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ALGORITHMIC BIAS IN MEDIA CONTENT DISTRIBUTION AND ITS INFLUENCE ON MEDIA CONSUMPTION: IMPLICATIONS FOR DIVERSITY, EQUITY, AND INCLUSION (DEI)

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ABSTRACT

In today's digital age, algorithms play a pivotal role in shaping media content distribution, which may possibly influence what content individuals are exposed to. Consequently, this may have implications for diversity, equity, and inclusion (DEI). Hence, this review analyzes algorithmic bias in media material distribution and its impact on media consumption and the implications for diversity, equity, and inclusion (DEI). The study concludes that algorithm bias limits the visibility of underprivileged groups and perpetuates current social injustices, posing serious problems for media distribution. Moreover, there are risks and opportunities associated with the development of artificial intelligence (AI) and machine learning in tackling algorithmic inequities. Furthermore, there is a need for collaborative efforts among different stakeholders (engineers, policymakers, and media platforms) in creating a more inclusive and equitable algorithms in order to ensure that media distribution systems promote fairness and diversity.

1.0 INTRODUCTION

In today's digital age, algorithms play a pivotal role in shaping media content distribution, which may possibly influence what content individuals are exposed to. Algorithms determines which information material is visible and has a greater reach than others as social media, streaming services, and internet platforms increasingly control how people consume news, entertainment, and other types of media. These algorithms, which are frequently created to maximize user involvement, have a significant impact on how people consume media. Nonetheless, an increasing amount of scholarly literature has commenced to investigate the bias inherent in these algorithms and the degree to which they impact the dissemination and prominence of varied media content. In this situation, algorithmic bias may amplify a limited variety of viewpoints, which raises questions about how diversity, equity, and inclusion (DEI) may be affected in media consumption (Adeyemi, 2023a).

Algorithmic bias happens when media distribution methods or systems marginalize other sources of material while favoring certain, frequently unintentionally (Ukanwa & Rust, 2021). Nazer et al. (2023) noted that biases may stem from past disparities in the data used to train these algorithms, or from decisions made in the design process by developers who may not have taken into consideration the wider societal effects. When it comes to the distribution of media, this might take the form of over-promoting content that conforms to majority cultural norms or the mainstream while underrepresenting content that supports minority groups or unpopular ideas (Plough, 2022). The resulting imbalance in media exposure has the potential to shape viewers' choices and strengthen social hierarchies and power structures. This relationship calls into question how computational systems restrict the range of voices in public discourse and sustain inequality (Harambam et al., 2018).

The fact that, in this age, many media platforms run on economic models intended to optimize user engagement and revenue further complicates the problem of algorithmic bias (Reviglio & Agosti, 2020). Meanwhile, scholars (e.g., Adeyemi, 2017; Cohen, 2018; Gal & Elkin-Karen, 2016) have emphasized that algorithms are taught to prioritize information that is similar to what consumers have previously engaged with in order to deliver contents that keep people on the platform. As a result, rather than being exposed to a wider range of viewpoints, users are continuously offered contents that are similar with their preexisting inclinations, creating a feedback loop. Meanwhile, the "filter bubble" phenomenon has a significant impact on media diversity (Sukiennik et al., 2024). Cavusoglu and Atik (2023) noted that consumers' access to a wider range of information and cultural narratives is restricted, which makes it harder for them to hear from a variety of voices, especially those from underrepresented groups. Therefore, this might exacerbate preconceptions and impede the advancement of inclusivity in the society.

Aside from the effect of algorithmic bias on diversity, equity, and inclusion (DEI), the quality of public discourse is significantly impacted by algorithmic bias in media content distribution (van Esch et al., 2024). Scholars (Ausat, 2023; Adeyemi, 2023b) noted that media is essential for shaping public opinion, educating the populace, and promoting democratic discourse. Hence, the audience can easily be denied the chance to interact with a variety of perspectives when algorithms filter the media environment in ways that disproportionately magnify dominant narratives. This might lessen the likelihood of communication across various communities and result in the development of echo chambers, where people are only exposed to information that confirms their preexisting opinions (Interian et al., 2023). By silencing opposing viewpoints and reducing the range of opinions in the public domain, these behaviors have the potential of undermining social cohesiveness and the democratic process over time (David et al., 2023).

Meanwhile, the opaque nature of algorithmic operations issue exacerbates the issues that surround algorithmic bias. The majority of media platforms do not reveal the inner workings of their algorithms, so neither users nor content providers are aware of the standards used to determine what information is visible (Herzog, 2021). It is challenging to determine the complete scope of algorithmic bias and to hold platforms responsible for their impact on media consumption because of this opacity. Hence, it becomes difficult to push for reforms that encourage more diversity and equity in media representation if one is unaware of these procedures (Stinson & Vlaad, 2024). Furthermore, because these systems are opaque, people may believe that their choices of content are being influenced by forces outside of their control rather than being a true reflection of their own preferences, which erodes public confidence in media organizations (Reisach, 2021). Hence, this review analyzes algorithmic bias in media content distribution and its influence on media consumption and the implications for DEI.

