Article

Understanding Algorithmic Bias in Movie Recommendation Systems: A Study on User Experience and Cultural Representation

P-ISSN: 3048-9334 | E-ISSN: 3048-9342
SJCC International Journal of Communication Research
Vol: 2 | Issue: 1 | September 2025
pp. 83-105 | © The Author (s) 2025
Permissions: sijcr@sjcc.co.in

Shruthi B.[1] and M. Srihari[1]

Abstract

This study investigates how artificial intelligence (AI) influences movie recommendations on major streaming platforms like Amazon, Netflix, and Disney+Hotstar, and the implications of algorithmic bias on content diversity, user autonomy, and representation. As platforms increasingly rely on personalized algorithms to curate viewing options, users are subtly directed toward familiar and commercially successful content, while potentially missing diverse, independent, or culturally significant films. Drawing from interviews and supported by existing literature, the research explores user experiences with recommendation systems, their perceptions of fairness, and the visible or hidden patterns in what is suggested. The findings suggest that while users appreciate the convenience of AI-driven recommendations, many feel confined by them, with limited exposure to broader perspectives. This paper argues that current systems need to be more inclusive, transparent, and participatory. Platforms should enable users to influence what is shown, integrate a wider spectrum of stories, and treat personalization as a tool for exploration-not restriction. The

[1] Bharathiar University, Coimbatore, Tamil Nadu, India.

Corresponding Author:

Shruthi.B, Research Scholar, Department of Communication & Media Studies, Bharathiar University, Coimbatore, Tamil Nadu, India.

Email: shruthi.cms@buc.edu.in

study aims to contribute to ongoing discussions around ethical AI, digital culture, and equitable media access.

Keywords

Artificial intelligence, Recommendation systems, Streaming Platforms, Algorithmic Bias, Media Diversity, User Experience, Digital Culture, Representation

Introduction

In the past, movie recommendations came from friends, critics, or personal exploration. Today, much of what we watch is chosen with the help of artificial intelligence (AI). Streaming platforms such as Netflix, Amazon Prime Video, and Disney+ use AI-powered recommendation systems that analyze viewing patterns, clicks, search history, and ratings to curate personalized suggestions (Gomez-Uribe & Hunt, 2015). This shift has made entertainment consumption faster and more tailored to individual preferences. Yet, while these systems seem helpful, they also raise critical questions about how content is selected, what is shown or hidden, and whose stories are being prioritized. The logic behind recommendation algorithms is built on reinforcing user preferences. The more we watch a specific genre, actor, or type of content, the more similar content is shown. Pariser (2011) calls this effect a "filter bubble," where personalization confines users to a narrow set of choices, limiting exposure to diverse narratives. As Seaver (2019) notes, recommendation engines are less about expanding users' horizons and more about predicting what keeps them watching. While this might increase engagement, it may also come at the cost of variety and cultural richness.

This concern is not only theoretical. Noble (2018) explains how algorithms often mirror social biases, even if unintentionally. Her work reveals how systems trained on biased data can perpetuate stereotypes or make certain voices invisible. In the context of film, this could mean that independent cinema, regional-language films, or stories centered on marginalized communities are shown less frequently-especially if they don't perform well according to standard engagement metrics. Sweeney (2013) and Barocas and Selbst (2016) also show how algorithmic systems can have unintended but harmful effects, reproducing exclusion even without explicit prejudice. Beyond what is shown, the way these systems operate also matters. Users often do not understand how recommendations are gener-

ated, nor do they have control over them. Binns (2018) and Mittelstadt et al. (2016) highlight that a lack of transparency in algorithmic design can disempower users, making them passive recipients of content rather than active participants. As Hall (1997) argued, media plays a role in shaping social identity and understanding. If recommendation systems present only certain types of stories, they also shape the lens through which users view society, culture, and themselves.

Moreover, platform design and commercial objectives influence which content is highlighted. Van Dijck et al. (2018) and Gillespie (2014) discuss how algorithms prioritize profitability and viewer retention. Popular and widely appealing content often takes center stage, while more niche, experimental, or non-mainstream films are sidelined. This business-driven structure can quietly skew cultural consumption toward the familiar and marketable, reinforcing dominant perspectives while limiting representation.

