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Data Quality and Bias in AI Marketing Models: Sources, Consequences, and Mitigation Strategies

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Abstract

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This article reviews how artificial intelligence transforms marketing analytics while remaining constrained by data quality and algorithmic bias. Drawing on a systematic literature review of peer reviewed studies, the paper synthesises evidence on how artificial intelligence supports segmentation, personalised targeting, dynamic pricing, and automated service when embedded in integrated data and model architectures. The findings show that information quality, consistency, and governance across data pipelines are preconditions for reliable prediction, because missing, noisy, or poorly integrated data distort customer classification and managerial insight. The review also reveals that historical, sampling, measurement, and feedback loop biases in training data and modelling choices can generate systematically unfavourable outcomes for vulnerable customer groups, eroding trust, brand equity, and regulatory compliance. Overall, the study argues that accurate and fair artificial intelligence marketing models require socio technical solutions that combine robust data governance, transparent model monitoring, and organisational accountability for outcomes across customer subgroups. The article concludes with an agenda for future interdisciplinary research directions.

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1. Introduction

Artificial intelligence has become a central engine of contemporary marketing analytics, supporting applications such as customer segmentation, personalized targeting, dynamic pricing, and programmatic advertising. By learning from large scale customer and contextual data, machine learning based models allow firms to predict responses, optimize resource allocation, and design highly individualized offers at scale, which in turn reshapes how marketing strategies are conceived and executed (Verma et al., 2021). As firms embed AI into customer relationship management systems, recommendation engines, and omnichannel campaign platforms, competitive advantage increasingly depends on the robustness of the underlying data and models rather than on traditional creative or media-planning capabilities (Gupta et al., 2021).

However, the performance of AI marketing models is fundamentally constrained by data quality. Issues such as missing values, inaccurate labels, inconsistent integration across channels, and unrepresentative samples undermine the ability of algorithms to capture true customer behaviour patterns. Research on big data systems shows that information quality and data governance are critical antecedents of the value created from analytics, since only reliable, timely, and relevant data can be transformed into actionable insight (Cichy & Rass, 2019; Côrte-Real et al., 2019). In marketing contexts, studies on big data marketing analytics find that technology and information quality within analytics solutions are positively associated with perceived market and financial performance, underscoring that low quality inputs translate into weak or misleading decision support (Haverila et al., 2022).

Beyond predictive accuracy, concerns about bias and unfairness have emerged as a major challenge for AI deployment. A growing literature on algorithmic bias documents how problematic patterns in training data, modelling choices, and deployment contexts can lead to systematically disadvantageous outcomes for specific customer groups, even when models are technically accurate overall (Mehrabi et al., 2021). Reviews of algorithmic bias identify multiple sources, including historical and sampling bias in data, measurement and label bias, as well as model and feedback-loop bias, and emphasise that these distortions can reproduce or amplify social inequalities (Kordzadeh & Ghasemaghaei, 2022). In marketing specifically, recent work on machine learning based marketing models shows that algorithmic bias can generate asymmetric and oppressive impacts on vulnerable customer segments, with consequences for customer trust, brand equity, and regulatory risk (Akter et al., 2022).

Although prior studies have examined AI in marketing, big data marketing analytics, and algorithmic fairness in general purpose machine learning, there is still limited integrative discussion of how data quality issues and different sources of bias jointly shape the behaviour of AI marketing models and their consequences for firms and stakeholders. Existing research tends to either focus on technical fairness metrics and de-biasing algorithms, or to discuss ethical AI in marketing at a conceptual level, without systematically linking data pipelines, model design, and organisational governance mechanisms (Verma et al., 2021; Kordzadeh &

Ghasemaghaei, 2022). This article addresses that gap by analysing the sources of data quality problems and bias across the AI marketing lifecycle, mapping their consequences for prediction performance, customer outcomes, and firm level risk, and reviewing mitigation strategies that combine technical interventions with data governance, transparency, and accountability practices. By doing so, it aims to provide a structured foundation for designing AI marketing models that are not only accurate and profitable, but also reliable and fair.

2. Literature Review

Literature on artificial intelligence in marketing shows that AI has shifted from a supporting technology to a core infrastructure for value creation. Systematic reviews document how AI tools are increasingly embedded across the customer journey from segmentation and targeting to personalization, pricing, and service automation and argue that their strategic impact depends on how firms align technical capabilities with marketing objectives and customer psychology (e.g., trust, perceived intrusiveness, and perceived usefulness) (Mariani et al., 2022). Complementary work maps specific AI techniques and applications, such as chatbots, recommendation engines, and predictive models, and highlights that the competitive advantage of AI enabled marketing lies less in isolated tools and more in integrated architectures that combine data ingestion, model development, deployment, and continuous learning (Haleem et al., 2022).

