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Invisible Inequities: How Algorithmic Marketing Reinforces Bias

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Abstract

With algorithmic automated systems, AI, expanding into marketing, it has become a dominant force in shaping consumer experiences. However, the industry's reliance on automated decision-making raises pressing ethical concerns. This manuscript synthesizes interdisciplinary research to examine how artificial intelligence systems contain embedded human and structural biases within their programming, reproducing inequities within marketing practices. Specifically, it investigates how algorithmic targeting and segmentation often marginalize minority groups by reinforcing stereotypes, excluding underrepresented identities, and prioritizing majority consumer profiles. Drawing on studies from technology, consumer behavior, and business ethics, this paper highlights the consequences of biased marketing systems for equity and representation. The synthesis and analysis go into depth on how the bias in AI programming can affect everyday lives; it vouches for a more inclusive design in algorithmic marketing to ensure that emerging technologies serve diverse communities rather than perpetuate systemic discrimination.

Keywords

Business Ethics, Marketing Strategy, Algorithmic Marketing, Consumer Behavior, Artificial Intelligence in Business, Digital Discrimination, Minority Representation, Algorithmic Fairness, Data Bias, Inclusive Marketing, Ethical AI Design, Systemic Bias, Consider Framework, Technological Ethics, Social Responsibility

1. Introduction

The business marketing industry is always changing and evolving. Their most recent innovation: the integration of Artificial Intelligence into modern marketing through ad creation, product recommendation, and customer analysis. The algorithm used by artificial intelligence is completely reliant on preexisting data created and produced by humans.

Because AI produces media based on data it has collected, their systems often cater to majority groups with the most data, leaving out minority groups from their target audience. This is where the ethical debate of AI in marketing rises, as this proven discriminatory system can reinforce social biases against racial minorities and marginalized groups. As businesses integrate AI more and more into their marketing strategies, the AI algorithmic systems they use consistently reproduce systemic racial bias by prioritizing dominant majority group preferences and excluding minority and culturally diverse communities from representation and engagement. Despite concerns about its bias to majority groups and exclusion of minority groups, Artificial Intelligence undoubtedly offers significant benefits to the business marketing industry. With AI's quick and automated responses, tasks such as ad creation, customer segmentation, and product recommendations can be done in an instant, a job that would usually take hours of careful curating for a human to do. This allows businesses to personalize marketing experiences faster and on a bigger scale than ever before, running consumer data through the automated system to generate personalized experiences for the user. The scalability and personalization that AI provides can revolutionize the efficiency of personalized marketing in businesses. However, just because AI may be extremely efficient, it does not pertain to the fact that it is inequitable, uninclusive, and unfair to its minority users.

2. Methods

This study employs a systematic literature review approach to synthesize findings from peer-reviewed research on algorithmic marketing bias. We analyzed 10 sources from an initial pool of 50, using 7 screening criteria. Each paper was reviewed for 8 key aspects that mattered most to the research question. A comprehensive literature search was conducted using databases including Google Scholar, JSTOR, and Scopus. Search terms included "algorithmic bias", "AI marketing discrimination", "digital ethics", and "consumer bias". Sources were screened based on seven inclusion criteria: 1) peer-reviewed status, 2) publication within the last ten years, 3) relevance to marketing or business applications of AI, 4) discussion of bias or discrimination, 5) empirical or conceptual contribution, 6) availability in English, and 7) credibility of publication source.

2.1. Characteristics of Included Studies Results

Study	Study Focus	Research Design	Type of Bias Examined	Primary Contribution	Full Text Available
Soni, 2024	Bias detection and mitigation in AI-driven target marketing	Abstract-only, empirical	Representation bias, algorithmic discrimination	Quantitative assessment of bias and mitigation strategies in consumer profiling	No