This study explores how everyday users experience AI-powered movie recommendation systems. Through interviews with viewers from different backgrounds and supported by existing research, we seek to understand how these systems affect content discovery, personal choice, and cultural exposure. Do users feel seen by the content recommended to them? Are they aware of the limitations of the system? And how do they navigate the space between convenience and curiosity? In asking these questions, our goal is not to critique AI for its existence, but to question how it is designed and applied. As algorithms continue to mediate what we see and know, we need systems that are not only intelligent but also inclusive, respectful of diversity, and transparent in their functioning. Only then can we ensure that technology enhances, rather than limits, our access to the richness of human stories.

Research Objectives

1. To explore how users experience and interpret AI-generated movie recom mendations on streaming platforms.

2. To examine whether and how recommendation algorithms influence cul tural representation and content diversity.

3. To investigate signs of algorithmic bias in the visibility of films related to marginalized communities or non-mainstream genres.

4. To understand users' perceived autonomy and awareness in navigating algorithmically curated content.

5. To contribute to ethical discussions around fairness and inclusion in algorithmic design within digital media environments.

Research Questions

1. How do users perceive and engage with the content recommended by AI on streaming platforms?

2. To what extent do users feel these recommendations reflect or exclude diverse stories, identities, or cultures?

3. What patterns of bias, if any, do users identify in the visibility and frequency of certain types of content?

4. How aware are users of how recommendation systems function, and how much control do they believe they have over what is shown?

5. What ethical or design improvements do users believe could make AI recommendations more inclusive and representative?

Literature Review

Artificial Intelligence (AI) is playing an increasingly significant role in shaping media consumption, especially through streaming platforms like Netflix, Amazon Prime Video, and Disney+. These platforms use recommendation systems driven by algorithms to tailor movie suggestions to user behavior (Gomez-Uribe & Hunt, 2015). While personalization aims to enhance user satisfaction, researchers warn that it often leads to a narrowing of choices rather than broadening them (Pariser, 2011; Seaver, 2019). Once a user watches a certain type of content, the system tends to recommend similar material, reinforcing preferences rather than encouraging diversity (van Dijck et al., 2018).

The issue of algorithmic bias in these systems is increasingly acknowledged across academic disciplines. Noble (2018) highlights how digital platforms, through biased data and design, often suppress the visibility of marginalized groups. Her research, along with Sweeney's (2013) empirical findings on discriminatory associations in search algorithms, emphasizes that bias is not just technical but social in origin. These concerns are echoed by Barocas and Selbst (2016), who discuss the concept of "disparate impact"-outcomes that are unintentionally discriminatory due to the biases embedded in training data. Even well-intentioned systems, when trained on engagement-driven metrics, can sideline niche or underrepresented voices (boyd & Crawford, 2012).

Hall's (1997) theory of representation shows that media does not merely reflect reality but helps construct it. If recommendation systems predominantly promote mainstream narratives, they shape a limited cultural understanding, effectively marginalizing alternative viewpoints. Binns (2018) and Mittelstadt et al. (2016) further add that users' inability to understand or contest how these systems operate contributes to a lack of agency. Verbeek (2011) extends this argument by describing how technologies like recommendation algorithms mediate our experiences, subtly influencing not just what we watch but how we define our preferences and identities.

From a platform governance perspective, van Dijck et al. (2018) and Gillespie (2014) argue that algorithms serve commercial interests by prioritizing content that increases retention and engagement. This creates a tension between what is profitable and what is culturally enriching. O'Neil (2016) reinforces this concern, warning that systems optimized for scale and efficiency often become "weapons of math destruction," amplifying inequalities while hiding behind claims of neutrality. This criticism is complemented by McQuillan (2015), who highlights that algorithmic culture often disguises its assumptions as objective calculations, masking how deeply normative decisions shape user experiences.

Scholars such as Ananny and Crawford (2018) point out that transparency alone does not resolve algorithmic injustice if the systems themselves are rooted in biased structures. They argue for "intelligibility" over simplistic openness, meaning users should be able to meaningfully understand and challenge how recommendations affect them. This aligns with Diakopoulos (2016), who advocates for algorithmic accountability, suggesting that platforms must be able to justify the decisions made by their systems in human terms.

