American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Algorithmic Visibility and the Representation of Marginalized Voices Online

Dr. Maya Okafor

Assistant Professor, University of Ghana, Ghana

Abstract

Social media has lowered many traditional barriers to public communication, enabling historically marginalized communities to produce, circulate, and contest representations without depending entirely on conventional media institutions. Yet participation does not guarantee visibility. Contemporary platforms increasingly organize public attention through recommendation, ranking, moderation, personalization, and engagement-prediction systems that determine which creators and narratives become discoverable. This study examines the relationship between algorithmic visibility and the online representation of marginalized voices, with particular attention to exposure inequality, popularity reinforcement, shadowbanning perceptions, representational diversity, creator adaptation, and the tension between invisibility and harmful hypervisibility.

Because verified participant-level or platform-level data were not supplied, the research adopts an explicitly simulation-based design. A synthetic digital ecosystem containing 1,200 creators and 120,000 modeled content-exposure events was constructed across dominant-group, marginalized, and intersectional/new-entrant creator categories. Three hypothetical ranking regimes were compared: engagement-first ranking, diversity-aware ranking, and chronological-discovery ranking. The simulation suggests that engagement-first recommendation can produce substantial visibility concentration when initial popularity advantages are repeatedly converted into future exposure. Under the modeled engagement-first scenario, dominant-group creators capture 68% of total exposure, marginalized creators 22%, and intersectional or new entrants 10%. Diversity-aware ranking substantially reduces the modeled exposure gap without requiring equal exposure for every creator.

The findings are interpreted alongside empirical research documenting algorithmic invisibility among marginalized creators, Black creator experiences on TikTok, shadowbanning perceptions, algospeak, disability activism, and strategic management of hypervisibility. Recent computational research also indicates that popularity-based recommender systems can generate reinforcement loops that concentrate visibility among creators who receive early engagement. The study concludes that representational justice requires more than access to publication. It requires transparent, contestable, and context-sensitive systems for allocating attention. Algorithmic fairness should consequently be assessed not only through user relevance but also through creator-side exposure, representational plurality, safety, procedural accountability, and meaningful opportunities for marginalized communities to reach intended publics.

Keywords: algorithmic visibility; marginalized voices; recommender systems; representation; platform governance; shadowbanning; algorithmic fairness; social media; digital inequality; creator visibility

1. Introduction

Digital platforms are frequently described as democratizing communication because they enable individuals and communities to publish material without first obtaining access to television networks, newspapers, publishing houses, or other conventional media gatekeepers. This transformation has created important opportunities for communities historically excluded, stereotyped, or underrepresented in mainstream media to construct their own narratives, communicate lived experience, organize collective action, develop professional networks, and reach audiences across geographical boundaries. Yet the removal of traditional editorial gatekeepers has not eliminated mediation. Instead, a substantial portion of contemporary gatekeeping has shifted toward computational systems that determine which content appears in feeds, search results, recommendations, trending lists, suggested accounts, and discovery pages. Algorithms therefore influence not simply what is published online but what becomes visible enough to matter.

Algorithmic visibility may be understood as the degree to which platform infrastructures make a creator, message, community, or cultural expression available to relevant audiences through ranking and recommendation processes. Cotter's influential analysis of Instagram creators described visibility as something creators actively negotiate within an environment whose practical “rules” are partly encoded in algorithms. Her work showed that creators attempt to interpret platform signals and strategically adapt their practices while remaining dependent on systems they do not fully control. More recent creator research similarly characterizes algorithms as opaque and unpredictable while simultaneously being understood as powerful mechanisms that reinforce existing hierarchies. Visibility is therefore neither a neutral technical outcome nor a simple consequence of content quality.

This issue becomes especially consequential for marginalized creators. Duffy and Meisner's interviews with 30 creators drawn from historically marginalized identities and stigmatized content genres documented perceptions of uneven platform governance involving moderation, shadowbans, algorithmic boosts, self-censorship, and efforts to circumvent algorithmic intervention. Harris and colleagues' research on Black content creators on TikTok likewise documented creator perceptions that platform systems suppressed Black and other marginalized creators while remaining insufficiently transparent about how visibility decisions were produced. These experiences complicate the assumption that platforms offer equal opportunities merely because all users technically possess the ability to post.