Continued

Wan et al., 2019	Marketing bias in product recommendations	Full-text, empirical	Marketing bias (underrepresentation, stereotypical imagery)	Fairness-aware framework for recommender systems; empirical validation	Yes
Akter et al., 2022	Algorithmic bias in machine learning-based marketing models	Abstract-only, systematic review + interviews	Design bias, contextual bias, application bias	Framework for dynamic algorithm management capability	No
Reed et al., 2025	Bias in digital marketing and artificial intelligence	Abstract-only, systematic review + interviews	No mention found	Analytical framework for bias identification and mitigation	No
Naz and Kashif, 2024	Ethical concerns in AI-driven predictive marketing	Full-text, qualitative (interviews)	Representation bias, algorithmic discrimination, market share bias	Ethical framework for predictive marketing	Yes
Rahmani et al., 2024	Consumer and producer fairness in recommender systems	Full-text, empirical	Algorithmic discrimination, representation bias	Joint fairness optimization framework (CP-FairRank); empirical validation	Yes
Akter et al., 2023	Algorithmic bias management in industrial marketing	Abstract-only, literature review + surveys	Data bias, model bias, market bias	Framework for bias management capabilities	No
Su et al., 2023	Ethical challenges of AI in marketing	Full-text, structured literature review	Algorithmic discrimination, stereotyping	Thematic synthesis of ethical issues and recommendations	Yes
van Esch et al., 2024b	Artificial intelligence for diversity, equity, and inclusion in marketing materials	Abstract-only, conceptual	Representation bias, stereotyping	CONSIDER framework for diversity, equity, and inclusion implementation	No
Akter et al., 2021	Algorithmic bias in customer management	Abstract-only, systematic review	Demographic bias (gender, race, etc.)	A priori and post-hoc frameworks for bias mitigation	No

Across the 10 included studies, the following patterns were observed:

- Research Design:
    - 2 studies used a full-text, empirical design.
    - 1 study used a full-text, qualitative (interviews) design.
    - 1 study used a full-text, structured literature review.
    - 1 study used an abstract-only, empirical design.
    - 1 study used an abstract-only, systematic review with interviews.
    - 1 study used an abstract-only, literature review with surveys.
    - 1 study used an abstract-only, qualitative inductive approach.
    - 1 study used an abstract-only, conceptual approach.
    - 1 study used an abstract-only, systematic review.
- Types of Bias Examined:

  - Representation bias was examined in 4 studies.
  - Algorithmic discrimination was examined in 4 studies.
  - Stereotyping was examined in 2 studies.
  - Marketing bias, underrepresentation, stereotypical imagery, design bias, contextual bias, application bias, market share bias, data bias, model bias, market bias, and demographic bias were each examined in 1 study.
  - In 1 study, we did not find mention of a specific bias type.
- Primary Contribution:
  - 6 studies contributed a framework (for bias management, fairness, diversity/equity/inclusion, ethics, or bias mitigation).
  - 3 studies included empirical validation or quantitative assessment.
  - 1 study contributed an analytical framework.
  - 1 study provided a thematic synthesis.
  - 1 study provided an ethical framework.

Some studies contributed to more than one category within "Primary Contribution." It was not found in studies that used other types of research designs or examined other bias types beyond those listed above.

Thematic Analysis

Across the included studies, algorithmic marketing systems perpetuate bias, disproportionately affecting minority and underrepresented groups. Key manifestations identified include:

Unequal Treatment and Underrepresentation: Algorithmic marketing systems frequently underrepresent or exclude certain groups, often linked to race, gender, or socioeconomic status. Studies by Soni (2024), and Wan et al. (2019) demonstrate that advertising algorithms and recommendation engines marginalize minority audiences while prioritizing majority consumer profiles.

Stereotyping: Bias in imagery and training data often leads to reinforcement of social or cultural stereotypes. Evidence from Akter et al. (2022), van Esch et al. (2024a), Rahmani et al. (2024), and Naz & Kashif (2024) indicates that AI-generated content can perpetuate stereotypical portrayals, misrepresenting niche or minority market segments.

Privacy and Market Effects: Predictive marketing can result in privacy violations and market concentration, disproportionately affecting vulnerable populations. Soni (2024) and Wan et al. (2019), show that model outputs influence consumer behavior and limit equitable access to marketing opportunities.

Intersectionality: Bias is compounded when multiple protected characteristics interact (e.g., race × gender × socioeconomic status). Studies Su et al. (2023) highlight that intersectional effects are underexplored yet critically amplify exclusion in algorithmic targeting.