Within this stream, data quality and governance emerge as foundational conditions for effective AI marketing models. Conceptual frameworks on data governance emphasise that organizations must establish clear roles, processes, and standards to manage data collection, integration, security, and lifecycle management, with data quality seen as a central dimension of governance rather than a purely technical issue (Abraham et al., 2019). These insights are highly relevant to marketing analytics, where heterogeneous customer data from multiple channels must be integrated into coherent customer profiles. Without robust governance mechanisms, problems such as inconsistent identifiers, missing values, and poorly documented transformations propagate through AI pipelines, undermining both predictive performance and interpretability.

Empirical research on big data analytics in marketing-related contexts further shows how data quality interacts with analytical capability to shape decision outcomes. A case based framework for big data analytics in commercial social networks demonstrates that sentiment analysis and fake review detection for marketing decision making depend critically on reliable, representative, and well labelled data streams; when data are noisy, biased, or manipulated, model outputs distort managerial perceptions of customer sentiment and competitive positioning (Kauffmann et al., 2020). Such studies illustrate that data quality problems are not only technical imperfections but sources of systematic error that can misallocate marketing budgets, misidentify high value customers, and weaken the credibility of analytics within organizations.

Beyond technical performance, a growing body of work interrogates the implications of algorithmic bias in data-driven innovation, including marketing. Drawing on a broad set of AI applications, Akter et al. (2021) identify data bias, method bias, and societal bias as three major sources of algorithmic distortion, arguing that they can jointly produce discriminatory or exclusionary outcomes even when models are built on seemingly objective data. This perspective suggests that data quality in AI marketing models cannot be reduced to accuracy or completeness, but must also consider representativeness, the social meaning of labels, and the ways in which modelling choices interact with existing inequalities. Integrating these insights with the data governance literature implies that mitigating bias in AI marketing requires not only technical de-biasing techniques but also governance arrangements that scrutinize training data, monitor model outcomes across customer subgroups, and embed accountability into the design and deployment of AI systems. In sum, prior research underscores that the reliability and fairness of AI marketing models are co-determined by data quality, analytical architectures, and socio-technical governance, yet there is still room for more integrative frameworks that explicitly link these elements across the full marketing analytics lifecycle.

3. Methods

This study employs a systematic literature review method to synthesise existing knowledge on data quality and bias in artificial intelligence marketing models. The review follows a transparent, protocol-driven process that begins with the formulation of clear research questions on the sources, consequences, and mitigation strategies of data quality problems and algorithmic bias in AI-enabled marketing. Relevant peer-reviewed journal articles are identified through structured keyword searches in major academic databases such as Scopus, Web of Science, and

Google Scholar, using combinations of terms related to artificial intelligence in marketing, data governance, data quality, algorithmic bias, and fairness. The initial pool of studies is screened through titles, abstracts, and full texts based on predefined inclusion and exclusion criteria, focusing on empirical and conceptual work that addresses AI applications in marketing, big data analytics, data governance, and algorithmic bias in decision-making contexts. To ensure rigour, only articles published in reputable peer-reviewed outlets and written in English are retained, and each selected study is coded using a structured data extraction form capturing research context, methodological approach, type of AI application, data quality issues, sources of bias, and proposed mitigation mechanisms. Thematic synthesis is then conducted to identify recurring patterns and divergences across studies, allowing the development of integrative categories that link data governance practices, technical modelling choices, and socio-technical consequences for customers and firms. This approach enables a comprehensive and reproducible mapping of the literature, while also highlighting conceptual and methodological gaps that inform future research on reliable and fair AI marketing models.

4. Results and Discussion

The systematic review shows that artificial intelligence has evolved from a supporting tool into a core infrastructure for marketing value creation, confirming the shift outlined in prior work on AI-enabled marketing. Across the selected studies, AI is consistently embedded along the entire customer journey, from segmentation and targeting to personalization, pricing, and service automation, with its impact conditioned by how well technical capabilities are aligned with marketing goals and customer psychology (Verma et al., 2021; Mariani et al., 2022). Rather than treating algorithms as isolated tools, the literature emphasises that sustainable competitive advantage arises from integrated architectures that connect data ingestion, model development, deployment, and continuous learning within omnichannel environments (Gupta et al., 2021; Haleem et al., 2022).