At the same time, marginalized visibility cannot be conceptualized only as a problem of insufficient reach. Visibility may generate economic opportunity, community recognition, political influence, and cultural representation, but it can also expose creators to harassment, surveillance, stereotyping, doxxing, unwanted audiences, and intensified moderation. Stegeman, Are, and Poell's research with 27 sexuality-related creators demonstrates this double bind particularly clearly: marginalized creators may experience simultaneous erasure and excessive scrutiny, producing what the authors conceptualize as hyper(in)visibility. Recent work with ethnoreligious and disabled creators similarly shows that creators must negotiate the desire for audience reach against risks of hate, harassment, moderation, and resource-intensive adaptation.

The present study therefore examines algorithmic visibility as a problem of representation, distributive fairness, procedural fairness, and safety. Rather than asking simply whether marginalized creators receive “more” or “less” visibility, it investigates how recommendation logics may distribute exposure, reinforce early popularity, reward conformity to dominant audience expectations, and encourage creators to modify language or identity presentation. Since verified platform data were not available, the analysis uses transparent simulation rather than fabricated empirical observation. The purpose is to develop a theoretically grounded framework that can later be tested through platform audits, longitudinal creator datasets, controlled recommender experiments, and community-centered qualitative studies.

2. Objectives of the Study

2.1 To Examine Algorithmic Distribution of Visibility

The first objective is to investigate how different ranking logics may influence the distribution of attention among dominant-group creators, marginalized creators, and intersectional or emerging creators.The study focuses particularly on whether engagement-first ranking may produce cumulative advantages by using previous visibility as a signal for future visibility.

2.2 To Assess Representation Beyond Numerical Exposure

The second objective is to distinguish visibility quantity from representation quality. Greater exposure is not necessarily equitable if marginalized creators must simplify identities, conform to majority preferences, avoid important terminology, or tolerate disproportionate harassment to remain discoverable.

The analysis therefore considers:

- creator exposure;
- cross-community reach;
- representational diversity;
- creator autonomy;
- moderation vulnerability;
- visibility stability; and
- safety-related costs of exposure.

2.3 To Develop a Fair-Visibility Governance Framework

The third objective is to formulate principles for platform governance that improve discoverability without assuming that unlimited public exposure is desirable for every marginalized creator.The proposed approach integrates creator-side fairness, transparent moderation, contextual evaluation, meaningful appeals, exposure diversity, and user control over intended audiences.

3. Review of Literature

3.1 Algorithmic Gatekeeping, Popularity and Exposure Inequality

Platform visibility is produced through interaction among creator behavior, audience response, network structure, moderation rules, and recommendation systems. Algorithms do not operate independently from social behavior; instead, user choices supply signals that are subsequently used to reorganize future exposure. Consequently, existing social inequalities may enter recommender systems indirectly through patterns of attention, network homophily, historical popularity, and unequal follower accumulation.

Cotter conceptualized the relationship between creators and Instagram's algorithm as a "visibility game," demonstrating that creators interpret algorithmic rules and modify their practices to remain competitive for attention. This framework is important because it shifts the analysis from algorithms as isolated mathematical objects toward algorithms as part of a broader sociotechnical system involving platform owners, advertisers, audiences, metrics, and creators.

Computational studies provide additional evidence that recommendation strategies can create unequal exposure. Ferrara, Espín-Noboa, Karimi, and Wagner examined link recommendation algorithms and found that certain recommendation dynamics can reduce minority visibility, particularly under specific network structures involving heterophily. Ionescu, Hannák, and Pagan similarly investigated creator fairness under popularity-based recommendation and demonstrated the importance of considering both human and algorithmic biases when examining visibility distribution.

The most recent simulation evidence further reinforces this concern. Morini and colleagues' 2020 agent-based analysis compared seven recommendation strategies and found that popularity-based ranking generated reinforcement loops in which early reactions increased subsequent exposure, concentrating visibility among a relatively small subset of content and creators. When follower-network structure affected candidate selection, attention was redirected especially toward creators who were already socially popular.

