

A SCOPING REVIEW ON GENDER BIAS IN AI-BASED DECISION MAKING SYSTEMS

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ABSTRACT

Artificial intelligence (AI)-based decision-making systems may display gender prejudice, according to industry studies and literature, which could have detrimental effects on both people and society as a whole. The control of gender bias in these systems and its negative repercussions are not well studied, despite the fact that the information systems area recognizes the important contributions of AI outcomes and their ramifications. As such, there is a rising concern about gender bias in AI decision-making, which is garnering more attention. In particular, there is an urgent need to comprehend the variables that contribute to gender bias in AI-based systems and to find practical solutions. The review's conclusions show that there is still a dearth of study on gender bias in AI decision-making, suggesting that there are a lot of untapped research opportunities in this area.

Keywords: Artificial Intelligence, Fairness, Gender Bias.

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INTRODUCTION

Decision-making systems based on artificial intelligence (AI) are becoming more prevalent in many industries and ingrained in our daily lives. Numerous advantages of these systems are highlighted in the literature currently under publication, including improved decision-making and organizational operations [1]. Due to less face-to-face encounters and a growing reliance on automation, recent research have revealed a spike in interest in AI-based decision-making systems during the COVID-19 pandemic [2]. The adoption of

these systems in numerous industries has been further accelerated by this trend. But while though AI-based decision-making systems can help with a variety of problems in different fields, they can also have unanticipated negative consequences, such as gender-biased results that negatively impact people or minority groups because of their gender, race, or color [3–7]. It's concerning that these systems are being used more and more to evaluate job applications, decide loan approvals, determine insurance rates and

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benefits, and provide access to social assistance, among other things [8, 9]. Instances of gender bias in AI-based decision-making have been documented in both scientific literature and mainstream media. For example, Facebook's job ads disproportionately targeted males for STEM (science, technology, engineering, and mathematics) positions and for credit loan applications. Additionally, Amazon abandoned an AI-based recruitment system due to its gender-biased outcomes [10], which stemmed from a lack of female applicant data in the training datasets.

Governments and academic groups have also expressed concerns about gender bias in AI-based decision-making systems [11, 12]. These systems have detrimental effects on families, communities, and society at large in addition to individuals. In order to guarantee fairness in their results—a core tenet of AI ethics—it is imperative to assess AI-based decision-making systems for gender bias. Organizations will also be able to make wise strategic decisions with a better grasp of this bias [13].

With a particular focus on gender bias in AI-based decision-making systems, this work aims to contribute to the growing corpus of information systems literature about the unintended negative effects of artificial intelligence (AI). The study's three primary goals are to describe and evaluate the traits of gender bias in these systems, as well as to look at the causes of gender prejudice and the methods that have been proposed to address it.

Making decisions automatically, without human intervention, is known as automated decision-making. These choices may be supported by inferred data, digitally generated profiles, or true information. An online loan decision and a recruitment aptitude test that uses pre-programmed algorithms and criteria are two examples of this.

AI-based decision-making systems are now foundational to the digital economy; however, they face criticism regarding fairness, accountability, and transparency [14].

It is asserted that studying fairness in AI-based decision-making systems is essential, as these systems have transitioned from industrial applications to everyday use [15]. Gender bias is the systemic, unfair difference in the treatment of men and women in a particular domain [16]. Additionally, little study has been done on controlling bias and its negative consequences in AI-based decision-making systems. Thus, it is crucial to create strategies to stop, deal with, and lessen gender bias in AI-based decision-making systems [17].

METHODOLOGY

We carried out a thorough literature assessment of pertinent works in information systems and associated domains in order to meet the goals of this study. Because the study phenomenon is still developing and a review can methodically synthesize and examine prior findings, this approach is appropriate [18]. A methodical approach was used to help identify and select pertinent publications. Scopus, one of the biggest databases for books and journals that has been widely used by AI researchers, was used for this study [19]. The first step of our systematic literature review involved an extensive selection of appropriate keywords. We began with a broad, multidisciplinary literature review [20] to iteratively refine and select relevant keywords. The scope of our study guided the subsequent evaluation and selection of these keywords. Then, to find published studies on gender bias in AI-based decision-making systems, we performed a keyword search for the years 2012–2022. This ten-year period is deemed appropriate and advised, and it includes all

pertinent research published in reputable publications. In order to address the social and behavioral components of gender bias, we combined the social sciences and psychology with the fields of computer science and business management, including information systems.

