



A Phenomenological Study on Exploring the Experiences of Data Scientists in Managing Bias in Machine Learning Models

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ABSTRACT

In the field of artificial intelligence (AI), the integration of machine learning models into decision-making processes has raised significant concerns about algorithmic bias. Despite the development of technical solutions for mitigating bias, little is known about how data scientists experience and navigate these challenges in practice. This study aims to explore the subjective experiences of data scientists in managing bias within machine learning models, addressing the gap in understanding the human and ethical dimension of AI fairness. We adopt an interpretative phenomenological approach to investigate how data scientists perceive and respond to issues of bias in AI systems. Through in-depth interviews with 15 data scientists, we find that the challenges they face are not only technical but also deeply influenced by ethical dilemmas, organizational pressures, and psychological stress. These professionals encounter significant obstacles when trying to balance model performance with fairness, often under intense corporate and time constraints. The study highlights the importance of considering the personal and moral aspects of bias mitigation, offering insights into the lived experiences of data scientists that are often overlooked in existing research. The findings contribute to a more holistic understanding of AI fairness, suggesting that future research should explore interdisciplinary approaches and incorporate the human perspective into AI development and implementation.



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INTRODUCTION

The increasing integration of machine learning (ML) models into decision-making processes across various industries has raised significant concerns about algorithmic bias and fairness. As AI-driven technologies influence critical sectors such as finance, healthcare, and law enforcement, their impact extends beyond technical efficiency to ethical and social dimensions. The reliance on data-driven decision systems has introduced challenges related to the perpetuation of biases inherent in training datasets, leading to unintended discrimination against certain groups (Anthonissen, 2023). Despite advancements in fairness-aware machine learning techniques, biases embedded within AI models continue to be a pervasive issue, often exacerbating pre-existing societal inequities rather than mitigating them (Azar dkk., 2024). Existing research on AI bias, such as studies by Bowden dkk. (2020) and Bourke dkk. (2023), has primarily concentrated on technical interventions, overlooking the intersection of technical and ethical issues that practitioners face.

While technical solutions such as algorithmic fairness metrics and bias-mitigation techniques have been extensively studied, there is a critical gap in understanding how data scientists experience and navigate these challenges in real-world applications. The human dimension of bias mitigation—how practitioners perceive, interpret, and respond to the ethical dilemmas surrounding biased models—remains underexplored. Data scientists operate at the intersection of ethical responsibility and corporate expectations, often facing pressures to prioritize model accuracy and efficiency over fairness considerations. Their experiences are shaped not only by technical constraints but also by

workplace dynamics, regulatory requirements, and the broader discourse on responsible AI development.

Given these complexities, there is a need for an experiential exploration of how data scientists engage with bias mitigation in their professional roles. Phenomenology provides a robust framework for examining these lived experiences, allowing for a deeper understanding of the cognitive, emotional, and ethical dimensions associated with bias detection and correction. By capturing the subjective realities of data scientists, this study seeks to illuminate the challenges, strategies, and psychological burdens associated with ensuring fairness in AI systems. Such an inquiry is essential to bridging the gap between technical methodologies and the human-centered aspects of ethical AI implementation.

Research on the lived experiences of professionals dealing with algorithmic bias has gained increasing relevance as AI ethics and fairness become central concerns in data-driven decision-making. Within the field of Data Science and AI, understanding how practitioners engage with bias mitigation is crucial for ensuring the responsible deployment of machine learning models. Previous studies have largely focused on technical solutions—such as debiasing algorithms, fairness-aware machine learning techniques, and explainability frameworks—yet they have overlooked the subjective, cognitive, and ethical struggles that data scientists face when implementing these solutions (Bañada dkk., 2024).