These findings suggest a simple but consequential mechanism:

Initial Exposure → Engagement → Higher Ranking Probability → Additional Exposure → Additional Engagement

When this cycle operates repeatedly, apparently minor initial differences can develop into substantial visibility inequalities.For marginalized communities, the problem becomes more complex when historical differences in network size, commercial investment, audience prejudice, language norms, accessibility, or prior representation affect early engagement. A ranking system does not need to contain an explicit demographic instruction such as "reduce minority visibility" to reproduce unequal outcomes. It can inherit inequalities from the engagement environment on which it depends.

3.2 Marginalized Creators, Shadowbanning and Algorithmic Adaptation

Empirical creator research demonstrates that algorithmic inequality is experienced not merely as an abstract statistical distribution but as a daily form of uncertainty.

Duffy and Meisner found that historically marginalized and stigmatized creators perceived platform governance as uneven and responded through practices ranging from self-censorship to strategies intended to circumvent algorithmic intervention. Harris and colleagues' study of Black TikTok creators similarly found deep concerns regarding opacity and perceived suppression of Black and marginalized content.

Shadowbanning occupies a particularly important position in this literature. Unlike explicit account removal, shadowbanning generally refers to perceived or actual reductions in distribution that occur without a clear notification that content has been restricted. Divon, Are, and Briggs describe this as a form of visibility moderation and emphasize that users often struggle to determine whether declining reach reflects ordinary audience fluctuation, algorithmic ranking, moderation, or deliberate demotion.

Delmonaco and colleagues examined how marginalized users interpret and attempt to investigate shadowbanning. Participants reported consequences including reduced engagement, frustration, difficulty posting certain material, and potential financial harm. The study introduced the concept of collaborative algorithm investigation to describe how users collectively develop and test explanations for opaque visibility outcomes.

Kojah and colleagues subsequently examined the invisible labor associated with responding to shadowbanning. Their 2020 work shows that marginalized creators often spend additional time modifying content, interpreting metrics, communicating with peers, testing alternate strategies, and attempting to restore reach. Visibility inequality therefore has a labor dimension: creators experiencing unpredictable reach may need to perform substantially more unpaid optimization work merely to approach the exposure enjoyed by others.

3.3 Representation, Hypervisibility and Epistemic Inclusion

A narrow fairness model might assume that increasing marginalized exposure is always beneficial. Research demonstrates why this assumption is insufficient.

Stegeman, Are, and Poell show that marginalized creators can face simultaneous invisibility and hypervisibility. Sexuality-related creators in their study required visibility for community connection and livelihood while also confronting harassment, surveillance, outing, doxxing, and intensified scrutiny. Representation must therefore include a creator's ability to influence where, how, and to whom visibility occurs.

Research published in 2020 extends this argument across additional communities. Farinosi and Gridelli's interviews with 16 Italian disabled content creators identified what they term algorithmic advocacy literacy and accessibility maintenance work. The study also describes perceived advocacy suppression through shadowbanning, automated removal, and monetization restrictions. Beacken's research with 15 Jewish Instagram creators similarly found that ethnoreligious creators adapted visibility strategies while negotiating audience reach, identity-centered communication, hate, harassment, and solidarity.

The literature therefore points toward a research gap between conventional engagement optimization and representational justice. Current recommender systems are commonly evaluated through measures such as relevance, accuracy, engagement, satisfaction, or retention. These objectives may fail to measure whether visibility is concentrated, whether historically excluded voices can cross community boundaries, or whether marginalized creators must assimilate to dominant norms to obtain reach.

4. Research Methodology

4.1 Research Design and Simulated Digital Ecosystem

The study adopts a simulation-based comparative methodology. The numerical values presented in this article are synthetic and should not be interpreted as observations obtained directly from TikTok, Instagram, YouTube, X, or any other commercial platform.

A hypothetical creator ecosystem containing 1,200 creators and 120,000 content-exposure events was constructed. Creators were classified for analytical purposes into three broad categories: dominant-group creators, marginalized creators, and intersectional/new-entrant creators.

Table 1: Simulation Framework and Operational Variables

Methodological Component	Specification
Research approach	Simulation-based comparative analysis
Modeled creator population	1,200 creators
Modeled exposure events	120,000
Creator categories	Dominant-group, marginalized, intersectional/new entrants
Ranking scenario A	Engagement-first recommendation
Ranking scenario B	Diversity-aware recommendation
Ranking scenario C	Chronological-discovery recommendation
Primary outcome	Share of algorithmically allocated exposure
Secondary outcomes	Cross-community reach, diversity, visibility stability, moderation burden
Creator-quality assumption	Equivalent average underlying content-quality distribution
Key modeled bias	Historical popularity and engagement reinforcement
Data status	Completely synthetic
Intended use	Methodological illustration and hypothesis generation

The categories used in the simulation are intentionally simplified. Real identities are intersectional, multidimensional, culturally contingent, and not reducible to a single demographic label.