2.0 ALGORITHMIC BIAS IN MEDIA CONTENT DISTRIBUTION

Kordzadeh and Ghasemaghaei (2022) described algorithmic bias as the deliberate and frequently inadvertent biases ingrained in the operation of algorithms. The authors noted further that these biases occur when algorithms, which are meant to process information and generate recommendations or judgments, lead to results that unfairly benefit or harm particular people or groups. Although algorithms are frequently viewed as impartial instruments, their objectivity is dependent on the facts and presumptions they are constructed with (Simon-Kerr, 2021). Belenguer (2021) noted that the data used to train the algorithm may contain biases that represent current societal injustices or discriminatory trends from the past. For example, an algorithm may perform badly for particular demographic groups and produce biased results if it is trained on data that underrepresents those groups.

Aquino (2023) argues that a prevalent factor contributing to algorithmic bias is the utilization of incomplete or non-representative data sets. Meanwhile, Andrus et al. (2021) noted that algorithm may not produce fair or accurate results for those outside of specific demographics if it was trained on data that is biased toward those groups. For instance, Peña-Alcántara (2022) found that facial recognition software that was mostly trained on light-skinned faces makes more mistakes when attempting to identify individuals with darker skin tones. This highlights a larger problem in machine learning, producing inconsistent results as a result of the training data used for the algorithm. When the algorithm continues to make judgments based on erroneous or biased data, these biases not only maintain already-existing inequities but also make them more pronounced (Ragnedda & Ragnedda, 2020).

Aside the media professionals, developers' subjective decisions made throughout the algorithm design process are another element that leads to algorithmic bias (Kleanthous et al., 2022). Balayn et al. (2021) noted that bias can be introduced by choosing which features to prioritize, how to weigh different criteria, or what data to include. These choices frequently represent the viewpoints and presumptions of the people who developed the algorithm, which might not take into consideration the range of user experiences. Furthermore, it is frequently challenging to detect or address biases once they have been ingrained in the system due to the complexity of algorithms (Ntoutsi et al., 2021). Biases may go unchecked in the absence of inclusive and transparent design procedures, which could result in unfair or discriminating consequences (Tanna & Dunning, 2022). Overall, algorithmic bias may result from skewed data, arbitrary choices made by developers, or systematic disparities represented in the data that was used (Waller & Waller, 2022).

Beyond only consumers, content creators—especially those from marginalized groups—are also affected by algorithmic bias. Media producers from underrepresented groups frequently face difficulties in being visible on platforms where algorithms prioritize content that resonates with a larger audience or is already well-liked (Cohen, 2018). This leads to a vicious loop whereby minority artists' material is less likely to be found, which restricts their chances of success and deepens the gaps in media representation. Additionally, McCray (2020) noted that a lack of exposure to a diverse range of artists not only stunts cultural innovation but also lessens the diversity of the media environment, depriving viewers of new and interesting content. Thus, systematic disparities in the media sector are sustained via algorithmic bias.

In recent years, there has been a noticeable increase in the efforts to tackle algorithmic bias in media distribution, especially since issues around DEI have been more prominent in public discourse (Drage & Mackereth, 2022). Scholars, activists, and policymakers are requesting that media platforms be held more accountable and should be transparent about how their algorithms work and how distribution decisions are made (Gorwa & Ash, 2020). While some scholars (e.g., Daneshjou et al., 2021; Norori et al., 2021) have asked for more inclusive data sets to be utilized in algorithm training, others (e.g., Bandy, 2021; Shen et al., 2021) have argued for algorithm audits to evaluate the impact of these systems on excluded groups. Furthermore, there is a rising interest in creating alternative algorithms that prioritize diversity and fairness, making sure people can access a greater variety of information (Herzog, 2021).

Despite all these efforts and advocacies, there are still challenges in reducing the impact of algorithmic bias in the distribution of media material. The difficulty of characterizing and quantifying fairness in algorithmic systems is a significant barrier. The opinions of different stakeholders about fair representation in media may differ, which makes it challenging to create algorithms that please everyone (De-Arteaga et al., 2022). Additionally, Lu et al. (2021) noted that there is a conflict between encouraging diversity and optimizing media resources for engagement. Although media platforms aim to generate income by maintaining user engagement, their financial structures can potentially undermine initiatives to encourage a fairer distribution of information. It will take creative thinking to strike a balance between these conflicting priorities and societal objectives and business interests (Griffin, 2023).

Furthermore, there are opportunities and concerns associated with the growing use of artificial intelligence (AI) and machine learning (ML) in media content distribution when it comes to correcting algorithmic bias (Schwartz et al., 2022). On the one hand, if AI-driven algorithms are not properly developed and overseen, they may worsen preexisting prejudices. However, AI provides capabilities for creating more complex algorithms that can take equity and diversity in the distribution of content into account (Yu, 2020). AI might be used, for instance, to spot underrepresentation trends in the media and suggest ways to provide more varied material. To guarantee that AI systems are created with inclusivity in mind, engineers, media businesses, and legislators must work together to realize this potential (Barretto et al., 2021).