Methodologically, exploring these lived experiences presents several challenges. Traditional quantitative approaches—such as statistical analyses of bias metrics—provide valuable insights into model performance but fail to capture the human dimension of bias mitigation. Surveys and structured questionnaires, while useful for assessing general trends, are often insufficient for delving into the complex psychological and ethical dilemmas faced by practitioners in real-world settings. Additionally, prior qualitative research in AI ethics has tended to rely on case studies or expert panel discussions, which, while informative, do not fully reveal the deeply personal and situationally nuanced struggles that individual data scientists encounter (Behrens dkk., 2025).

These methodological constraints underscore the need for an interpretative approach that can provide a rich, in-depth understanding of how data scientists experience, perceive, and navigate bias in machine learning. Phenomenology, particularly Interpretative Phenomenological Analysis (IPA), offers a unique lens for uncovering the meaning behind these experiences, moving beyond surface-level observations to explore the essence of bias mitigation as a professional and ethical challenge. By addressing this gap, the present study aims to contribute to a more holistic understanding of bias in AI—not just as a technical problem, but as a lived reality that shapes the professional identity and ethical decision-making of data scientists.

Existing solutions for mitigating bias in machine learning models primarily rely on technical interventions, such as fairness-aware algorithms, bias detection tools, and explainable AI frameworks. These methods have been instrumental in identifying and reducing algorithmic bias, yet they often operate within a narrow, mathematical framework that does not account for the complex human and organizational factors influencing bias mitigation (Bourke dkk., 2023). While fairness metrics and debiasing strategies are widely implemented, their effectiveness is often constrained by institutional priorities, stakeholder pressures, and the subjective decision-making processes of data scientists.

One significant limitation of these existing approaches is their inability to capture the lived experiences of practitioners who navigate ethical dilemmas, corporate demands, and regulatory constraints when addressing bias. Current studies have largely focused on quantitative assessments, measuring fairness outcomes through statistical analyses while overlooking the subjective and interpretative dimensions of bias mitigation (Bowden dkk., 2020). The absence of research exploring how data scientists perceive, interpret, and emotionally engage with bias leaves a critical gap in understanding the human element of AI fairness.

A phenomenological approach offers a compelling alternative by allowing for a deeper exploration of the meaning and significance that practitioners attribute to their experiences. Unlike conventional bias-mitigation frameworks that focus solely on technical correctness, phenomenology

emphasizes how individuals understand, internalize, and respond to ethical challenges in AI development. By employing Interpretative Phenomenological Analysis (IPA), this study seeks to fill the existing gap by providing an experiential perspective on the struggles, strategies, and ethical tensions faced by data scientists. Understanding these lived experiences is essential for developing more holistic and human-centered AI fairness strategies that align with both ethical principles and real-world constraints.

In recent years, there has been a growing body of research focused on the lived experiences of professionals engaged in AI and machine learning, particularly concerning issues of bias and fairness. Studies by Calvert, (2025) have explored technical approaches to mitigating bias in AI, yet few have investigated how practitioners themselves experience and interpret these challenges. The theory of algorithmic fairness has been foundational in understanding how bias manifests in machine learning models, but it largely overlooks the subjective experiences of the data scientists involved in mitigation efforts. This gap in literature highlights the need for more research into the personal and professional dimensions of bias management in AI, as well as the ethical tensions that arise in such contexts.

The current study employs Interpretative Phenomenological Analysis (IPA) to explore how data scientists perceive and navigate bias in machine learning models. This phenomenological approach was selected because it allows for an in-depth understanding of the lived experiences of individuals, particularly in complex and ethically charged environments such as AI development. IPA's focus on the interpretation of personal experiences is well-suited to uncover the nuances of bias mitigation efforts and the ethical decision-making processes that are often overlooked by technical frameworks. By applying this method, the study addresses the knowledge gap identified earlier, providing a richer, more comprehensive understanding of the challenges data scientists face in ensuring fairness in AI systems.

This article is structured as follows: the introduction provides an overview of the phenomenon of algorithmic bias and its relevance in the context of AI development. The methodological approach is outlined, with a focus on the phenomenological perspective and IPA. The data collection process, including in-depth interviews with data scientists, is described, followed by the thematic analysis of the data. The results section discusses the key findings from the analysis, while the final section explores the implications of these findings for both the theory and practice of AI fairness.