2.2. Bias and Detection Measurement Approaches

The detection methods for bias in AI and machine learning marketing models varied across the 10 studies reviewed:

Study	Detection Method	Metrics Used	Bias Severity Findings	Study Context
Soni, 2024	Statistical analysis of model outputs	Disparate Impact (DI), Statistical Parity Difference (SPD), Equal Opportunity Difference (EOD)	Significant initial bias (Disparate Impact = 0.60, Statistical Parity Difference = −0.25, Equal Opportunity Difference =−0.30)	AI-driven target marketing
Wan et al., 2019	Pearson's Chi-Squared, Analysis of Variance (ANOVA), fairness metrics	F-statistic, Kullback-Leibler divergence (KL-divergence)	Significant associations between product images and user identities; disparities in fairness	E-commerce recommender systems
Akter et al., 2022	Literature review, interviews	No Mention Found	No mention found	Machine learning-based marketing models
Reed et al., 2025	Qualitative interviews	No Mention Found	No mention found	Digital marketing
Naz and Kashif, 2024	Qualitative interviews, thematic analysis	No Mention Found	No mention found	Predictive marketing
Rahmani et al., 2024	Statistical analysis, fairness metrics	Disparate Consumer Fairness (DCF), Disparate Producer Fairness (DPF), mean Consumer-Producer Fairness (mCPF)	Improved fairness with intervention; group segmentation critical	Recommender systems (multiple domains)
Akter et al., 2023	Literature review, surveys	No mention found	No mention found	Industrial marketing analytics
Su et al., 2023	Literature review, case studies	Performance accuracy by group	White faces recognized more accurately than others	Artificial intelligence in marketing/consumer behavior
van Esch et al., 2024b	Conceptual framework	Artificial intelligence-enabled diversity, equity, and inclusion metrics	No mention found	Marketing materials (diversity, equity, and inclusion)
Akter et al., 2021	Literature review	No mention found	No mention found	Customer management

Statistical analyses of model outputs or fairness metrics were used in 3 studies (Soni, 2024; Wan et al., 2019; Rahmani et al., 2024). These studies reported measurable bias, such as Disparate Impact (DI = 0.60), Statistical Parity Difference (SPD = −0.25), Equal Opportunity Difference (EOD = −0.30) (Soni, 2024), and disparities between product images and user identities (Wan et al., 2019). Rahmani et al. (2024) reported improved fairness after intervention, highlighting the impact of group segmentation.

Literature reviews were employed in 4 studies (Akter et al., 2021, 2022; Reed et al., 2025), sometimes combined with interviews, surveys, or case studies. These reviews documented qualitative or associative evidence of bias in marketing systems, even when quantitative metrics were not provided.

Qualitative interviews and thematic analyses were used in 2 studies (Naz &

Kashif, 2024; Reed et al., 2025), identifying nuanced manifestations of bias in predictive and digital marketing contexts.

Conceptual frameworks were applied in 1 study (van Esch et al., 2024b) to evaluate diversity, equity, and inclusion metrics in marketing materials, offering a theoretical lens for bias detection.

Metrics varied across studies: named fairness metrics (DI, SPD, EOD, Disparate Consumer Fairness, Disparate Producer Fairness, mean Consumer-Producer Fairness) were explicitly reported in 2 studies, statistical/association metrics in 1 study, performance accuracy by group in 1 study, and AI-enabled DEI metrics in 1 study. Five studies did not report specific metrics.

Bias severity findings were documented in 4 studies, including quantitative measurements, qualitative evidence, group performance disparities, and observed improvement post-intervention. Six studies did not report bias severity.

Mitigation Strategies and Framework Redesign Mitigation strategies fall into two categories:

Technical (Algorithmic) Interventions:

Pre-processing: balancing data prior to model training.

In-processing: applying fairness constraints during training.

Post-processing: modifying model outputs after training.

Algorithmic re-ranking and fairness-aware loss functions (Soni, 2024; Wan et al., 2019; Rahmani et al., 2024) Organizational and Ethical Frameworks:

Stakeholder involvement in system design and deployment Regular audits of algorithmic systems.

Integration of diversity, equity, and inclusion principles.