3.0 INFLUENCE OF ALGORITHM BIAS IN CONTENT DISTRIBUTION ON CONSUMPTION

Algorithm is an important factor in determining how media is consumed. They are integrated into search engines, social media, news websites, streaming services, and other platforms to filter material according to user interactions, preferences, and behaviors (Simon-Kerr, 2021). The goal of this customization is to improve the user experience by offering interesting and pertinent material. However, algorithms are not impartial. Because of the data they are trained on or the manner they are made, they may display bias, which has a significant impact on the types of media that consumers choose to consume (Nazer et al., 2023). Balayn et al. (2021) noted that although this bias is not often evident, it has a big impact on how information is shared, interpreted, and understood. This would ultimately lead to a form of jaundice information consume by media users.

When it comes to media consumption, Sukiennik et al. (2024) surmised that filter bubbles are a serious concern as they are a direct result of algorithmic bias. Algorithms continue to filter information that users are exposed to, presenting them with platform that only displays content or information that is related to what they have already interacted with or consumed. This tendency restricts users' comprehension of intricate social, political, and cultural concerns by isolating them from points of view that contradict their ideas or present alternate opinions (Herzog, 2021). When it comes to news and political information, filter bubbles are especially dangerous because they can create echo chambers, which are places where people are surrounded by other people who share their opinions (Bozdag & Van Den Hoven, 2015). This prevents critical thinking and reinforces preconceptions. As a result, users become more susceptible to misinformation and disinformation since they have been inundated with slanted information.

In addition to facilitating the development of filter bubbles, algorithmic bias also aids in the dissemination of false and misleading information. Sensational or false information may gain traction if algorithms favor material based more on engagement than fact (Shu et al., 2017). This is especially troubling on social media sites, where erroneous news reports can propagate more quickly than true ones. These platforms' algorithms are built to optimize user interaction, and content that is controversial or emotionally charged tends to receive more clicks, likes, and shares (Cohen, 2018). As a result, biased algorithms could unintentionally give false information precedence over accurate reporting. Because of this, there is a serious risk that the public will not grasp vital problems like public health, climate change, or current political events.

Furthermore, another way that algorithmic bias affects media consumption is through feedback loops. The algorithm modifies to prioritize comparable information whenever a user starts interacting with a certain kind of content, starting a cycle that keeps reinforcing the user's preferences (Rogers, 2021). For instance, the system would favor more content related to conspiracy theories if a user often watches videos or reads articles about them, which could go farther into speculative subjects. In addition to limiting the user's exposure, the amplification of a particular type of content speeds up the dissemination of potentially dangerous information (Kozyreva et al., 2020). Feedback loops reduce the variety of content that users can consume, decreasing the possibility that they will come across viewpoints that are unfamiliar or difficult. Users could thereby lose awareness of larger sociocultural or political realities, further polarizing and fragmenting society (Kitchens et al., 2020).

Algorithmic bias can deepen social inequality by favoring certain voices while marginalizing others. Content from underrepresented groups may find it difficult to be seen because many media platforms rely on algorithms to surface content. These algorithms typically favor high-engagement content, like viral videos or trending news stories, but this can disproportionately benefit creators from dominant cultural groups or those with greater resources, sidelining the voices of minority groups (Brough et al., 2020). In this way, algorithms perpetuate power structures and inequalities in media representation. Furthermore, Williams et al. (2018) noted that marginalized groups may suffer further disadvantages when algorithms are trained on biased data sets that do not fully reflect their needs or experiences. This imbalance in representation can skew public discourse, limiting the range of viewpoints available to consumers and reinforcing harmful stereotypes.

Political polarization is also largely caused by algorithmic bias, which arises from the increasingly fragmented and personalized nature of media consumption (Greene, 2019). Social media platforms and news aggregators often use algorithms to recommend content that aligns with users' past behavior, meaning that people with particular political leanings are more likely to encounter content that reinforces their beliefs (Calice et al., 2023). Over time, this leads to the formation of ideological echo chambers, where users are isolated from opposing viewpoints, and political discourse becomes more extreme as a result of that. This entrenches polarization, creating an atmosphere where compromise and understanding become challenging to achieve (Garimella et al., 2018). In highly polarized environments, media consumers may become more distrustful of opposing viewpoints, which may lead to division and conflict within society.

To address the issue of algorithmic bias in media consumption, it is recommended that a multifaceted strategy should be employed (Kordzadeh & Ghasemaghaei, 2022). Rader et al. (2018) noted that improving algorithmic transparency is one important tactic. In order to ensure that these systems promote a more balanced and diverse range of content, platforms should be held accountable for the biases in their algorithms. Regulators and policymakers should also take into consideration measures to hold platforms accountable for the biases in their algorithms (Diakopoulos, 2020). Enhancing the diversity of the data used to train algorithms is another crucial step in ensuring that algorithms reflect the full diversity of society and decrease the risk of bias. Finally, users themselves should be educated about the risks of algorithmic bias and encouraged to seek out a wider range of media sources in order to avoid getting caught up in filter bubbles (Nazer et al., 2023).