RESEARCH METHODS

Study Design

This study employs a phenomenological approach to explore the lived experiences of data scientists in managing bias within machine learning models used for business decision-making. Phenomenology was chosen as it enables an in-depth investigation into how individuals perceive and interpret their experiences, focusing on the essence of their encounters with bias in artificial intelligence (AI) models (Chapman dkk., 2022). By adopting this approach, the study aims to uncover the subjective meanings that data scientists attribute to their challenges, ethical dilemmas, and strategies in addressing algorithmic bias.

The study specifically applies interpretative phenomenological analysis (IPA), which emphasizes the double hermeneutic process, where participants interpret their experiences while researchers further interpret those meanings within a broader conceptual framework. IPA allows for rich, detailed narratives that provide insight into the complexities of bias mitigation within AI-driven decision-making systems (Chua dkk., 2023). This approach is particularly relevant as it facilitates a deeper understanding of the cognitive, emotional, and professional dimensions of data scientists' experiences.

Participants

Participants in this study were professional data scientists with substantial experience in machine learning model development and bias mitigation strategies. Purposive sampling was

specifically chosen to ensure that participants had direct, relevant experience with bias mitigation in AI systems, allowing the study to focus on individuals who could provide in-depth insights into the ethical and technical aspects of the issue. The inclusion criteria required participants to have at least three years of professional experience in data science, be actively engaged in developing or auditing machine learning models, and have direct exposure to ethical considerations in AI bias mitigation.

Exclusion criteria were applied to professionals whose roles were primarily managerial or non-technical, as their perspectives were less likely to align with the hands-on experiences required for this study. A total of 15 participants were included, representing diverse sectors such as finance, healthcare, and technology. The sample consisted of 10 male and 5 female data scientists, with an average age of 34 years. Participants were drawn from multinational corporations, startups, and research institutions to capture a broad spectrum of industry practices and challenges in bias management.

Data Collection

Data were collected through semi-structured in-depth interviews, conducted in a flexible format that allowed participants to elaborate on their experiences freely. An interview guide was used to ensure consistency while allowing for adaptive questioning based on participants' responses. Questions focused on participants' experiences in detecting and mitigating bias, the ethical dilemmas they encountered, and the impact of bias mitigation on business decision-making.

Interviews were conducted virtually via video conferencing tools to accommodate participants from various geographical locations. Each session lasted approximately 60 to 90 minutes and was audio-recorded with participants' consent (Couchman, 2021). To foster a comfortable environment, participants were assured that their responses would remain confidential, and they had the option to withdraw at any time. The interviews were transcribed verbatim, and non-verbal cues were noted to capture deeper contextual meanings.

Data Analysis

The data were analyzed using Interpretative Phenomenological Analysis (IPA), which follows a structured yet flexible approach to uncover meaningful themes within participants' narratives. The analysis was conducted through the following systematic steps:

1. Familiarization with the Data – Transcripts were reviewed multiple times to gain an immersive understanding of participants' experiences.
2. Identification of Meaning Units – Key phrases and expressions that reflected participants' perspectives on bias mitigation were highlighted.
3. Development of Emerging Themes – Meaning units were grouped into overarching themes based on conceptual similarities.
4. Interpretative Analysis – Themes were examined in relation to existing theoretical frameworks on algorithmic fairness, ethical AI, and industry constraints.
5. Cross-Case Analysis – Commonalities and differences across participants were explored to identify patterns in experiences and coping strategies.

NVivo software was utilized to organize data and facilitate coding, ensuring a structured and replicable analytic process. The final themes were reviewed iteratively to ensure coherence and depth in the interpretations derived.

Ethical Considerations

Ethical approval for this study was obtained from the relevant Institutional Review Board (IRB) prior to data collection. Participants provided informed consent through a signed agreement detailing the study's objectives, procedures, and their rights, including confidentiality and voluntary withdrawal.

