully automated system, known as the Online Compliance Intervention system, was operational with the ability to send computer-generated debt notices to welfare recipients who may have been overpaid, and critically, to do so without the need for human intervention. The number of debt notices skyrocketed from 20,000 per annum to 20,000 per week (Martin, 2016). This figure alone should have been the reason for alarm but instead, the Government heralded it a success in January 2017 when after just four months into the scheme, 169,000 debt notices had been sent to some of Australia's most vulnerable population, with A$300 million recovered (Redden, 2018). It was announced at that time that the Government had also considered expanding the Online Compliance Intervention to incorporate the Aged Pension and Disability Pension.

6.1. Criticism of robo-debt

According to Services Australia (2021), Centrelink distributes electronic payments to eligible welfare recipients in relation, but not limited to, the following contexts: retirees; the unemployed; families, carers, parents; people with disabilities; Indigenous Australians; students and apprentices; rural and remote Australians; migrants and refugees; people from diverse cultural & linguistic backgrounds, among other categories. Services Australia offers critical social security support to Australia's most vulnerable population, particularly when they belong to one or more of the above-mentioned contexts. For example, an individual living with a mental health condition on a disability pension who is also a single parent living in rural Australia where access to services may be limited.

The mailing of debt notices directly to vulnerable people, in particular, those living with physical or mental health conditions, was considered very poor practice, especially for a system that was supposed to be "intelligent". Additionally, the very basic requirement to cross-check address details with the physical address of the welfare recipient was not conducted before a debt notice was mailed out, and a lack of response was regarded as a refusal to engage.

The Online Compliance Intervention system, dubbed 'robo-debt' by the Australian media, did not target those who were on a stable salary but those who required social security payments for housing and basic necessities like food and paying energy bills. A salary is a fixed amount of money over an annual period, whereas many welfare recipients can only work casually, if at all, and are reliant on sporadic work in the form of wages, sourced often from one or more different employers with some level of unpredictability in earnings. The most significant problem identified with the robo-debt scheme was in the estimation of hours worked by welfare recipients. If the recipient did not enter specific details in a two-week period, then taxation income records were used to estimate a welfare recipient's average income, even if they did not work any hours in that period. While this sounds rather simplistic, there are three biases that can be identified here:

1. Data bias: the algorithm relied on data found in past taxation income records of the welfare recipient, assuming because a certain transactional pattern of historical waged employment had been prevalent, that the same pattern would continue (Parliament of Australia, 2017, ch. 6). The data bias was prevalent in neglecting to consider that welfare recipients might have needed to forego work hours due to obstacles that may have prevented them from working their allotted hours. This was a gross overgeneralization. For example, under the National Employment Standards (2021) in Australia, casual workers have very limited leave options with respect to sick leave, bereavement leave, domestic violence leave or other entitlements that would allow for longer than usual disruptions to individual work patterns due to unforeseen circumstances such as temporary illness, instability or difficulty at home;
2. Method bias: the algorithmic model estimated an average of hours worked in lieu of the actual hours worked. The model used in the Online Compliance Intervention system was flawed. The use of averaged income data to calculate welfare overpayments was not only bad design but blatantly "unlawful" (ABC News, 2020).
3. Socio-cultural bias: the algorithm targeted the marginalized based on their income level. Additionally, it required individuals to input their "hours worked" into the future, i.e., to predict and estimate their expected work hours to the best of their ability. Of course, individuals were not always offered the work that had been promised by their employers, or were not always able to fulfill those commitments given other factors. On other occasions, when some welfare recipients did not enter an income figure because they had not earned any money in a two week period given their personal circumstances, they assumed a value of "zero" would be recorded by default in the system but this was not the case. When a debt notice was sent, the algorithm also shifted the burden of proof onto the welfare recipient, away from Centrelink staff and back onto the citizen. Instead of Centrelink needing to verify the information of debt collection was accurate, the welfare recipient, with already limited resources, had to present counter-evidence to a vague debt collection notice (Glenn, 2017). Many citizens lacked the capacity to respond adequately, if at all. And some customers even pointed to online departmental advice at the Department of Human Services that had stipulated that there was a requirement to keep income records for the preceding 6 months only (Parliament of Australia, 2017, ch. 6).

The fact that there was very limited human interaction in the dispatch of debt letters to Australia's most "at risk" persons, demonstrates at least short-sightedness on the side of the Government, too strong an emphasis on efficiency, and too much faith in technology.