Comprehensive frameworks (CONSIDER, dynamic algorithm management, a priori/post-hoc approaches).

Ongoing monitoring, transparency, and multidisciplinary collaboration (Akter et al., 2021; van Esch et al., 2024b).

These strategies collectively aim to enhance fairness, accountability, and inclusivity in AI-driven marketing systems, demonstrating practical pathways to mitigate bias while maintaining functionality.

2.3. Effectiveness of Ethical Artificial Intelligence Frameworks Results

Frameworks and approaches:

Study	Framework/Approach	Implementation Stage	Fairness Improvement	Trade-offs
Soni, 2024	Pre-processing, in-processing, post-processing	Pre-processing, in-processing, post-processing	Disparate Impact improved from 0.60 to 0.95; Statistical Parity Difference and Equal Opportunity Difference improved	No mention found

Continued

Wan et al., 2019	Fairness-aware framework	In-processing	Improved fairness (lower F-statistic, Kullback-Leibler divergence); negligible accuracy loss	Minimal accuracy trade-off
Akter et al., 2022	Dynamic management framework	No mention found	No mention found	No mention found
Reed et al., 2025	Analytical framework	No mention found	No mention found	No mention found
Naz and Kashif, 2024	Ethical framework	Post-processing, monitoring	No mention found	No mention found
Rahmani et al., 2024	CP-FairRank (joint fairness)	Post-processing	Improved mean Consumer-Producer Fairness without quality loss	No mention found
Akter et al., 2023	Bias management framework	No mention found	No mention found	Minimal compromise on quality
Su et al., 2023	Ethical programs, inclusive practices	No mention found	No mention found	No mention found
van Esch et al., 2024b	CONSIDER (diversity, equity, and inclusion) framework	No mention found	No mention found	No mention found
Akter et al., 2021	A priori/post-hoc frameworks	Pre-processing and post-processing	No mention found	No mention found

The 10 studies reviewed implemented a variety of ethical AI frameworks and approaches to mitigate bias in algorithmic marketing systems. Each study applied a distinct framework, including multi-stage (Soni, 2024), fairness-aware (Wan et al., 2019), dynamic management (Akter et al., 2022), analytical (Reed et al., 2025), ethical (Naz & Kashif, 2024), joint fairness CP-FairRank (Rahmani et al., 2024), bias management, inclusive/ethical programs (Su et al., 2023), CONSIDER for diversity, equity, and inclusion (van Esch et al., 2024b), and a priori/post-hoc interventions (Akter et al., 2021). Implementation stage:

Post-processing was the most commonly reported stage, used in 4 studies (Naz & Kashif, 2024; Rahmani et al., 2024; Su et al., 2023; van Esch et al., 2024b). Pre-processing and in-processing were reported in 2 studies each (Soni, 2024; Wan et al., 2019; Akter et al., 2021), while monitoring was mentioned in 1 study (Naz & Kashif, 2024). The implementation stage was not reported in 5 studies.

Fairness improvement:

Post-processing was the most commonly reported stage, used in 4 studies (Naz & Kashif, 2024; Rahmani et al., 2024; Su et al., 2023; van Esch et al., 2024b). Pre-processing and in-processing were reported in 2 studies each (Soni, 2024; Wan et al., 2019; Akter et al., 2021), while monitoring was mentioned in 1 study (Naz & Kashif, 2024). The implementation stage was not reported in 5 studies.

Trade-offs:

Two studies (Wan et al., 2019; Rahmani et al., 2024) mentioned trade-offs, describing minimal accuracy or quality compromises when applying fairness interventions. No trade-off data was reported in 8 studies.

Overall, these findings indicate that while diverse frameworks can effectively reduce bias in algorithmic marketing systems, implementation details and measurable outcomes are inconsistently reported. Post-processing interventions being most common, and ethical and fairness frameworks provide practical guidance for integrating equity into AI deployment.

3. Discussion

The implicit bias that AI carries stems from the data being fed to it, as it teaches and reinforces biased ideologies into the system. Because AI works off of gathered data, when the data comes mostly from one dominant group, such as White American consumers, AI learns to cater their content towards these majority groups to serve them better.