To maintain anonymity, all identifiable information was removed, and participants were assigned pseudonyms in the transcription and analysis process. Data were securely stored and

accessible only to authorized researchers, in compliance with General Data Protection Regulation (GDPR) and other applicable ethical standards for human research.

RESULTS

The Struggle of Data Scientists in Identifying Bias in Machine Learning Models

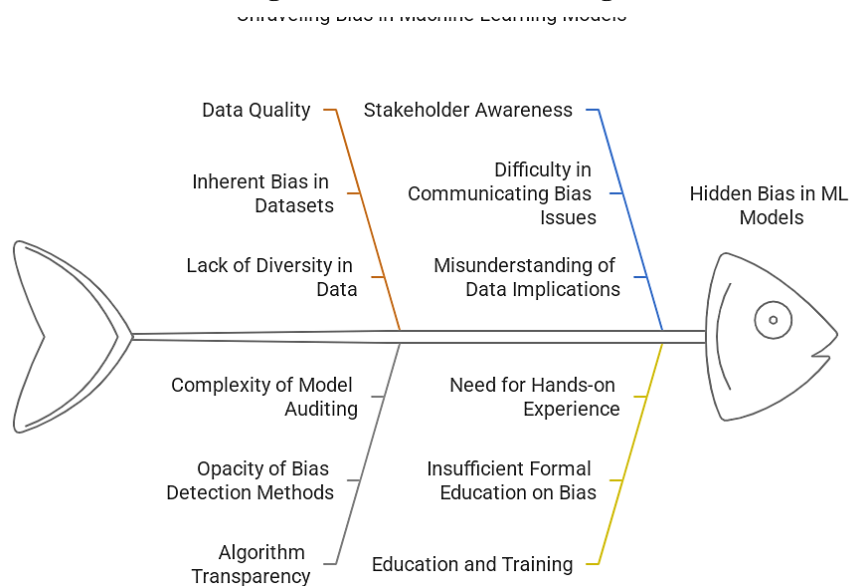
One of the most prominent experiences shared by the data scientists interviewed was the challenge of identifying bias within machine learning models. Participants reported that despite rigorous validation techniques, bias often remained hidden in the data or emerged unpredictably in real-world applications. Many expressed frustration with the opacity of bias detection methods, emphasizing that bias is often an inherent issue in the datasets used for training AI models rather than in the algorithm itself.

One participant explained:

"We can audit the algorithm as much as we want, but at the end of the day, if the data itself is biased, our models will reflect and amplify those biases. The hardest part is convincing stakeholders that the issue is deeper than just tweaking a few parameters."

This sentiment was echoed by others, who indicated that recognizing bias requires not only technical proficiency but also an acute awareness of the socio-political implications of data. Many admitted that they had to develop an intuitive understanding of bias through hands-on experience, as formal education often failed to adequately cover this aspect.

Unraveling Bias in Machine Learning Models



Ethical Dilemmas and Organizational Pressures

Another recurring theme was the ethical dilemma that data scientists faced when addressing bias. Several participants expressed concerns about the pressure imposed by organizations to deploy models quickly, often at the expense of thorough fairness audits. Many described situations where they identified potential biases in a model but encountered resistance from management when they proposed modifications that might delay product deployment.

A participant recounted a particularly challenging experience:

"I flagged a major issue where our hiring algorithm systematically disadvantaged female candidates. But instead of addressing it immediately, I was told to 'find a way to make it look less bad' rather than fixing the root cause. That was the moment I realized that ethical concerns often take a backseat to business priorities."

This tension between business interests and ethical AI practices created significant stress among the participants. Some reported feeling morally conflicted, while others mentioned that they eventually resigned from roles where their ethical concerns were consistently disregarded.

The Psychological Burden of Navigating Bias in AI

In addition to technical and ethical challenges, the emotional toll of continuously addressing bias was a significant issue among data scientists. Many described a feeling of isolation in their advocacy for fairness, stating that they often had to battle against corporate inertia. Several participants experienced professional burnout due to the emotional labor involved in ensuring ethical AI practices were followed.