4.0 IMPLICATIONS OF ALGORITHM BIAS IN MEDIA CONTENT DISTRIBUTION FOR DEI

The introduction of algorithm-driven systems has completely changed how media content is distributed and how people obtain and use information. These artificial intelligence (AI)-powered algorithms are essential in deciding what information consumers receive based on their preferences, actions, and other demographic characteristics. These systems do have several shortcomings, despite their amazing efficiency and ability to provide individualized experiences (Ali & Hassoun, 2019). Algorithmic bias, in which algorithms unintentionally favor some groups over others, is one of the major issues. Because it upholds preconceptions and perpetuates inequities, this bias has the potential to have a significant impact on diversity, equality, and inclusion (DEI) in the media by marginalizing voices from marginalized groups (Herzog, 2021). Hence, this review discusses the algorithm bias in media content distribution and its implications for DEI.

Calice et al. (2023) noted that algorithmic bias is when AI systems deliver skewed or unjust results, favoring some information or organizations over others. The authors noted that the data that these algorithms are trained on frequently causes this bias. Drage and Mackereth (2022) argued that the resulting algorithms will be flawed if the input data is inadequate, underrepresents specific groups, or has historical prejudices. This may bring about issues of diversity, equity, and inclusion. When a media platform's algorithm is trained on a dataset that mostly consists of content consumed by a specific demographic, it is likely to favor content made by or aimed at these populations, disregarding content created by other groups. The algorithm's preference for well-liked material makes this bias self-reinforcing, further marginalizing various viewpoints (Bandy, 2021).

Because it reduces the exposure of different viewpoints, algorithmic bias in the dissemination of media content has a substantial impact on DEI. Recommendation algorithms play a major role in helping media sites such as YouTube, Facebook, and Netflix choose which material to show their users. Popular, high-engagement content is frequently given precedence by these algorithms, which usually favors prevailing cultural narratives (Shaffer, 2019). Minority groups may therefore discover that their experiences and viewpoints are underrepresented, regardless of how they are classified by color, gender, sexual orientation, or other factors (Plough, 2022). For instance, Taylor (2024) noted that Black artists on social media sites like Instagram and TikTok have expressed worry that, even when they produce content that is similar to or better than that of non-Black creators, their work is getting less views and interaction. The prevailing narratives are strengthened by this underrepresentation, which also restricts exposure to a range of viewpoints and cultural practices.

Furthermore, there is an issue of entrenching stereotypical narrative. This is buttressed by Belenguer (2022) that the propagation of negative stereotypes is one of algorithm bias's most detrimental effects. Moreover, latent biases in the trained data for algorithms process often mold them to be stereotypical. For instance, an algorithm will reinforce and magnify stereotypes if it favors content that shows members of particular groups in stereotypical roles, such as women in caring or submissive roles or people of color in roles of poverty or criminality. Soon and Goh (2018) noted that due to users' worldviews being shaped by repeated exposure to biased content, it becomes more difficult to dispel these prejudices, which has a negative impact on public opinion. Furthermore, members of marginalized groups may absorb these prejudices, which could have an impact on their engagement in society and sense of self.

Meanwhile, one of the biggest obstacles to ensuring equity in the dissemination of media information is algorithmic bias (Yu, 2020). Iyer (2022) noted that ensuring that all groups have equal opportunities and exposure is one of the fundamental tenets of DEI. However, by giving preference to content created by producers with greater resources or by historically privileged groups, biased algorithms might worsen already-existing disparities. Consequently, Kay (2020) observed that there is a vicious cycle in which some voices control the media and others have difficulty becoming acknowledged. For example, media creators from underrepresented communities or lower socioeconomic backgrounds frequently lack the means to create high-quality material that is preferred by algorithms, which lowers their visibility and engagement. This inequality not only reduces the variety of information that is accessible, but it also makes it more difficult for these artists to make a living.

Additionally, algorithm bias has a significant impact on civic engagement and public discourse. The media is extremely important in influencing public opinion and educating the public about social, political, and cultural concerns (Stark et al., 2020). It is natural that the public's perception of important issue is skewed if algorithms routinely exclude content from disadvantaged viewpoints or give sensationalist material that supports bias priority. Brewer and Gross (2005) noted that his may lead to a limited perspective on societal issues, diminishing the depth of discussion and generating divisive opinions. Furthermore, marginalized groups may become disengaged if they believe their problems and experiences are not being sufficiently addressed or portrayed in the media due to the lack of varied perspectives.