Furthermore, media scholars have highlighted that recommendation systems not only filter content but influence users' future preferences, a phenomenon discussed by Beer (2009) as "algorithmic shaping." The process is cyclical: users engage with content, algorithms learn and reinforce patterns, and gradually, the user's exposure becomes limited. This closed loop not only affects cultural consumption but also erodes the serendipity that often characterizes media discovery.

To counter these risks, researchers propose more inclusive and ethical design practices. Floridi et al. (2018) call for AI systems to be guided by principles such as fairness, transparency, and inclusivity. Similarly, Sandvig et al. (2014) stress the importance of algorithmic audits to uncover hidden biases, while Raji and Buolamwini (2019) advocate for inclusive training data that represents a wide spectrum of users and creators. Gillespie (2020) adds that policy interventions must go hand in hand with platform-level reforms to ensure long-term equity and diversity in algorithmic systems.

In conclusion, the literature collectively suggests that AI-based recommendation systems do not merely streamline content delivery—they actively shape media access, visibility, and representation. The challenge is not only technical but ethical, requiring greater accountability in system design, user agency in navigation, and commitment to cultural diversity in platform curation. Addressing these concerns involves not just better code, but better values embedded within the systems that increasingly mediate our cultural lives. Artificial Intelligence (AI) is playing an increasingly significant role in shaping media consumption, especially through streaming platforms like Netflix, Amazon Prime Video, and Disney+. These platforms use recommendation systems driven by algorithms to tailor movie suggestions to user behavior (Gomez-Uribe & Hunt, 2015). While personalization aims to enhance user satisfaction, researchers warn that it often leads to a narrowing of choices rather than broadening them (Pariser, 2011; Seaver, 2019). Once a user watches a certain type of content, the system tends to recommend similar material, reinforcing preferences rather than encouraging diversity (van Dijck et al., 2018).

The issue of algorithmic bias in these systems is increasingly acknowledged across academic disciplines. Noble (2018) highlights how digital platforms, through biased data and design, often suppress the visibility of marginalized

groups. Her research, along with Sweeney's (2013) empirical findings on discriminatory associations in search algorithms, emphasizes that bias is not just technical but social in origin. These concerns are echoed by Barocas and Selbst (2016), who discuss the concept of "disparate impact"-outcomes that are unintentionally discriminatory due to the biases embedded in training data. Even well-intentioned systems, when trained on engagement-driven metrics, can sideline niche or underrepresented voices (boyd & Crawford, 2012).

Hall's (1997) theory of representation shows that media does not merely reflect reality but helps construct it. If recommendation systems predominantly promote mainstream narratives, they shape a limited cultural understanding, effectively marginalizing alternative viewpoints. Binns (2018) and Mittelstadt et al. (2016) further add that users' inability to understand or contest how these systems operate contributes to a lack of agency. Verbeek (2011) extends this argument by describing how technologies like recommendation algorithms mediate our experiences, subtly influencing not just what we watch, but how we define our preferences and identities.

From a platform governance perspective, van Dijck et al. (2018) and Gillespie (2014) argue that algorithms serve commercial interests by prioritizing content that increases retention and engagement. This creates a tension between what is profitable and what is culturally enriching. O'Neil (2016) reinforces this concern, warning that systems optimized for scale and efficiency often become "weapons of math destruction," amplifying inequalities while hiding behind claims of neutrality. This criticism is complemented by McQuillan (2015), who highlights that algorithmic culture often disguises its assumptions as objective calculations, masking how deeply normative decisions shape user experiences.

Scholars such as Ananny and Crawford (2018) point out that transparency alone does not resolve algorithmic injustice if the systems themselves are rooted in biased structures. They argue for "intelligibility" over simplistic openness, meaning users should be able to meaningfully understand and challenge how recommendations affect them. This aligns with Diakopoulos (2016), who advocates for algorithmic accountability, suggesting that platforms must be able to justify the decisions made by their systems in human terms. Furthermore, media scholars have highlighted that recommendation systems not only filter content but influence users' future preferences, a phenomenon discussed by Beer (2009) as

"algorithmic shaping". The process is cyclical: users engage with content, algorithms learn and reinforce patterns, and gradually, the user's exposure becomes limited. This closed loop not only affects cultural consumption but also erodes the serendipity that often characterizes media discovery.