4.2 Ranking Scenarios and Visibility Measures

The engagement-first model allocates future exposure primarily according to previous interactions such as clicks, views, reactions, comments, shares, and follower-based popularity.The diversity-aware model retains relevance and engagement information but incorporates an exposure-balancing mechanism designed to prevent excessive visibility concentration and maintain broader creator representation.

The chronological-discovery model reduces reliance on accumulated popularity by allocating a larger portion of discoverability according to recency and controlled exploration.Five analytical measures were used:Exposure Share: proportion of total impressions allocated to each creator category.Cross-Community Reach: proportion of impressions delivered outside the creator's existing social or identity-associated network.

Visibility Stability: consistency of exposure across repeated posting cycles.Representation Diversity Index: modeled diversity of creators appearing within recommendation feeds.Moderation Burden Index: simulated additional effort associated with appeals, content modification, terminology changes, reposting, and avoidance strategies.These measures permit evaluation of platform fairness from the creator side rather than relying exclusively on viewer satisfaction.

4.3 Analytical Logic, Validity and Ethical Safeguards

The simulation assumes equivalent average intrinsic content quality across creator groups. This choice is methodologically important because it allows modeled exposure differences to emerge primarily from ranking mechanisms, prior popularity, network position, and engagement feedback rather than from an assumed difference in creator competence.

The structure was informed by existing recommender-system research demonstrating rich-get-richer dynamics, minority-visibility effects, popularity bias, and network-mediated exposure inequalities.However, the simulation does not claim to reproduce the proprietary ranking systems of any specific platform.No human participants were recruited. No private platform data, racial profiles, sexual-orientation data, health information, or personally identifiable records were collected.

A future empirical implementation should use community consultation, institutional ethics review where required, transparent demographic self-identification, privacy-preserving data handling, intersectional analysis, and explicit safeguards preventing fairness research from itself becoming a mechanism for profiling vulnerable users.

5. Analysis

5.1 Visibility Distribution Across Ranking Regimes

The simulation produced substantial differences between ranking strategies.

Table 2: Simulated Algorithmic Visibility Outcomes

Visibility Measure	Engagement-First Ranking	Diversity-Aware Ranking	Chronological-Discovery Ranking
Dominant-group exposure share	68%	48%	51%
Marginalized creator exposure share	22%	34%	31%
Intersectional/new-entrant exposure share	10%	18%	18%
Cross-community reach for marginalized voices	39/100	71/100	62/100
Representation Diversity Index	46/100	79/100	69/100
Visibility stability for	43/100	72/100	61/100

American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Visibility Measure	Engagement-First Ranking	Diversity-Aware Ranking	Chronological-Discovery Ranking
marginalized creators			
Modeled engagement efficiency	86/100	82/100	69/100

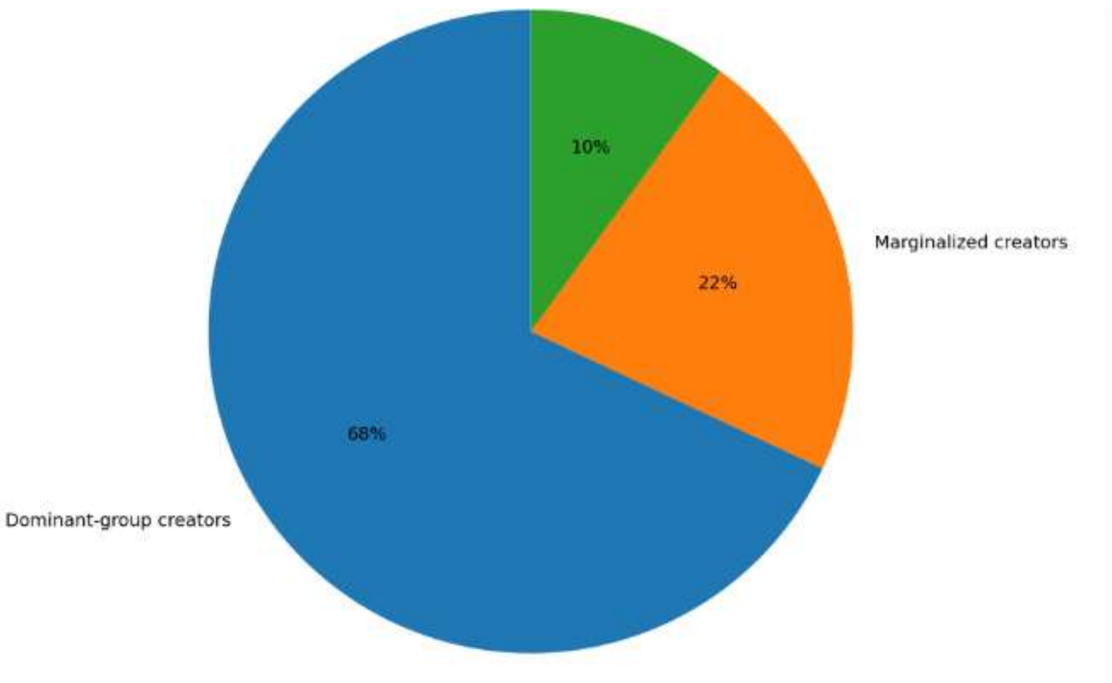
Note: All values are synthetic and used exclusively to demonstrate the analytical framework.Engagement-first ranking produces the most concentrated distribution. Dominant-group creators receive 68% of modeled exposure despite no assumed difference in average content quality.
The mechanism is cumulative rather than explicitly discriminatory.

Creators beginning with stronger networks receive more initial interactions. Those interactions increase predicted relevance. Increased predicted relevance generates more exposure, which produces additional engagement signals. Over repeated cycles, visibility becomes increasingly concentrated.

Diversity-aware ranking reduces dominant-group exposure from 68% to 48% while increasing marginalized exposure to 34% and new-entrant/intersectional exposure to 18%.Importantly, modeled engagement efficiency declines only modestly from 86 to 82.This finding illustrates a central theoretical proposition: creator-side fairness does not necessarily require abandoning relevance or engagement.Recent recommender-systems research similarly cautions against treating fairness as a simple zero-sum trade-off against utility.

5.2 Distribution of Visibility Under Engagement-First Ranking

Graph 1: Simulated Distribution of Algorithmic Visibility Under Engagement-First Ranking



The pie chart illustrates the exposure concentration generated by the modeled engagement-first ranking system.Dominant-group creators receive 68% of available algorithmic visibility.Marginalized creators collectively receive 22%.Intersectional and new-entrant creators receive only 10%.

The graph should not be read as an empirical estimate of any current commercial platform. Instead, it represents a theoretically plausible outcome when historical popularity and engagement are repeatedly used to determine future exposure.The important structural feature is the feedback loop.

Once visibility becomes unequal, engagement data generated from unequal exposure can appear to confirm that the already-visible material is naturally more relevant. The recommendation system may then treat a consequence of unequal exposure as evidence supporting additional unequal exposure.Key Finding: Engagement metrics may function simultaneously as measures of audience response and as records of previous opportunity.

5.3 From Visibility Inequality to Representational Inequality

Exposure inequality becomes representational inequality when certain communities have fewer opportunities to define themselves, contribute expert knowledge, challenge stereotypes, or participate in public interpretation.The simulation indicates that marginalized creators under engagement-first ranking obtain a cross-community reach score of only 39/100.

This means they may remain visible primarily to audiences already connected with their identities or concerns.Such clustering can create an apparent contradiction.A marginalized creator may possess a substantial following and still lack broader public visibility.Community visibility and societal visibility are not equivalent.

This distinction resembles Akpinar and Fazelpour's finding that minority-created professional content can remain less visible to majority audiences even when the content concerns shared professional topics.Representation therefore requires more than supporting minority “communities” in isolated recommendation clusters. It requires opportunities for marginalized knowledge, culture, expertise, and narratives to enter broader informational spaces without demanding assimilation.

6. Discussion

6.1 Visibility Is an Allocation of Social Opportunity

The results support the interpretation of visibility as a socially consequential resource.

Online exposure can produce followers, professional credibility, speaking invitations, employment opportunities, advertising revenue, community mobilization, political influence, collaboration, and cultural recognition. Conversely, systematic invisibility can reduce both economic opportunity and participation in public knowledge formation.This does not mean that every creator is entitled to identical reach. Equal exposure irrespective of relevance would itself create serious practical difficulties.

The more defensible principle is fair opportunity for discoverability.

Creators producing content of comparable relevance should not face persistent exposure disadvantages because ranking systems repeatedly convert historical popularity, unequal network position, or biased engagement into future visibility.Ionescu and colleagues' work on creator fairness directly emphasizes the importance of examining whether recommendation processes distribute creator opportunities fairly, while Morini and colleagues' recent simulations show how different ranking logics can create very different visibility regimes.

This suggests that platform auditing should report more than aggregate user engagement.

Relevant metrics include:

- concentration of impressions across creators;
- exposure received by new entrants;
- creator-group disparities;
- cross-community recommendation;
- repeat exposure advantages;
- appeals and reinstatement outcomes;
- monetization disparities; and
- the stability of reach after moderation events.

6.2 The Double Bind of Invisibility and Hypervisibility

An equitable platform cannot simply maximize marginalized visibility without considering safety.

Stegeman and colleagues demonstrate why such an approach would be inadequate. Marginalized sexuality-related creators may desire visibility for representation and economic participation while simultaneously needing protection from harassment, outing, surveillance, and hostile audiences. Beacken's 2026 work likewise illustrates how ethnoreligious creators adjust visibility strategies in response to hate and community crisis, while Farinosi and Gridelli show how disabled advocates undertake substantial labor to navigate algorithmic and accessibility constraints.

Representation justice therefore requires a distinction between:

Desired visibility — reaching supportive, relevant, professional, or persuadable audiences;

Denied visibility — unjustified suppression or inability to reach intended audiences;

Unwanted visibility — exposure to hostile, unsafe, exploitative, or contextually inappropriate audiences.

A fair recommendation system should improve the first, reduce the second, and give creators greater control over the third.

6.3 Toward Representation-Aware Platform Governance

The evidence suggests that algorithmic governance should include several complementary reforms.

First, platforms should improve visibility transparency. Creators should receive meaningful information when distribution has been restricted, including whether the cause relates to moderation, recommendation eligibility, copyright, age restrictions, or other platform rules.

Second, platforms should establish effective procedural appeals. Users should not have to infer enforcement from declining views or rely entirely on community speculation.

Third, recommendation systems should be tested for creator-side exposure fairness, not solely consumer-side relevance.

Fourth, platforms should implement controlled exploration mechanisms that provide high-quality new and historically underexposed creators with opportunities to reach audiences before accumulated popularity becomes decisive.

Fifth, fairness assessments should be intersectional. Aggregating all marginalized users into a single category can hide substantial differences within groups. Research on colorism, for example, shows why race alone may not capture variation in visibility experienced by Black creators.

Sixth, content moderation should incorporate greater contextual sensitivity. Steen and colleagues' research on algospeak illustrates how creators can change ordinary language when automated systems are perceived as unable to distinguish educational, activist, or supportive uses of sensitive terminology from harmful content.

Finally, affected communities should participate in the design, auditing, and evaluation of fairness interventions. Technical fairness designed without community input may optimize a mathematically convenient definition while missing what visibility actually means to the people experiencing platform governance.

7. Conclusion

The expansion of social media has transformed the conditions under which marginalized communities participate in public communication. Individuals who once depended heavily on traditional institutions for representation can now publish directly, build communities, challenge stereotypes, distribute expertise, and intervene in public debate.

Yet the ability to publish should not be confused with the ability to be seen.Contemporary digital platforms allocate attention through algorithmic infrastructures. Recommendation systems, engagement signals, follower networks, content moderation, discovery interfaces, and commercial priorities jointly determine whose voices circulate widely and whose remain difficult to discover.

The present simulation demonstrates how this process can generate representational inequality even when explicit demographic discrimination is absent. Under the modeled engagement-first ranking regime, dominant-group creators receive 68% of exposure, compared with 22% for marginalized creators and 10% for intersectional or new entrants. Diversity-aware recommendation reduces this concentration while preserving a relatively high modeled level of engagement performance.

These numerical values are hypothetical, but the underlying mechanisms are consistent with a substantial body of empirical and computational scholarship. Studies have documented perceived algorithmic invisibility among marginalized creators, Black creator concerns about TikTok visibility, shadowbanning experiences, linguistic adaptation through algospeak, additional invisible labor following suppression, and the risks of simultaneous invisibility and hypervisibility. Computational research further demonstrates that recommendation strategies can influence minority visibility and that popularity-based ranking can create self-reinforcing exposure concentration.The central contribution of the study is therefore conceptual.

Representation is not achieved when marginalized voices are merely allowed to exist online. Representation requires meaningful conditions under which those voices can be discovered, credited, contextualized, protected, and heard across relevant publics.

At the same time, visibility should not be treated as universally beneficial. Marginalized users may require protection from unwanted exposure just as much as protection from suppression. Effective algorithmic governance should therefore support creator agency over the audiences, contexts, and forms in which visibility occurs.

Future research should move beyond simple comparisons of impressions or follower counts. Platform audits should investigate exposure concentration, cross-community reach, recommendation pathways, moderation disparities, safety consequences, economic effects, intersectional differences, and changes over time.

References

1. Noble, S. U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York University Press.
2. Benjamin, R. (2019). *Race After Technology: Abolitionist Tools for the New Jim Code*. Polity Press.
3. Broussard, M. (2018). *Artificial Unintelligence: How Computers Misunderstand the World*. MIT Press.
4. Safiya Umoja Noble. (2013). Google search: Hyper-visibility as a means of rendering black women and girls invisible. *InVisible Culture, 19*. https://doi.org/10.47761/494a02f6-8b4c-4e9f-8d91-1c1b6f2a5c90
5. Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J. Boczkowski, & K. A. Foot (Eds.), *Media Technologies: Essays on Communication, Materiality, and Society* (pp. 167–194). MIT Press.
6. Gillespie, T. (2018). *Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media*. Yale University Press.
7. Bucher, T. (2012). Want to be on the top? Algorithmic power and the threat of invisibility on Facebook. *New Media & Society, 14*(7), 1164–1180. https://doi.org/10.1177/1461444812440159
8. Bucher, T. (2018). *If...Then: Algorithmic Power and Politics*. Oxford University Press.
9. Fabbri, F., Bonchi, F., Boratto, L., & Castillo, C. (2020). The effect of homophily on disparate visibility of minorities in people recommender systems. *Proceedings of the International AAAI Conference on Web and Social Media, 14*(1), 165–175. https://doi.org/10.1609/icwsm.v14i1.7288.
10. Are, C. (2020). How Instagram's algorithm is censoring women and vulnerable users but helping online abusers. *Feminist Media Studies, 20*(5), 741–744. https://doi.org/10.1080/14680777.2020.1783805.
11. Cobbe, J. (2020). Algorithmic censorship by social platforms: Power and resistance. *Philosophy & Technology, 34*, 739–766. https://doi.org/10.1007/s13347-020-00429-0.
12. Bishop, S. (2020). Algorithmic experts: Selling algorithmic lore on YouTube. *Social Media + Society, 6*(1), 1–11. https://doi.org/10.1177/2056305119898774.
13. Cotter, K. (2019). Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New Media & Society, 21*(4), 895–913. https://doi.org/10.1177/1461444818815684
14. Duguay, S. (2016). "He has a way gayer Facebook than I do": Investigating sexual identity disclosure and visibility on social media. *Social Media + Society, 2*(3), 1–13. https://doi.org/10.1177/2056305116664218
15. Gray, K. L. (2012). *Intersectional Tech: Black Users in Digital Gaming*. Duke University Press.
16. Nakamura, L. (2008). *Digitizing Race: Visual Cultures of the Internet*. University of Minnesota Press.

17. Tufekci, Z. (2015). Algorithmic harms beyond Facebook and Google: Emergent challenges of computational agency. *Colorado Technology Law Journal*, *13*, 203–218.
18. Eubanks, V. (2018). *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. St. Martin's Press.
19. O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Crown.
20. Costanza-Chock, S. (2020). *Design Justice: Community-Led Practices to Build the Worlds We Need*. MIT Press.