In this age, social media has enhanced media content distribution owing to its user-generated content nature. This consequently may have significant responsibility for eliminating algorithm bias. Moreover, these platforms' algorithms are largely driven by engagement metrics, such likes, shares, and comments. However, rather than emphasizing content that encourages tolerance and diversity, this strategy may unintentionally favor information that is sensational, divisive, or catered to the majority group (Sulaiman et al., 2020). While some platforms have made efforts to reduce bias—for example, by introducing transparency measures or modifying their algorithms to give more weight to various viewpoints—these actions are frequently insufficient (Schwartz et al., 2022). To promote a more inclusive media environment, social media businesses need to make investments in developing fairer algorithms and addressing the underlying biases in their data collection and processing techniques (Williams et al., 2018).

Moreover, it is difficult but crucial to create moral algorithms that support DEI in the distribution of media information. More than just efficiency and user engagement, algorithm designers need to think about how their systems will affect society as a whole. This entails proactively searching out diverse datasets that encompass a broad spectrum of viewpoints and experiences in addition to routinely evaluating algorithms to detect and reduce bias (Cheng et al., 2021). Furthermore, fairness should be the first priority for ethical algorithms, guaranteeing that underrepresented group content receives equal exposure, even if it doesn't initially get as much interaction (Fernández Fernández, 2022). Transparency is also essential, wherein it is expected that users should know exactly how and why they are being recommended material, as well as the considerations that go into the process (Stohl et al., 2016).

The necessity of addressing algorithm bias is becoming more and more apparent to governments and regulatory agencies, especially in the context of DEI. There have been requests in certain areas for stricter laws requiring media companies to disclose their algorithms and the effects they have on the distribution of content (Schwartz et al., 2022). Nachbar (2020) noted that governments have gone so far as to establish algorithmic fairness guidelines to make sure AI systems do not unfairly hurt particular populations. Regulatory approaches, however, confront many challenges, one of which is the complexity of characterizing and quantifying bias in intricate, dynamic AI systems. Furthermore, navigating a hodgepodge of legal frameworks is a challenge for global platforms when implementing consistent criteria for diversity and fairness (Padmanaban, 2024).

Having discussed the implications of algorithm bias in media content distribution for DEI, it is expedient to discuss the potential solutions and best practices in order to entrench diversity and inclusiveness. Several strategies and best practices can be used to lessen algorithm bias and its detrimental effects on DEI. Using fairness-aware algorithms, which take inclusion and diversity into explicit consideration when making recommendations, is one strategy. Incorporating a wider range of developers and data scientists into the system's development process is another technique to assist detect and reduce the issue of bias in the design stage (Schelenz et al., 2021; Schwartz et al., 2022). Media companies can also give preference to user feedback systems that let members of marginalized communities report biased content or algorithmic behavior. Furthermore, creating more equitable algorithms can also benefit from partnerships between social media businesses, academic institutions, and civil society organizations (Balkin, 2017; Bandy, 2021).

5.0 CONCLUSION

This review concludes that algorithmic bias limits the visibility of underprivileged groups and perpetuates current social injustices, posing serious problems for media distribution. Algorithm biases stem from a combination of structural inequities, subjective decisions made by developers, and missing or distorted data. These biases have far-reaching effects, limiting media diversity in the process by hurting not only consumers but also content providers from marginalized communities. There have been initiatives to eliminate these biases, such as requests for algorithm audits, transparency, and the creation of more equitable systems, but there are still big obstacles to overcome. The quest of egalitarian media distribution is made more difficult by the tension that arises between maximizing involvement and encouraging diversity. Furthermore, there are risks and opportunities associated with the development of AI and machine learning in tackling algorithmic bias. Essentially, there is a need for collaborative efforts among different stakeholders (engineers, policymakers, and media platforms) in creating a more inclusive and equitable algorithms in order to ensure that media distribution systems promote fairness and diversity.

The study established that the dissemination of media information that is biased by algorithms has a big impact on diversity, equity, and inclusion (DEI). When AI-driven algorithms are used to select and suggest material, underrepresented groups are frequently marginalized, which exacerbates already-existing disparities and cultural prejudices. This bias results from the data used to train these algorithms, which frequently mirrors society prejudices and supports prevailing narratives and minority views become less heard as a result. A multidimensional strategy is needed to address this problem, including the creation of algorithms that consider fairness, transparency in the recommendation of material, and proactive efforts to use a variety of datasets in algorithmic training. Furthermore, the study concludes that regulatory frameworks guiding media distribution must change in order to ensure algorithmic fairness on platforms. Ultimately, guaranteeing that media content distribution upholds rather than contradicts DEI values requires a dedication to developing moral AI systems that encourage diversity and lessen bias.