This issue expands as AI continues to grow with this biased data, creating a feedback loop. As a result of this, AI marketing systems start to perpetuate personal bias in their marketing content, resulting in minority consumers receiving less opportunities, products, and beneficial services.

This issue illustrates ethnocentrism, defined in this context as the tendency to assume that the behaviors and preferences of one cultural group (Western consumers here) are universal and should guide output systems (Shankar et al., 2017). For example, in a study by Shankar and his colleagues (2017), it was found that AI automated systems process mostly Western datasets, but still use that AI system on users outside of America (Shankar et al., 2017). Therefore, consumers from a place such as India would receive marketing that is meant to be catered to users in America. This is a problem that cannot just be easily fixed, it has been rooted deeply in AI's automated system and data collection methods, and unfortunately, this bias will only continue to grow as the amount of Western users climbs and continues to dominate minority users. This connects to ethnocentrism, where AI assumes every consumer behaves like a Western consumer. As Artificial Intelligence grows and continues to be integrated into marketing systems worldwide, cultural representation continues to be buried, power dynamics are exemplified, and access to resources even becomes inaccessible to minorities with this biased automated system.

AI algorithms are built on collecting data from existing users. Therefore, preexisting societal biases present in any data that AI collects are learned and perpetuated into the content it creates, excluding minority consumer groups. In Vishvesh Soni's 2024 journal article published in the International Journal of Innovative Science and Research Technology, Soni deep dives into the deep rooted bias in AI marketing, and how it profiles consumers unfairly on race, gender, and other identity aspects (Soni, 2024). In his experiment, he created multiple profiles with differing variables such as age, gender, location, and racially coded names. Control variables, such as interests, searching history, remained identical across all profiles. After running these profiles through marketing platforms that target their users using AI, advertisements from Google and Facebook, Soni found clear patterns of AI's discrimination. Profiles with Afrocentric names received only 60% of luxury products ads over Eurocentric named profiles. Female profiles received advertisements for high paying technology jobs at a 25% lower rate than male profiles. Profiles with a minority racial background received financial and educational opportunities at a 30% lower rate than profiles with a white background. Soni's findings are especially concerning given how saturated AI is in the marketing field. With the widespread adoption of AI automated content in marketing, the deepening of racial and gender discriminatory practices is especially concerning given how the biased algorithms can shape systematic bias through public perception and equal access to opportunity.

Artificial intelligence learns aspects of systematic bias through the cultural values, power structures, and inequalities that society carries. Culture in society is the combination of shared norms, values, and behaviors within the majority group. The data used to train AI comes from real human behaviors that AI systems have observed and have since then adapted, this data can come from anything such as social media, shopping patterns, employment history. Because AI is trained and designed based on massive datasets that pertain to dominant cultural narratives, then reproduces these norms without any implication of its fairness to minority groups. AI picks up these biased and Eurocentric patterns, replicates them, and even magnifies them. Looking at this from an anthropological point of view, the bias found in Artificial Intelligence marketing systems runs deeper than just a technical flaw, but it is a reflection of cultural power structures, how majority groups hold the most influence, and how dominant groups are seen as the "norm" while minority groups are marginalized. An anthropological study by Cite West, Whittaker, & Crawford (2019) explored how AI systems replicate and reinforce social inequalities of race and class (West, Whittaker, & Crawford, 2019). They found that the teams building AI technologies lacked diversity, exuding numbers of under 5% of the team being black or women. This lack of diversity within the teams programming Artificial Intelligence is cultural blind spot embedded into Artificial Intelligence design decisions. Without proper representation in the designing of AI marketing tools, these blind spots lead to exclusionary marketing algorithms and products that fail to serve marginalized communities. Tying this back to an anthropological standpoint, the bias found in Artificial Intelligence Marketing systems favor and serve only dominant group values, viewing them as the "norm" while minority groups continue to be marginalized in technology and therefore social systems.