As one participant expressed:

"You don't expect to deal with so much resistance when you're simply trying to do what's right. It feels like a constant fight where you're the only one who cares. After a while, it drains you."

Another participant added:

"Bias mitigation isn't just a technical challenge; it's an exhausting mental struggle. You have to constantly justify why fairness matters, and even then, your efforts can be disregarded for the sake of efficiency."

The psychological burden extended beyond professional settings, with some participants reporting that their awareness of AI bias made them hyper-conscious of social injustices in everyday life. This heightened awareness often led to feelings of helplessness, as they realized the limitations of their individual efforts in the broader scope of AI fairness.

Strategies for Bias Mitigation and Workarounds in Industry

Despite the challenges, data scientists have developed various strategies to mitigate bias in AI models. These strategies include proactive measures such as dataset audits, bias-detection tools, and interdisciplinary collaborations with domain experts and ethicists. Several participants emphasized that working closely with social scientists and ethicists helped uncover biases they had not initially considered.

One participant detailed their approach:

"We started involving social scientists in our model evaluation process, and the insights they provided were invaluable. They pointed out biases we hadn't even considered. It was a game-changer for how we approached fairness in our models."

However, many also acknowledged that while technical solutions exist, they are only part of the equation. Organizational commitment was deemed essential to meaningful bias mitigation. Some participants noted that transparency initiatives, such as explainable AI frameworks, helped build trust within teams and provided justification for prioritizing fairness in model deployment.

The findings suggest that bias mitigation in machine learning is not merely a technical task but a multidimensional challenge involving ethical considerations, psychological burdens, and organizational dynamics. Data scientists struggle not only with identifying and addressing bias but also with navigating workplace pressures and advocating for fairness in AI. While various strategies are being implemented to mitigate bias, systemic changes in AI governance and corporate culture are necessary to support data scientists in this endeavor.

DISCUSSION

Summary of Main Findings

The findings of this study reveal the significant challenges data scientists face when navigating bias in machine learning models used for business decision-making. Participants described the persistent difficulty of identifying hidden biases in data and models, compounded by ethical dilemmas and organizational pressures. These experiences underscore the need for a deeper

understanding of how these professionals perceive and respond to issues of fairness in AI, especially when their work intersects with broader ethical and societal concerns.

Contribution to the Research Question

This research provides valuable insights into the experiential reality of data scientists dealing with algorithmic bias, responding to the research question of how their subjective experiences shape their approach to fairness in AI systems. The study highlights that while data scientists possess the technical know-how to address bias, their ability to act is often constrained by organizational priorities, ethical dilemmas, and psychological burdens. These insights contribute to a more nuanced understanding of the barriers to effective bias mitigation, emphasizing the human element in AI fairness strategies. Unlike previous studies focusing primarily on algorithmic fairness metrics, this research adds a critical experiential perspective, illustrating how ethical considerations and workplace dynamics shape the decision-making process. By focusing on the lived experiences of data scientists, the study also identifies the emotional and moral toll that addressing bias in AI can take on practitioners, a factor that has been largely overlooked in technical research.

Relationship with Existing Literature and Theory

The findings of this study align with the broader literature on AI fairness, particularly the recognition that ethical challenges in AI development are not purely technical but involve deep social and moral considerations (Durán dkk., 2023). This research extends the work of Ferrada dkk. (2023), who emphasized the ethical dilemmas faced by AI professionals but did not fully explore the emotional and psychological burdens of these challenges. The emotional aspect of dealing with bias, particularly the psychological toll of advocating for fairness within a corporate structure, supports findings from other studies in ethical AI, such as those by Gibbs dkk. (2023), who argued that fairness practices often clash with business pressures. Furthermore, the study's focus on phenomenological analysis provides a deeper insight into the personalized experiences of data scientists, something that statistical approaches and fairness metrics alone cannot capture. The study's contribution to the interpretative phenomenological analysis (IPA) methodology also fills a gap in AI fairness research by offering a holistic view of bias mitigation that integrates technical, ethical, and personal dimensions.