6.2. *Algorithmic fallout*

Fallout can be defined as the adverse results of a situation or act. It, therefore, follows that algorithmic fallout are the adverse results that humans suffer at the hands of automated processes that are data-driven leading to unjust or unfair rulings with financial repercussions (on individuals causing direct hardship or taxpayers at large), an increase in societal burden (undue feelings of anxiety and distress), distrust in the effectiveness and operationalization of AI-based systems (e.g. automated surveillance-based welfare systems), asymmetric attacks on one's character (causing personal shame, hurt and anguish), and even ultimately death (suicidal ideation or suicide). We cannot continue to create "algorithms of oppression" (Noble 2018). When data driven AI algorithms are used in public administration and are inextricably linked to people's livelihoods, especially in the context of welfare payments, there has to be a clear management capability and real accountability (Henriques-Gomes, 2021a). According to the First Senate inquiry into the Compliance program, there was a "lack of procedural fairness" (Parliament of Australia, 2017, ch. 6) that no doubt was exacerbated by AI. The Senate concluding chapter noted that the Compliance program "disempowered people, causing emotional trauma, stress and shame. This was intensified when the Government subsequently publicly released personal information about people who spoke out about the process" (Parliament of Australia, 2017, ch. 6; OAIC, 2019). Monolithic government agency systems with broad reach require commensurate socio-technical design, detailed piloting, rigorous testing, external risk assessment and evaluation. AI might have a reputation for being "fast" but at what cost (Hill, 2016)? No doubt, in this case study, a human cost. While these systems are large in scale and seemingly impersonal (i.e., one algorithm for all), the fallout is personal, asymmetric and leads individual customers to feel polarized. In the class action against the Federal Government, witnesses presented evidence of the indirect and direct impact that they perceived the robo-debt scheme had on loved ones, including suicidal ideation and, in a number of cases, confirmed suicide. One ABC report cited 633 vulnerable people had died (i.e., those living with mental health conditions or victims of abuse) during the robo-debt program roll-out (Medhora, 2019), among whom was Rhys Cauzzo, 28 years of age, who had battled with his mental health. Rhys' mother, Jennifer Miller, told the Federal Court that she believed her son's suicide was directly linked to a $17,000 Centrelink debt he received on Australia Day 2017 (Henriques-Gomes, 2021b). If this case study has acted to heighten awareness of the repercussions and unintended consequences of highly biased algorithms embedded in AI-based systems that also remove the human from the process altogether, then it will have served its purpose. Technology can be used to great positive effect, but managers are a necessity, so are their operational staff. Above all, human rights count (AHRC 2019).

7. Discussion and future research guidelines

> *"The development and use of AI hold the potential for both positive and negative impact on society, to alleviate or to amplify existing inequalities, to cure old problems, or to cause new ones"*. (Floridi & Cowls, 2019, 11).

In line with the above statement, our research into DDI in the age of AI highlights the need to mitigate algorithmic bias with a broader goal to establish ethical DDI. Based on the ethical AI guidelines of Floridi and Cowls (2019), our findings necessitate the development of ethical DDI algorithms that are bias-free and embrace beneficence in terms of the common good and benefits for humanity. In a similar spirit, DDI algorithms should be based on the motive of non-maleficence, i.e. they should do no harm and assure privacy and security of data. In addition, the decision making autonomy of both humans and machines should both be augmented in the DDI process without absolute reliance on artificial autonomy. Furthermore, DDI algorithms should ensure justice, enabling, as Floridi & Cowls (2019, 7) state, "the use of AI to correct past wrongs such as eliminating unfair discrimination, promoting diversity, and preventing the rise of new threats to justice". Finally, the DDI process should be based on the principle of explicability, which can illuminate transparency at different phases of innovation by including intelligibility of and accountability of the algorithms used in each phase. Fig. 2 synthesizes all the phases of DDI in which algorithmic biases might result in unjust and unfair outcomes.