While systematic bias is rooted deep within AI, there is a way AI can be retrained to support and produce equitable and inclusive marketing content instead. In a case study done by van Esch and colleagues (2024b), they developed a framework that can be a guide for AI marketing systems that leads to an inclusive and representative content creation (van Esch et al., 2024b). Their framework was named "CONSIDER," aimed to, "**C**ontextualize identity differences, **O**vercome default norms in data, **N**avigate inclusive inputs, **S**pot exclusionary patterns, **I**ntegrate diverse voices, **D**esign for equity, **E**valuate impact, **R**eflect on power and privilege" van Esch et al. (2024b). When his framework was applied to AI marketing campaigns in companies, there was a 40% increase of minority representation. This includes features of cultural elements such as traditional clothing and diverse family structures, elements previously underrepresented, and a decrease of stereotypical advertisement targeting. The addition of this framework yielded a 20% increase in consumer click rates. However, in this study, no specific companies are publicly documented of implementing this framework into their active AI automated marketing systems. While the framework proposed in this study is a strong proposal, it still remains theoretical as it has yet to be applied to documented and active companies. Without a concrete case study and a recorded corporation adoption, the effectiveness of equitable frameworks is uncertain as it faces data limitations and real market pressures. From an anthropological perspective, this study exhibits that Artificial Intelligence is a reflection of the values and biases of the users who design and feed it. If AI can reflect discriminatory bias, humans can use the same reflection system to promote equity and cultivate cultural inclusion.

The reflection of dominant social norms and behaviors from Artificial Intelligence systems mirrors evolutionary processes in which variation is crucial to adaptation and survival. When AI is trained and designed on data that favors majority groups, they create marketing content to serve the predominant demographic, diminishing the aspect of variation which excludes minority groups. The lack of variation and representation of minority groups in data used to train Artificial Intelligent systems can be described as a selective pressure. Diversity in cultural data can be compared to genetic variation, it is crucial to adaptability and fairness. Similarly to how environmental pressures in natural selection favor certain genetic traits over others, AI algorithms select and favor majority group preferences over minority groups. AI marketing systems contain and even amplify dominant patterns, marginalizing minority groups in a similar way to how selective pressures reduce genetic diversity within a population. AI feedback loops that reinforce and grow biased content mirrors evolutionary processes that reinforce certain traits. By increasing cultural variation through diverse data and teams, the selective pressure that AI produces through its bias can be counteracted.

4. Conclusion

The continuous and widespread adoption of Artificial Intelligence in marketing exemplifies the concept of "living beyond human scale." AI extends human capabilities, processing data and in mass volumes, allowing businesses to serve millions of users at the same time, shaping both cultural norms and consumer behavior on a global scale. As this expansive reach mirrors evolutionary practices, it also highlights the urgent need for systematic changes so that an AI-driven market can promote inclusivity and equity to eventually succeed beyond human direction, acting autonomously, rather than reinforcing biases and marginalizing minority groups. AI systems are built on data that is rooted in deep historical cultural inequalities, leading towards the exclusion of minority groups in AI-based marketing. The lack of diversity within development teams further amplifies these disparities, embedding majority-group bias into algorithmic design. While equity-based frameworks such as the CONSIDER model show promise, their effectiveness remains limited by the data and system structures they rely on.

AI systems are built off data that is biased and rooted in historical and cultural inequalities, causing these disparities to result in excluding minority groups in AI based marketing. The teams who develop these systems lack diversity, reinforcing majority group bias and excluding minority groups. Equity based frameworks, such as the CONSIDER model, have been proven to be promising, but it is still restricted on data and system models which therefore cannot erase the systematic biases integrated into AI marketing deep into its design. Ultimately, eliminating the bias integrated deep into AI's design requires a human effort for systematic change: a shift towards more diverse teams, reworking data sources to make them more inclusive and fair to minority groups, and redefining the goals of marketing algorithms to prioritize equity over efficiency. In terms of goals for marketers, this means implementing bias audits to ensure diversity in the data. This would mean that AI tools within marketing would shift their focus towards ethical engagement as opposed to profit maximization. In terms of policymakers, a progressive turn would be a call towards a stronger AI governance with establishing accountability frameworks that carry algorithmic transparency.

Looking forward, future research should explore how collaboration between computer scientists, marketing professionals, and marketers can maximize fairness in AI systems. Most importantly, a progression in empowering underrepresented entrepreneurs to navigate digital markets more equitably.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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