The terms artificial intelligence, machine learning, analytics, gender, and fairness were chosen, and then the publications were identified. We used inclusion criteria based on source type to filter these. Articles that were not written in English or that were not published between 2012 and 2022 were not included in the final selection. After that, we looked over the identified articles' titles and abstracts. Following this first selection, we carefully reviewed all of the full papers, paying close attention just to those that specifically addressed gender bias in AI-based decision-making systems.

RESULTS

This section summarizes the main conclusions of the systematic literature study, which finds and classifies information about how gender bias manifests itself in AI-based decision-making systems, what causes it, and possible countermeasures. Our research contributes to the expanding corpus of information systems literature on the negative impacts of AI and countermeasures.

We initially divided the published article types into categories, such as conceptual research, literature reviews, design science, empirical studies, surveys, and case-based research, in order to obtain a thorough grasp of this field of study. Our analysis reveals that most of the reviewed articles are conceptual in nature, with a notable scarcity of empirical studies and detailed literature reviews. Furthermore, while discussions of fairness and gender bias in AI exist in broader literature, the IS field has yet to fully engage with this critical topic. Our

findings suggest that research on gender bias in AI remains underdeveloped, highlighting substantial opportunities for future inquiry within the IS field and beyond.

Factors of Gender Bias in AI-Based Decision-Making Systems

We have identified three main characteristics of gender bias in these systems: design and implementation, institutional factors, and societal influences.

Design and Implementation Characteristics

The design of AI-based decision-making systems, including any flaws in this phase, can significantly impact their implementation and use. A major challenge contributing to these design flaws is the misrepresentation of datasets, which may be biased, incomplete, or incorrect. Societal gender inequalities are reflected in AI algorithms due to unfair representations in datasets—such as overrepresentation, underrepresentation, or misrepresentation of certain groups—and a lack of gender diversity in AI development teams, leading to "blind spots" [20-23]. Our literature review indicates that the design and implementation characteristics are influenced by these contributing factors.

Additionally, the correlation between sensitive variables and features, known as proxy variables, infiltrates AI algorithms and modeling, resulting in biased outcomes. Previous studies have shown that these proxy variables can discriminate against certain groups, such as using salary as a proxy for gender or zip code as a proxy for background [24].

According to the research, the absence of gender diversity in AI development teams raises the possibility that gender bias may arise during the training stage of AI-based decision-making algorithms due to the gender gap between systems and software developers and data miners. It was observed

that the underrepresentation of women in STEM fields, including AI development, is indicative of a homogeneous, male-dominated IT sector, which may lead to a dearth of varied viewpoints in development teams. This uniformity could result in gender-biased outcomes by reinforcing the dominance of one gender (male) in managing algorithms and decision-making. In AI-based decision-making systems, the lack of human feedback and "humans-in-the-loop" might intensify preexisting biases [25] and affect the selection and use of particular modeling techniques during algorithm training. These biases are sustained by the systems' self-training procedures once they have been ingrained in the algorithmic training datasets. According to research, some AI-based decision-making systems tend to favor particular groups more and more over time, which reinforces societal inequality by learning from biased results. Additionally, decisions that disfavor particular social groups may result from algorithms that are not properly tested for particular settings. Important external and contextual elements are frequently ignored in AI-based decision-making systems [26].

Institutional Characteristics

Institutions using AI-based decision-making systems exhibit gender bias, which is impacted by the larger social environment. These mechanisms both reinforce and reflect prevailing biases in society.