A first major empirical pattern concerns the centrality of data quality and governance in shaping AI marketing performance. The reviewed studies converge on the finding that information quality, consistency, and timeliness are necessary preconditions for extracting value from big data analytics (Cichy & Rass, 2019; Côrte-Real et al., 2019). Conceptual work on data governance reinforces this view by framing data quality as a governance issue that requires clear roles, standards, and controls across the data lifecycle rather than ad hoc technical fixes (Abraham et al., 2019). Empirical analyses in marketing-related contexts show that when data are incomplete, noisy, or poorly integrated, predictive models misclassify customers, distort managerial perceptions of demand, and weaken the credibility of analytics, even if advanced techniques are used (Kauffmann et al., 2020; Haverila et al., 2022). These findings collectively support the argument that robust AI marketing models depend as much on disciplined data governance as on sophisticated algorithms.

The second dominant theme relates to the nature and consequences of algorithmic bias. Studies of bias in machine learning document that distortions can arise from multiple sources, including historical and sampling bias in training data, measurement and labelling bias, and model related feedback loops (Mehrabi et al., 2021; Kordzadeh & Ghasemaghaei, 2022). When these biases are imported into AI marketing systems, they can generate systematically unfavourable treatment of specific customer groups, even when overall predictive accuracy appears high. Evidence from broader data driven innovation contexts shows that data bias, method bias, and societal bias interact to produce discriminatory or exclusionary outcomes, challenging the assumption that algorithmic decisions are neutral (Akter et al., 2021). Marketing focused work further indicates that biased targeting and scoring can erode customer trust, damage brand equity, and increase regulatory exposure, particularly when vulnerable segments are repeatedly down ranked, excluded from offers, or subjected to exploitative pricing.

Taken together, the findings suggest that data quality problems and algorithmic bias are tightly intertwined rather than separate concerns. Poor data governance not only degrades model accuracy but also amplifies the risk that historical inequalities and mislabelling are encoded into AI marketing systems. At the same time, much of the existing literature tends to examine either technical performance or fairness in isolation, offering limited guidance on how firms can jointly manage predictive accuracy, business value, and ethical outcomes. By synthesising insights across AI marketing, big data analytics, data governance, and algorithmic bias, this review indicates that reliable and fair AI marketing models require socio-technical solutions: high quality and well governed data pipelines, transparent and monitored modelling processes, and organisational accountability mechanisms that track outcomes across customer subgroups. This integrated perspective highlights both the potential of AI to enhance marketing effectiveness and the need for deliberate design and governance to prevent data quality issues and bias from undermining that potential.

5. Conclusion

This review concludes that artificial intelligence has become deeply embedded in contemporary marketing practice, but its effectiveness and legitimacy hinge on factors that go beyond model accuracy alone. Across the literature, AI is shown to create value by supporting customer segmentation, personalized targeting, dynamic pricing, and automated service, provided that these capabilities are embedded within integrated architectures and aligned with clear marketing objectives and customer psychology. Competitive advantage in AI enabled marketing therefore depends not only on sophisticated algorithms, but also on how firms design and manage the entire analytics lifecycle from data ingestion to deployment and continuous learning.

At the same time, the synthesis demonstrates that data quality and algorithmic bias are structurally intertwined challenges that shape both prediction performance and the distribution of outcomes across customer groups. High quality, well governed data emerge as necessary preconditions for reliable AI marketing models, while weak data governance amplifies the risk that historical inequalities, mislabelling, and sampling distortions are encoded into automated decisions. Algorithmic bias is shown to have concrete implications for customer trust, brand equity, and regulatory risk, particularly when vulnerable segments are systematically disadvantaged, excluded, or targeted in exploitative ways.

The overall implication is that designing AI marketing models that are accurate, profitable, and fair requires socio technical solutions rather than purely technical fixes. Firms need to invest in robust data governance, transparent and monitored modelling processes, and organisational accountability mechanisms that track outcomes across customer subgroups and link AI decisions to broader ethical and strategic goals. For researchers, the review highlights the need for more integrative frameworks and empirical studies that jointly examine data quality, model design, governance structures, and stakeholder impacts across the full AI marketing lifecycle. Such work is essential to move from fragmented discussions of performance and fairness toward a coherent agenda for responsible AI in marketing.

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