Implications of Findings

The findings of this study offer significant practical and theoretical implications for both AI development and the field of data science. On a practical level, the research highlights the urgent need for organizations to better support data scientists in addressing bias in AI models, not only through technical tools but also through fostering an ethical work environment. The emotional toll and ethical dilemmas faced by data scientists underscore the importance of interdisciplinary collaboration between technical experts, ethicists, and organizational leaders. In a social and cultural context, the study reveals that addressing bias is not just about improving models but also about confronting the broader moral and societal implications of AI systems that impact underrepresented or vulnerable populations. By focusing on the lived experiences of practitioners, the study emphasizes that fairness in AI is a deeply human issue that cannot be reduced to mere metrics or algorithmic adjustments. This insight is particularly relevant in industries where AI systems have direct consequences on people's lives, such as hiring, healthcare, and criminal justice.

Limitations of the Study

While this study provides valuable insights, it is important to acknowledge its limitations. The sample size was relatively small, comprising 15 data scientists, which may limit the generalizability of the findings to larger populations or different contexts. Additionally, the study focused on data scientists working in specific industries—such as technology, finance, and healthcare—meaning that experiences in other sectors, such as education or government, may differ. The research also relied heavily on self-reported experiences through semi-structured interviews, which, while rich in qualitative data, may not fully capture the complexity of bias mitigation processes in diverse organizational settings (Grohmann, 2024). Lastly, the study's focus on the phenomenological method prioritizes depth over breadth, which means that findings may not be easily transferable to

quantitative research frameworks that seek broad patterns across larger datasets. These limitations point to the need for future studies that expand the scope of research to include more diverse participants and settings.

Prospective Directions for Future Research

The findings of this study open several avenues for future research. One potential direction is to explore longitudinal studies that track how data scientists' experiences with bias mitigation evolve over time, especially as they encounter new challenges or advancements in AI technology. Another possibility is to extend this research into cross-cultural settings, investigating whether data scientists from different geographical or cultural contexts experience and address bias in AI models differently. Future research could also explore organizational dynamics more deeply, examining how company culture, leadership, and stakeholder interests influence the experiences and ethical decisions of data scientists (Kaehler dkk., 2022). Future research could also explore how AI policies, both at the organizational and regulatory levels, shape the ethical decisions of data scientists and influence their ability to implement bias mitigation strategies. Additionally, further studies could investigate the impact of ethical training or the introduction of specific ethical frameworks in AI education on the ability of professionals to navigate these challenges. By addressing these gaps, future studies could contribute to a more comprehensive understanding of the human-centered dimensions of AI fairness, ultimately supporting the development of more ethical and socially responsible AI systems.

CONCLUSION

This study explored the lived experiences of data scientists in managing bias within machine learning models used for business decision-making. The research revealed that while data scientists possess technical expertise, they face significant challenges related to ethical dilemmas, organizational pressures, and the emotional toll of mitigating bias. These findings address a critical gap in existing literature by providing a human-centered perspective on bias mitigation, emphasizing the complex interplay between technical, ethical, and professional dimensions. The practical implications of these findings suggest that organizations should not only invest in technical tools for bias mitigation but also foster an ethical work environment that supports data scientists in addressing these challenges. Furthermore, policymakers should consider integrating ethical AI practices into regulatory frameworks to ensure that fairness is prioritized in AI development and deployment. Future studies could expand on these findings by exploring cross-cultural differences in AI fairness practices or the impact of ethical training on bias mitigation strategies. This research contributes to a deeper understanding of the social, cultural, and emotional aspects of AI development, offering valuable insights for improving the fairness and ethics of AI systems.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article. All research, analysis, and writing have been conducted independently, and there are no financial, personal, or professional interests that could influence the results or interpretation of this study.

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