According to our analysis of the literature, one of the main institutional variables influencing these systems is the absence of legislation pertaining to AI. Due to deliberate or unintentional classification based on sociocultural characteristics, institutions may unintentionally penalize particular minority or social groups [27]. Furthermore, the development of legislation to eliminate gender bias in AI decision-

making systems has not advanced very far. As a result, institutional features reinforce social gender stereotypes and discrimination, highlighting the pressing need for AI laws and policy changes to advance equity [28].

Societal Characteristics

Persistent societal inequalities, such as gender stereotyping, often manifest as preferential treatment toward masculinity in AI algorithms. According to our review, gender stereotyping contributes to gender bias in AI systems in cultures where historical biases and norms are upheld. This isn't often because discrimination is intentional, but rather because the dominant culture encourages exclusivity and masculinity. AI systems that exhibit this biased behavior end up reflecting human prejudices against people based on their gender, color, or heritage. Furthermore, because they are accepted in the community, some societal rules are blindly followed. These socioeconomic status-based variables (such as location, zip code, and neighborhood) can result in inaccurate presumptions about specific people. The social standing of people from poorer socioeconomic backgrounds may put them at a disadvantage, and because AI systems are created with unconscious biases, this bias may be replicated in the systems themselves.

Mitigation of Gender Bias in AI-Based Decision-Making Systems

Based on the reviewed literature, we identify four primary approaches to mitigating gender bias in AI-based decision-making systems: AI technology-related approaches, fair AI management strategies, AI governance and regulatory measures, and community-focused initiatives.

AI Technology-Related Initiatives

When designing decision-making algorithms, it is recommended to gather

information from all gender-diverse, vulnerable groups in society and to use multi-dimensional datasets. According to them, this can assist in neutralizing unfair or incorrect datasets [29].

Researchers also stress that when analyzing and interpreting data, AI-based decision-making algorithms must be created and programmed to prevent reproducing preexisting biases, including gender biases. The resulting AI systems are likely to generate biased results if the implementation context is not consistent with the training datasets. As a result, testing algorithms for particular applications improves bias detection techniques and increases responsibility [30].

Although it is suggested that context-specific decision-making algorithms are more successful, they require constant development in order to adjust to particular circumstances. The context in which AI-based decision-making systems are implemented must be taken into consideration when choosing them. Furthermore, discriminating effects can be considerably decreased by carefully examining the environment of AI systems, the data they use, and the individuals involved.

Fair AI Management Initiatives

Biased AI decision-making has been proven to be influenced by unethical data practices, such as misreporting and misbehavior during data collecting and preparation. The ability of AI algorithms to self-learn from their own imperfect outputs exacerbates this bias. Researchers advise incorporating testing and auditing of AI decision-making algorithms into the design and implementation stages in order to address this problem. Internal compliance auditors or external auditors may be involved in this process [31].

The importance of human decision-makers is emphasized by other tactics. These people can successfully modify AI-generated results when given the necessary authority. Training decision-makers in diversity and inclusivity can also assist reduce unconscious prejudice and improve their capacity to discern when to step in when AI-generated decisions need to be changed. It has also been demonstrated that identifying gender-biased outcomes can be facilitated by institution-wide education that encourages ethical norms for all parties involved in AI techniques. It is advised to pursue further educational programs, such as professional certifications and classes aimed at increasing awareness of gender bias in AI systems [32].

Organizations must also establish fair and ethical internal structures, corporate strategies, and governance frameworks to manage gender imbalances. Encouraging gender diversity among board members, management, senior developers, and overall leadership can foster a more inclusive environment and contribute to mitigating gender bias.

AI Governance and Regulatory Initiatives

It is argued for the development and implementation of institutional AI regulations to improve transparency and accountability in AI decision-making. Moreover, AI algorithms ought to be created in a way that does not release people from accountability. Additionally, researchers argue that people who are impacted by AI judgments should be able to give input and comprehend the reasoning behind those decisions [33]. Fair results are anticipated from regulations addressing formal verification, adherence to AI ethical norms, and testing AI decision-making systems. This involves making certain that third-party datasets are appropriately evaluated for their particular context and

that governmental and regulatory organizations set higher ethical AI requirements for data selection and gathering [34]. It is advised that interdisciplinary and global partnerships implement AI governance in order to reach an agreement on AI principles and encourage ethical AI practices.