With regard to data bias, Abbasi-Yadkori et al. (2019, 3) state that "Bias can manifest itself in many forms across various stages of the machine learning process, including data collection, data preparation, modeling, evaluation, and deployment". The findings of our study on data bias in Fig. 2 show that a DDI process is embedded with selection bias, anchoring bias, out of group homogeneity bias and sample adequacy bias. If training data reflects such biases, an AI model used in DDI can reproduce or amplify such biases when it is deployed to develop new data products (Gebru et al., 2020). Thus, it is critical to develop a document of provenance, creation and use of algorithms in DDI to avoid

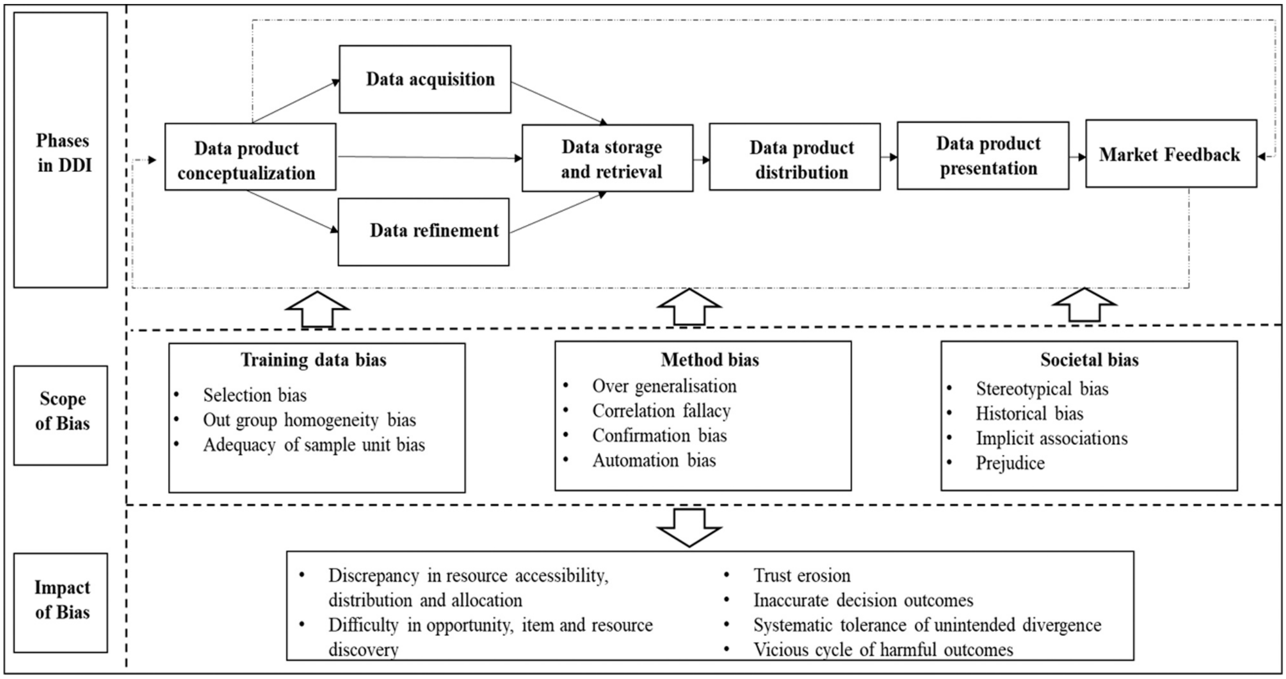

Fig. 2. Algorithmic biases in DDI phases.

any unfair outcomes (WE forum 2018). Based on the guidelines of Gebru et al. (2020), we advocate exploring datasheets for datasets as a future research direction to serve the needs of dataset creators and dataset consumers. With the help of a datasheet, DDI managers can check all the embedded assumptions and risks during the creation, distribution of maintenance of a dataset. Furthermore, consumers can make sure they have all the required information to make an informed decision utilizing the data product. Throughout the DDI process, the datasheet for each data product should clearly address questions on the motivation for developing new data products, data collection objectives, collection process, data formatting and labeling procedures, uses, distribution and maintenance of the dataset.

In the context of method bias, we have explicated various types of bias linked to methodological approaches for building and applying algorithms in DDI. Fig. 2 illustrates that bias may originate due to various methodological issues, such as overgeneralization, correlation fallacy, confirmation bias and automation bias. The issues of method related algorithmic bias can result in inappropriate or unintended outcomes of machine learning applications (Thiem et al., 2020; Tsamados et al., 2021; Walsh et al., 2020). It is imperative to consider, adopt and institute procedural approaches to ensure transparency, explainability, accountability, fairness and ethical considerations of the underlying models used in lifecycles of machine learning applications (Garcia et al., 2018; Lee et al., 2018; Shin & Park, 2019; Lorenzoni et al., 2021). It is critical to attaining the necessary effectiveness of the algorithmic decision making to overcome the challenges of bias during the DDI phases (Akkiraju et al., 2020; Ng, 2019). We, therefore, emphasize the need to consider preparing, disseminating and maintaining a model card, detailed documentation, representing the key attributes of an algorithmic model (Mitchell et al., 2019). This can articulate metrics capturing the bias, fairness, considerations of inclusion and performance characteristics. Therefore, the practice of deploying a model card can foster superior engagement with the stakeholders, such as AI practitioners, model developers, software developers, policymakers and the focal users (Mitchell et al., 2019). The practice of using a model card can better inform relevant stakeholders about the embedded features of the models with vivid disclosure of the appropriate contextual suitability to ensure effective delivery of the intended service in a specific context. During DDI phases, a model card should contain information regarding evaluation factors, performance measures, decision thresholds and variation approaches, evaluation data, training data, quantitative analysis including unitary and intersectional results, ethical consideration, caveat and recommendations to foster transparency throughout the innovation phases. Adopting these recommendations not only help foster social justice, but they can also help mitigate risk for organizations and governments who may unwittingly breach anti-discrimination legislation through the naive or ill-informed application of AI capabilities in DDI.