To counter these risks, researchers propose more inclusive and ethical design practices. Floridi et al. (2018) call for AI systems to be guided by principles such as fairness, transparency, and inclusivity. Similarly, Sandvig et al. (2014) stress the importance of algorithmic audits to uncover hidden biases, while Raji and Buolamwini (2019) advocate for inclusive training data that represents a wide spectrum of users and creators. Gillespie (2020) adds that policy interventions must go hand in hand with platform-level reforms to ensure long-term equity and diversity in algorithmic systems.

Theoretical Framework

Artificial Intelligence (AI) is playing an increasingly significant role in shaping media consumption, especially through streaming platforms like Netflix, Amazon Prime Video, and Disney+. These platforms use recommendation systems driven by algorithms to tailor movie suggestions to user behavior (Gomez-Uribe & Hunt, 2015). While personalization aims to enhance user satisfaction, researchers warn that it often leads to a narrowing of choices rather than broadening them (Pariser, 2011; Seaver, 2019). Once a user watches a certain type of content, the system tends to recommend similar material, reinforcing preferences rather than encouraging diversity (van Dijck et al., 2018).

The issue of algorithmic bias in these systems is increasingly acknowledged across academic disciplines. Noble (2018) highlights how digital platforms, through biased data and design, often suppress the visibility of marginalized groups. Her research, along with Sweeney's (2013) empirical findings on discriminatory associations in search algorithms, emphasizes that bias is not just technical but social in origin. These concerns are echoed by Barocas and Selbst (2016), who discuss the concept of "disparate impact"-outcomes that are unintentionally discriminatory due to the biases embedded in training data. Even well-intentioned systems, when trained on engagement-driven metrics, can sideline niche or underrepresented voices (boyd & Crawford, 2012).

Hall's (1997) theory of representation shows that media does not merely reflect reality but helps construct it. If recommendation systems predominantly promote mainstream narratives, they shape a limited cultural understanding, effectively marginalizing alternative viewpoints. Binns (2018) and Mittelstadt et al. (2016) further add that users' inability to understand or contest how these systems operate contributes to a lack of agency. Verbeek (2011) extends this argument by describing how technologies like recommendation algorithms mediate our experiences, subtly influencing not just what we watch, but how we define our preferences and identities.

From a platform governance perspective, van Dijck et al. (2018) and Gillespie (2014) argue that algorithms serve commercial interests by prioritizing content that increases retention and engagement. This creates a tension between what is profitable and what is culturally enriching. O'Neil (2016) reinforces this concern, warning that systems optimized for scale and efficiency often become "weapons of math destruction," amplifying inequalities while hiding behind claims of neutrality. This criticism is complemented by McQuillan (2015), who highlights that algorithmic culture often disguises its assumptions as objective calculations, masking how deeply normative decisions shape user experiences.

Scholars such as Ananny and Crawford (2018) point out that transparency alone does not resolve algorithmic injustice if the systems themselves are rooted in biased structures. They argue for "intelligibility" over simplistic openness, meaning users should be able to meaningfully understand and challenge how recommendations affect them. This aligns with Diakopoulos (2016), who advocates for algorithmic accountability, suggesting that platforms must be able to justify the decisions made by their systems in human terms. Furthermore, media scholars have highlighted that recommendation systems not only filter content but influence users' future preferences, a phenomenon discussed by Beer (2009) as "algorithmic shaping". The process is cyclical: users engage with content, algorithms learn and reinforce patterns, and gradually, the user's exposure becomes limited. This closed loop not only affects cultural consumption but also erodes the serendipity that often characterizes media discovery.