Societal and Community-focused Initiatives

In order to promote greater diversity and inclusivity, social interventions that improved gender diversity education and training within the community were promoted. In order to increase confidence in AI-based decision-making systems, they also recommend enacting laws to protect users' personal data, especially when it comes to the sharing of personal data for these procedures. It was suggested that governments or legislators create a "ecosystem of trust" to guarantee adherence to essential laws safeguarding consumer and human rights, particularly in AI-based decision-making systems [35].

DISCUSSION

Our knowledge of gender bias in AI-based decision-making systems is improved by the study's findings. Research communities have concentrated on using programming and mathematical modeling to make AI systems fair, even while considerable efforts have been made to investigate and lessen prejudice through technological means. Because of this, gender bias in these systems is largely seen by AI researchers as a technical problem. However, gender bias has non-technological roots, indicating that technical fixes might not be sufficient. Despite the fact that computer scientists have created mathematical methods to identify and reduce algorithmic biases, information systems research has not yet sufficiently addressed the behavioral, organizational, and societal implications,

antecedents, and consequences of this problem [36].

It is not enough to merely modify the algorithms in AI-based decision-making systems to address prejudice. AI-based decision-making systems require cooperation from specialists in organizational, technological, and human domains because they are multidisciplinary phenomena. Furthermore, the social ramifications of this problem must be at the forefront of its analysis and possible remedies because the bias found in decision-making algorithms is socio-technical in nature. We consider gender bias in AI-based decision-making systems to be socio-technical, multi-layered, and multi-dimensional. Integration of organizational, societal, and technical approaches is necessary for the creation and deployment of these systems.

Reducing gender bias in AI system design and implementation can be achieved by removing proxy variables for protected qualities and making sure that equitable datasets that reflect all community groups are available, i.e., varied and inclusive datasets. By guaranteeing fair data collection, preparation, and regularization, standards for fair datasets can help developers avoid bias in training data and encourage equal outcomes. In order to promote a multidisciplinary approach to developing and deploying AI systems that successfully reduce gender bias, these socio-technical strategies may entail matching data scientists with social scientists. The comprehension and identification of bias in algorithmic models can also be improved by ongoing testing for algorithmic accountability and transparency.

Gender bias in AI-based decision-making systems can be lessened by AI rules that require the incorporation of important

ethical norms, compliance with laws and policies for better AI governance, and the encouragement of gender diversity and inclusivity in organizations. Thus, we suggest that institutionally associated contributing variables can be efficiently addressed by AI governance and regulatory measures.

It has been observed that management tactics for fair AI, which include policy promotion and awareness-raising, increase the efficacy of having "humans in the loop." This method raises the possibility that AI-based decision-making systems will be fair [37]. Specifically, creating awareness through training, workshops, and seminars about gender-biased outcomes in AI decision-making can motivate AI developers and users to advocate for gender-diverse workplaces and implement public policies that promote fairness, thereby supporting demographic and cultural diversity in the data used by these systems [38].

AI is one of the new technologies that frequently reflects the gender prejudice that permeates society. It has been demonstrated that socially expressed gender bias can be effectively reduced by focusing on social interventions, such as increasing awareness of gender equity and justice through educational programs like workshops and

seminars. Enhancing public policies that safeguard fundamental rights and the well of society can also raise awareness of human rights issues and fight discrimination, including gender bias.

CONCLUSION

With AI-based decision-making systems becoming common in corporate and social settings, gender-related prejudice is a serious worry. The results of our study show that companies need to take an active role in putting moral and equitable AI results into practice. We specifically highlight tactics pertaining to increased responsibility and openness in algorithms, diversity in the workplace, and continuing education on ethical AI. New hires should also be given consideration for ethical AI training and certification programs, which should be periodically updated. Establishing AI governance procedures can also help organizations prevent, identify, and lessen gender bias in their decision-making processes.

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