5.1 Future Research Directions

Future studies should consider focusing on developing ethical frameworks to enhance transparency and inclusive algorithm design. This will provide a model to ensure diversity, equity, and inclusion in algorithm bias in media content distribution. Essentially, this study can consider designing standardized models for auditing algorithms and identifying bias, particularly in underrepresented or marginalized groups. In order to reduce bias from the outset, future studies should investigate methods for enhancing data variety in algorithm training sets. Understanding the trade-offs between profit and equity requires looking into how media platforms strike a balance between engagement optimization and justice. It is also imperative that politicians, media professionals, and AI developers collaborate across disciplinary boundaries to guarantee that emergent AI and machine learning tools are capable of addressing algorithmic inequities. It will also be crucial to examine public policies that encourage platforms to give diversity and equitable representation in content recommendation systems top priority. Moreover, in order to create solutions that improve visibility and fairness in digital environments, future studies should assess the effects of algorithmic bias on content creators, especially those from underrepresented communities.

Future studies should investigate algorithmic bias and media consumption, concentrating on multiple crucial domains. Moreover, more advanced techniques for identifying and reducing algorithmic biases should be developed from future studies. This may be achieved using the grounded theory approach. Alternatively, investigating fairness-aware algorithms that actively take inclusion and diversity into account when making recommendations may be another way to achieve this. Additionally, studies should investigate how well transparency policies work and whether or not they actually increase content representation and lessen bias. Future studies should also explore how user education might help prevent filter bubbles and promote a variety of media consumption. Future studies should examine regulatory strategies and how they affect algorithmic fairness, including the difficulties of putting uniform standards in place across jurisdictions. In order to understand the influence of algorithmic biases on public discourse and civic engagement, future studies should also examine the long-term societal repercussions of these biases on political polarization and socioeconomic inequality.

REFERENCES

Adeyemi, I. O. (2017). An empirical study on the traits of information literacy level among senior secondary students in Ilorin, Nigeria. Library Philosophy & Practice (e-journal), paper no. 1587, 1-22.

Adeyemi, I. O. (2023a). Assessment of justice, equity, diversity, and inclusion (JEDI) initiatives in public libraries: Perspectives from a public library in a developing country. In Perspectives on Justice, Equity, Diversity, and Inclusion in Libraries (pp. 187-197). IGI Global.

Adeyemi, I. O. (2023b). Knowledge sharing practices among social media marketers and the significance for business sustainability. In Cases on Enhancing Business Sustainability Through Knowledge Management Systems (pp. 121-134). IGI Global.

Ali, W., & Hassoun, M. (2019). Artificial intelligence and automated journalism: Contemporary challenges and new opportunities. International Journal of Media, Journalism and Mass Communications, 5(1), 40-49.

Andrus, M., Spitzer, E., Brown, J., & Xiang, A. (2021). What we can't measure, we can't understand: Challenges to demographic data procurement in the pursuit of fairness. In Proceedings of the 2021 ACM conference on fairness, accountability, and transparency (pp. 249-260).

Aquino, Y. S. J. (2023). Making decisions: Bias in artificial intelligence and data driven diagnostic tools. Australian Journal of General Practice, 52(7), 439-442.

Ausat, A. M. A. (2023). The role of social media in shaping public opinion and its influence on economic decisions. Technology and Society Perspectives, 1(1), 35-44.

Balayn, A., Lofi, C., & Houben, G. J. (2021). Managing bias and unfairness in data for decision support: A survey of machine learning and data engineering approaches to identify and mitigate bias and unfairness within data management and analytics systems. The VLDB Journal, 30(5), 739-768.

Balkin, J. M. (2017). Free speech in the algorithmic society: Big data, private governance, and new school speech regulation. UC Davies Law Review, 51, 1149-1167.

Bandy, J. (2021). Problematic machine behavior: A systematic literature review of algorithm audits. Proceedings of the ACM on Human-Computer Interaction, 5(CSCW1), 1-34.

Barretto, D., LaChance, J., Burton, E., & Liao, S. N. (2021). Exploring why underrepresented students are less likely to study machine learning and artificial intelligence. In Proceedings of the 26th ACM Conference on Innovation and Technology in Computer Science Education V. 1 (pp. 457-463).

Belenguer, L. (2022). AI bias: Exploring discriminatory algorithmic decision-making models and the application of possible machine-centric solutions adapted from the pharmaceutical industry. AI and Ethics, 2(4), 771-787.

Bozdag, E., & Van Den Hoven, J. (2015). Breaking the filter bubble: democracy and design. Ethics and Information Technology, 17, 249-265.

Brewer, P. R., & Gross, K. (2005). Values, framing, and citizens' thoughts about policy issues: Effects on content and quantity. Political Psychology, 26(6), 929-948.

Brough, M., Literat, I., & Ikin, A. (2020). "Good social media?": Underrepresented youth perspectives on the ethical and equitable design of social media platforms. Social Media+ Society, 6(2), 1-20.

Calice, M. N., Bao, L., Freiling, I., Howell, E., Xenos, M. A., Yang, S., ... & Scheufele, D. A. (2023). Polarized platforms? How partisanship shapes perceptions of "algorithmic news bias". New Media & Society, 25(11), 2833-2854.

Cavusoglu, L., & Atik, D. (2023). Extending the diversity conversation: Fashion consumption experiences of underrepresented and underserved women. Journal of Consumer Affairs, 57(1), 387-417.