To counter these risks, researchers propose more inclusive and ethical design practices. Floridi et al. (2018) call for AI systems to be guided by principles such as fairness, transparency, and inclusivity. Similarly, Sandvig et al. (2014) stress

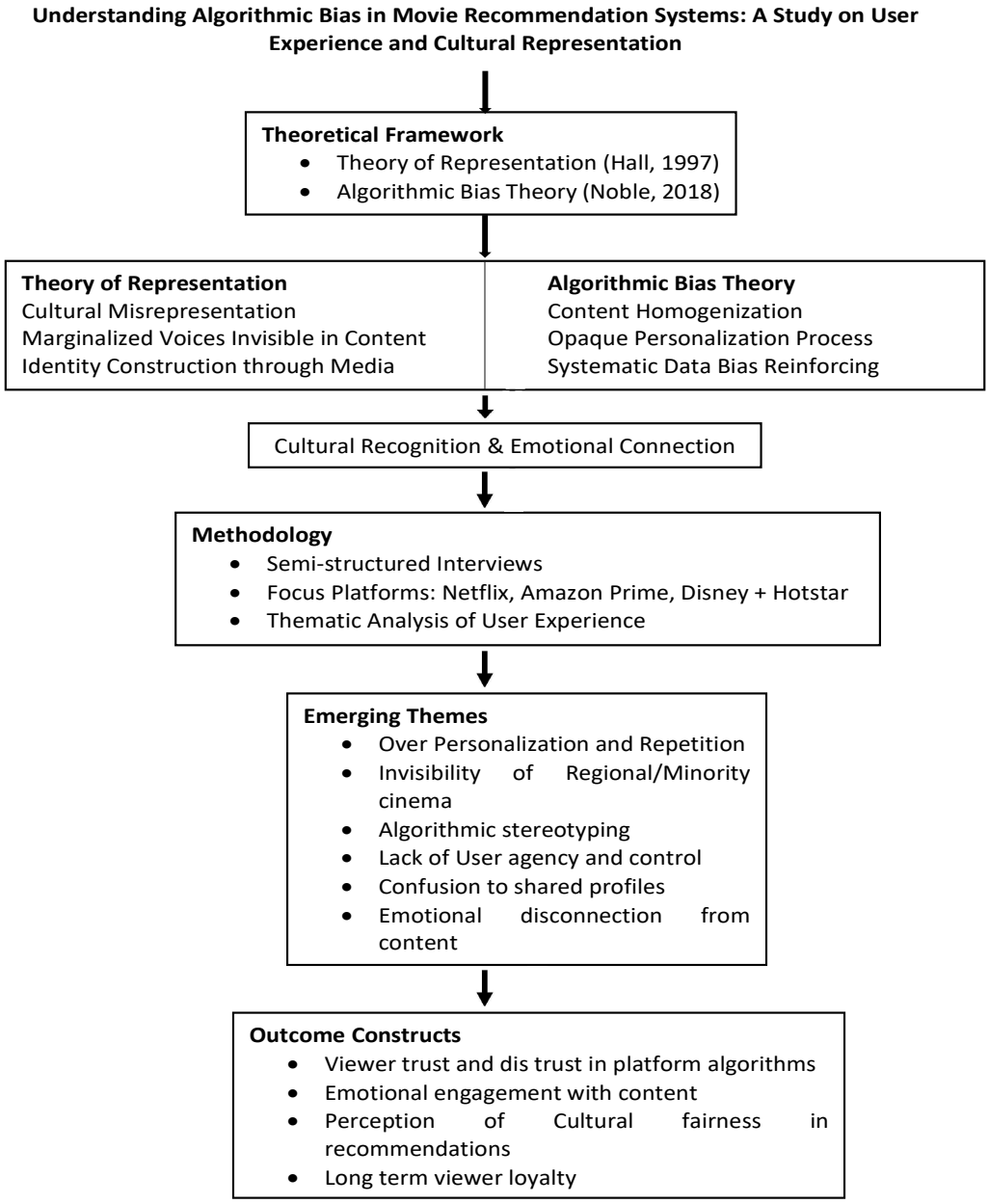
the importance of algorithmic audits to uncover hidden biases, while Raji and Buolamwini (2019) advocate for inclusive training data that represents a wide spectrum of users and creators. Gillespie (2020) adds that policy interventions must go hand in hand with platform-level reforms to ensure long-term equity and diversity in algorithmic systems.

Methodology

This study uses a qualitative research approach to explore how users engage with AI-driven movie recommendation systems on streaming platforms, with particular attention to content diversity, cultural representation, and algorithmic bias. The research focused on gathering in-depth, personal insights rather than numerical data, making qualitative methods the most suitable choice. Twenty-five participants aged between 18 and 45 were selected using purposive sampling to ensure a diverse pool of active streaming users. