



(RESEARCH ARTICLE)



## The impact of data bias on decision making

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### Abstract

The increasing reliance on data-driven decision-making across public policy, business, and scientific research has brought unprecedented opportunities for evidence-based strategies and resource allocation. However, this reliance also exposes decision processes to significant risks when the underlying data is biased. Data bias—whether introduced through sampling, measurement, selection, or reporting—can systematically distort the representation of populations, events, or phenomena. Such distortions not only compromise the accuracy of analyses but also have the potential to reinforce existing social inequities, misinform policy, and erode public trust in institutions and technologies.

This paper provides a comprehensive examination of the origins and impacts of data bias, drawing on a wide range of literature and real-world case studies from domains such as social policy and finance. It explores the mechanisms by which bias infiltrates data, the consequences for decision outcomes, and the ways in which these outcomes can perpetuate cycles of disadvantage. In response, the paper outlines a framework for identifying, mitigating, and governing data bias, emphasizing the need for transparency, stakeholder engagement, and robust ethical oversight. The findings underscore the urgent necessity for systemic reforms in data collection and analysis to ensure that data-driven decisions are both equitable and effective.

**Keywords:** Data quality; Data governance; Data profiling; Data integrity; Data bias; Data quality measurement

### 1. Introduction

The exponential growth of data in the digital era has transformed the landscape of decision-making. Policymakers, business leaders, and researchers increasingly rely on quantitative analysis to guide strategies and allocate resources. While data is often perceived as objective, the processes of data collection, curation, and interpretation are susceptible to various forms of bias, which can significantly compromise the validity of decisions derived from such data (1). Data bias, whether introduced intentionally or inadvertently, can reinforce existing inequalities, misinform policy, and undermine public confidence in data-driven systems.

This paper investigates the multifaceted nature of data bias, its impact on decision-making, and the strategies available for its mitigation. The discussion begins with a review of the literature on data bias and its typologies, followed by an analysis of its consequences in real-world scenarios. The paper then proposes best practices and governance frameworks to address and reduce data bias, concluding with recommendations for future research and policy.

### 2. Literature Review

Data bias refers to systematic errors or distortions in data that lead to inaccurate, misleading, or unfair conclusions (2). Bias can arise at any stage of the data lifecycle, from sampling and measurement to analysis and reporting. King and

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Zeng (2006) argue that data bias is particularly pernicious in policy analysis, where flawed data can result in policies that fail to address the needs of the most affected populations (1).

Sampling bias occurs when the data collected does not accurately represent the target population, often due to non-random sampling methods or exclusion of certain groups (1). Measurement bias results from errors in data collection instruments or procedures, leading to systematic inaccuracies (3). Selection bias arises when certain data points are preferentially included or excluded, skewing the analysis (1). Reporting bias involves the selective disclosure or suppression of data, often influenced by external incentives or confirmation bias (4). Survivorship bias focuses on entities that have “survived” a process, ignoring those that did not, leading to over-optimistic conclusions (5).

Data bias can have far-reaching implications. Biased data can lead to policies that are ineffective or unjust, disproportionately affecting marginalized groups (1). Inaccurate data can result in inefficient allocation of resources, failing to address actual needs (6). Persistent bias in data-driven decisions can diminish public trust in institutions and technologies (7). Biases in data often reflect and reinforce societal inequalities, compounding disadvantage (8).

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### 3. Methodology

This study employs a qualitative research approach, combining an extensive literature review with the analysis of empirical case studies to explore the origins, mechanisms, and impacts of data bias on decision-making processes. The literature review synthesizes findings from interdisciplinary sources, including political science, information systems, and psychology, to build a comprehensive understanding of how data bias manifests and influences decisions across various domains (1)(2)(4).

The research draws heavily on seminal works that identify key types of data bias—such as sampling bias, measurement bias, and representation bias—and their effects on the reliability of datasets used in decision-making (1)(4). For example, Paulus (2022) highlights how political and accessibility biases skew crisis management data, leading to cycles of bias reinforcement in operational decisions (1). Similarly, Shelke and Kadam (2025) provide a framework for understanding representation bias, emphasizing its roots in imbalanced sampling and historical disparities, and outlining mitigation strategies like stratified sampling and weighted adjustments (4).

To ground the theoretical insights, the study incorporates case studies from social policy and finance, domains where data bias has demonstrably impacted resource allocation and fairness. These cases are selected based on documented evidence of bias-related distortions in census data, credit scoring, and survey participation, illustrating the real-world consequences of biased data on vulnerable populations (1)(2)(5).

Additionally, this research critically evaluates existing bias mitigation methods, including statistical techniques such as data imputation and reweighting, as well as organizational practices like data governance and ethical oversight. The analysis is informed by interdisciplinary reviews that stress the importance of transparency, stakeholder engagement, and continuous auditing to detect and reduce bias in datasets (2)(5)(6).

The methodology also acknowledges the interplay between cognitive biases and data biases, recognizing that decision-makers' interpretation of data can further compound distortions (1)(6)(9). This dual perspective informs the recommendation of holistic approaches that address both data quality and human factors in decision-making systems.

By integrating theoretical frameworks, empirical case studies, and practical mitigation strategies, this methodology aims to provide a nuanced and actionable understanding of data bias. It seeks not only to document the problem but also to inform the development of more equitable and reliable data-driven decision-making practices across sectors.

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### 4. Case Studies

In the realm of social policy, government agencies rely on census and survey data to allocate funding and design programs. However, undercounting of minority and low-income populations due to sampling and reporting biases has historically led to resource misallocation and policy gaps. For example, the 2010 U.S. Census undercounted Black and Hispanic populations, which affected federal funding for education, healthcare, and infrastructure in those communities (13). The underrepresentation of certain groups in social surveys can result in the misdirection of public services, leaving the most vulnerable populations underserved (12).

Business and finance provide further illustration of the consequences of data bias. Credit scoring models, widely used to assess loan eligibility, depend on the quality and representativeness of the underlying data. If the training data for these models is biased—such as underrepresenting certain demographic groups or geographic regions—credit decisions may systematically disadvantage minorities or low-income individuals (14). Selection and measurement biases in financial data can thus perpetuate economic inequalities and limit access to essential services (15). In the insurance industry, historical data used to set premiums may reflect past discriminatory practices, resulting in higher costs for groups that have been unfairly penalized, even when current risk profiles do not justify such disparities (16).

In academic research, data bias can influence the validity of scientific findings. Nonresponse bias in social science surveys, where certain individuals or groups are less likely to participate, can distort the conclusions drawn from the data (2). Publication bias, where studies with positive or significant results are more likely to be published than those with null or negative findings, can skew the scientific literature and misinform subsequent research and policy (4).

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## 5. Discussion

The mechanisms of data bias are deeply rooted in both societal structures and technical processes. Structural inequalities, such as disparities in access to technology or education, can result in sampling bias when certain populations are systematically excluded from data collection efforts. Technological limitations, such as poorly designed survey instruments or inconsistent data entry protocols, can introduce measurement bias. Institutional priorities or external pressures, such as political or financial incentives, often influence selection and reporting biases (17).

Identifying data bias requires transparency in data collection, with detailed documentation of data sources, collection methods, and sampling criteria. Regular audits of datasets are necessary to detect patterns of underrepresentation or distortion (18). Engaging a diverse range of stakeholders in the design and evaluation of data collection and analysis processes can help uncover hidden biases and ensure that multiple perspectives are considered (20).

Mitigating data bias involves diversifying data sources to ensure that datasets capture the full spectrum of the target population (21). Statistical techniques such as data imputation and weighting can be applied to correct for missing or underrepresented data (3). Bias correction algorithms, when carefully designed and implemented, can adjust for known biases in data (22). Ethical oversight, through the establishment of review boards and governance structures, is essential to monitor data practices and enforce standards (23).

Robust data governance is crucial for maintaining data quality and ethical standards. Data stewardship assigns responsibility for data management and integrity, ensuring that data is handled appropriately throughout its lifecycle (24). Privacy and security measures must be implemented to protect sensitive information and comply with relevant regulations (25). Accountability mechanisms, such as channels for reporting and addressing data-related concerns, are necessary to maintain public trust and ensure that data practices align with ethical and legal standards (26).

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## 6. Conclusion

Data bias represents a critical and persistent obstacle to the integrity and effectiveness of data-driven decision-making. As this paper has demonstrated, bias can infiltrate data at multiple stages, from initial collection and sampling to analysis and reporting. Its presence is not merely a technical flaw but often reflects deeper societal structures and institutional practices that shape who is represented, whose voices are heard, and which outcomes are prioritized.

The consequences of data bias are profound and far-reaching. When unchecked, bias distorts the evidence base upon which policies, business strategies, and scientific conclusions are built. This can result in the misallocation of resources, the design of interventions that fail to reach those most in need, and the perpetuation of historical and structural inequities. For example, biased census data can lead to chronic underfunding of essential services in marginalized communities, while skewed financial data can restrict access to credit and economic opportunity for disadvantaged groups. In the research domain, biased datasets can undermine the validity of scientific findings, erode public trust in research, and stifle innovation.

Addressing data bias requires a holistic and sustained approach. Transparency in data practices is essential, including clear documentation of data sources, collection methodologies, and potential limitations. Regular auditing and critical evaluation of datasets help to identify patterns of underrepresentation or distortion before they influence high-stakes decisions. Engaging a diverse array of stakeholders throughout the data lifecycle ensures that multiple perspectives inform both the identification and mitigation of bias, making data practices more inclusive and equitable.

Furthermore, robust data governance frameworks are indispensable for institutionalizing best practices and ethical standards. These frameworks should assign clear responsibility for data stewardship, enforce privacy and security protections, and establish accountability mechanisms for addressing grievances and correcting errors. The integration of statistical and computational techniques, such as data imputation, weighting, and bias correction algorithms, can further enhance the representativeness and reliability of datasets.

Ultimately, the challenge of data bias is dynamic and evolving, especially as new technologies and sources of data emerge. Continued research is needed to develop innovative tools and methodologies for bias detection and mitigation. Policymakers, organizations, and researchers must remain vigilant and adaptive, fostering a culture of critical reflection and ethical responsibility. Only by confronting data bias directly and comprehensively can we ensure that data-driven decision-making fulfills its promise of advancing fairness, effectiveness, and social good.

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## Compliance with ethical standards

### *Disclosure of conflict of interest*

All authors declare that they have no conflict of interest.

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