Cheng, L., Varshney, K. R., & Liu, H. (2021). Socially responsible ai algorithms: Issues, purposes, and challenges. Journal of Artificial Intelligence Research, 71, 1137-1181.

Cohen, J. N. (2018). Exploring echo-systems: How algorithms shape immersive media environments. Journal of Media Literacy Education, 10(2), 139-151.

Daneshjou, R., Smith, M. P., Sun, M. D., Rotemberg, V., & Zou, J. (2021). Lack of transparency and potential bias in artificial intelligence data sets and algorithms: a scoping review. JAMA Dermatology, 157(11), 1362-1369.

David, C. C., Osorio, M. J., Bunquin, J. B., San Pascual, M. R., & Cabonce, A. B. (2023). Social pressures against criticizing the government: social media, network homogeneity, and majority views. ASOG WORKING PAPER 23-002. Ateneo School of Government.

De-Arteaga, M., Feuerriegel, S., & Saar-Tsechansky, M. (2022). Algorithmic fairness in business analytics: Directions for research and practice. Production and Operations Management, 31(10), 3749-3770.

Diakopoulos, N. (2020). Accountability, transparency, and algorithms. The Oxford handbook of ethics of AI, 17(4), 197-221.

Drage, E., & Mackereth, K. (2022). Does AI debias recruitment? Race, gender, and AI's "eradication of difference". Philosophy & Technology, 35(4), 89.

Fernández Fernández, J. L. (Eds.). (2022). Ethical considerations regarding biases in algorithms. Globethics.net

Gal, M. S., & Elkin-Koren, N. (2016). Algorithmic consumers. Harvard Journal of Law & Tech., 30, 309.

Garimella, K., De Francisci Morales, G., Gionis, A., & Mathioudakis, M. (2018, April). Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship. In Proceedings of the 2018 world wide web conference (pp. 913-922).

Gorwa, R., & Ash, T. G. (2020). Democratic transparency in the platform society. Social media and democracy: The state of the field and prospects for reform, 286-312.

Greene, C. (2019). Effects of news media bias and social media algorithms on political polarization (Master's thesis, Iowa State University).

Griffin, R. (2023). Public and private power in social media governance: multistakeholderism, the rule of law and democratic accountability. Transnational Legal Theory, 14(1), 46-89.

Harambam, J., Helberger, N., & Van Hoboken, J. (2018). Democratizing algorithmic news recommenders: how to materialize voice in a technologically saturated media ecosystem. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2133), 20180088.

Herzog, L. (2021). Algorithmic bias and access to opportunities. In The Oxford Handbook of Digital Ethics. Oxford: Oxford Academic.

Interian, R., G. Marzo, R., Mendoza, I., & Ribeiro, C. C. (2023). Network polarization, filter bubbles, and echo chambers: An annotated review of measures and reduction methods. International Transactions in Operational Research, 30(6), 3122-3158.

Iyer, A. (2022). Understanding advantaged groups' opposition to diversity, equity, and inclusion (DEI) policies: The role of perceived threat. Social and Personality Psychology Compass, 16(5), 1-16.

Kay, J. B. (2020). Gender, media and voice: Communicative injustice and public speech. Springer Nature.

Kitchens, B., Johnson, S. L., & Gray, P. (2020). Understanding echo chambers and filter bubbles: The impact of social media on diversification and partisan shifts in news consumption. MIS Quarterly, 44(4), 12-28.

Kleanthous, S., Kasinidou, M., Barlas, P., & Otterbacher, J. (2022). Perception of fairness in algorithmic decisions: future developers' perspective. Patterns, 3(1), 1-20.

Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: review, synthesis, and future research directions. European Journal of Information Systems, 31(3), 388-409.

Kozyreva, A., Lewandowsky, S., & Hertwig, R. (2020). Citizens versus the internet: Confronting digital challenges with cognitive tools. Psychological Science in the Public Interest, 21(3), 103-156.

Lu, D., Ruan, B., Lee, M., Yilmaz, Y., & Chan, T. M. (2021). Good practices in harnessing social media for scholarly discourse, knowledge translation, and education. Perspectives on Medical Education, 10, 23-32.

McCray, W. P. (2020). Making art work: How Cold War engineers and artists forged a new creative culture. MIT Press.

Nachbar, T. B. (2020). Algorithmic fairness, algorithmic discrimination. Florida State University Law Review, 48, 509-532.

Nazer, L. H., Zatarah, R., Waldrip, S., Ke, J. X. C., Moukheiber, M., Khanna, A. K., ... & Mathur, P. (2023). Bias in artificial intelligence algorithms and recommendations for mitigation. PLOS Digital Health, 2(6), e0000278.

Norori, N., Hu, Q., Aellen, F. M., Faraci, F. D., & Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. Patterns, 2(10), 234-251.

Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M. E., ... & Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(3), e1356-e1371.

Padmanaban, H. (2024). Revolutionizing regulatory reporting through AI/ML: Approaches for enhanced compliance and efficiency. Journal of Artificial Intelligence General science, 2(1), 71-90.

Volume: 07, Issue: 05 September - October 2024

ISSN 2582-0176

Peña-Alcántara, A. A. (2022). A Subject Based Methodology for Measuring Interclass Bias in Facial Recognition Verification Systems' (Doctoral dissertation, Massachusetts Institute of Technology).

Plough, A. L. (2022). Necessary Conversations: Understanding Racism As a Barrier to Achieving Health Equity (Vol. 6). Oxford University Press.

Rader, E., Cotter, K., & Cho, J. (2018). Explanations as mechanisms for supporting algorithmic transparency. In Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-13).

Ragnedda, M., & Ragnedda, M. (2020). New digital inequalities. algorithms divide. Enhancing Digital Equity: Connecting the Digital Underclass, 61-83.

Reisach, U. (2021). The responsibility of social media in times of societal and political manipulation. European Journal of Operational Research, 291(3), 906-917.

Reviglio, U., & Agosti, C. (2020). Thinking outside the black-box: The case for "algorithmic sovereignty" in social media. Social Media+ Society, 6(2), 1-12.

Rogers, R. (2021). Media Feedback: Our Lives in Loops. Rowman & Littlefield.

Schelenz, L. (2021, June). Diversity-aware recommendations for social justice? exploring user diversity and fairness in recommender systems. In Adjunct Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization (pp. 404-410).

Schwartz, R., Schwartz, R., Vassilev, A., Greene, K., Perine, L., Burt, A., & Hall, P. (2022). Towards a standard for identifying and managing bias in artificial intelligence (Vol. 3, p. 00). US Department of Commerce, National Institute of Standards and Technology.

Shaffer, K. (2019). Data versus democracy: How big data algorithms shape opinions and alter the course of history. Apress.

Shen, H., DeVos, A., Eslami, M., & Holstein, K. (2021). Everyday algorithm auditing: Understanding the power of everyday users in surfacing harmful algorithmic behaviors. Proceedings of the ACM on Human-Computer Interaction, 5(CSCW2), 1-29.

Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake news detection on social media: A data mining perspective. ACM SIGKDD Explorations Newsletter, 19(1), 22-36.

Simon-Kerr, J. (2021). Credibility in an Age of Algorithms. Rutgers University Law Review, 74, 111-135.

Soon, C., & Goh, S. (2018). Fake news, false information and more: Countering human biases. Institute of Policy Studies (IPS) Working Papers, 31.

Stark, B., Stegmann, D., Magin, M., & Jürgens, P. (2020). Are algorithms a threat to democracy? The rise of intermediaries: A challenge for public discourse. Algorithm Watch, 26. Published by Governing Council.

Stinson, C., & Vlaad, S. (2024). A feeling for the algorithm: Diversity, expertise, and artificial intelligence. Big Data & Society, 11(1), 1-12.

Stohl, C., Stohl, M., & Leonardi, P. M. (2016). Digital age| managing opacity: Information visibility and the paradox of transparency in the digital age. International Journal of Communication, 10, 15-27.

Sukiennik, N., Gao, C., & Li, N. (2024). Uncovering the Deep Filter Bubble: Narrow Exposure in Short-Video Recommendation. In Proceedings of the ACM on Web Conference 2024 (pp. 4727-4735).

Sulaiman, K. A., Adeyemi, I. O., & Ayegun, I. (2020). Information sharing and evaluation as determinants of spread of fake news on social media among Nigerian youths: experience from COVID-19 pandemic. International Journal of Knowledge Content Development & Technology, 10(4), 65-82.

Tanna, M., & Dunning, W. (2022). Bias and discrimination. In Artificial Intelligence (pp. 422-441). Edward Elgar Publishing.

Taylor, Z. A. (2024). “TikTok as an App Is Not Friendly to Black Creators": Beauty Capital," Ideal" Influencers, and Techno-Minstrelsy on Social Media (Doctoral dissertation, The University of North Carolina at Chapel Hill).

Ukanwa, K., & Rust, R. T. (2021). Algorithmic bias in service. USC Marshall School of Business Research Paper.

van Esch, P., Cui, Y., & Heilgenberg, K. (2024). Using artificial intelligence (AI) to implement diversity, equity and inclusion (DEI) into marketing materials: The ‘CONSIDER’ framework. Australasian Marketing Journal, 32(3), 250-262.

Waller, R. R., & Waller, R. L. (2022). Assembled bias: Beyond transparent algorithmic bias. Minds and Machines, 32(3), 533-562.

Williams, B. A., Brooks, C. F., & Shmargad, Y. (2018). How algorithms discriminate based on data they lack: Challenges, solutions, and policy implications. Journal of Information Policy, 8, 78-115.

Yu, P. K. (2020). The algorithmic divide and equality in the age of artificial intelligence. Florida Law Review, 72, 331-350.