As a theoretical foundation, we propose applying dynamic managerial capabilities, which are critical to predicting, detecting and mitigating potential biases within AI-based data products to ensure fairness. This can be accomplished through conducting audits and specifically contemplating the behavior of underlying algorithms through diverse perspectives validated by empirically sound methodologies (Israeli & Ascazra, 2020). Rozado (2020) suggests building a heterogeneous well-educated workforce and recommends engaging in adversarial collaboration to appropriately scrutinize, detect and address issues of bias to mitigate the risk of harmful impact. Mobilizing expertize and talents from diverse backgrounds is necessary for building AI-driven products in general (Ransbotham, Kiron, & Prentice, 2015). Managerial social capital can be highly valuable in accommodating diverse perspectives and conflicting viewpoints while developing algorithm-based data-driven products to ensure fairness in addressing the potential scope of bias. Based on the guidelines of Abbasi-Yadkori et al. (2019), we suggest applying fairness by design principles to mitigate method bias by pairing data scientists with social scientists, careful annotations of variables, robust representation of target population and potential de-biasing mechanisms in mind. In addition, a framework of ethical principles with well-crafted regulation and common standards can help DDI grow and flourish to secure a positive social outcome (Floridi & Cowls, 2019).

8. Papers in this special issue

The focus of this Special Issue (SI) was to invite DDI scholars and practitioners on exploring the challenges and opportunities of DDI in digital markets. In achieving this objective, this SI provides a holistic picture of DDI, which will help organizations prepare for this new paradigm of innovation. The SI selected methodologically rigorous and theoretically relevant papers, which are aligned with this objective mentioned above through a strict review process. A total of three papers have been selected.

The first paper, entitled “From user-generated data to data-driven innovation: A research agenda to understand user privacy in digital markets”, by Saura, Ribeiro-Soriano, and Palacios-Marqués (2021), provides a comprehensive understanding of the main challenges related to user privacy that affect DDI. The paper identifies 14 topics related to the study of DDI and user-generated data (UGD) strategies, applying three unique research phases; (i) a systematic literature review (SLR); (ii) in-depth interviews framed in the perspectives of UGD and DDI on user privacy concerns, and finally, (iii) topic-modeling using a Latent Dirichlet allocation (LDA) model.

The second paper titled “Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda”, by Bresciani, Ciampi, Meli, and Ferraris (2021), demonstrates three thematic clusters, which respectively focused on (i) big data (BD) as a knowledge creation enabler within co-innovation contexts, (ii) BD as a driver of co-innovation processes based on customer engagement, and finally (iii) the impact of BD on co-innovation within service ecosystems.

In the third paper, “Swarm intelligence goal-oriented approach to data-driven innovation in customer churn management” by Kozak, Kania, Juszczuk, and Mitręga (2021), the authors present the specific features and the role of swarm intelligence machine learning (SIML) methods in customer churn management and to test if a modified SIML algorithm may increase the effectiveness of churn-related segmentation and an improved decision making process. The study brilliantly used publicly available customer data to show how SIML methods facilitate managerial decision-making with regard to customers potentially leaving the company in the context of changing conditions.

9. Concluding remarks

Advances in algorithmic bias research offer avenues to unmask DDI black-box in the age of AI. The findings of our study show that biases may originate from various sources, specifically data, method and societal factors. Understanding the nature and type of these biases opens exciting research avenues for DDI scholars in developing transparent, explainable and auditable algorithms. Leveraging such algorithms across the development, deployment, and use of data products can help establish fairness and build a trustworthy AI.

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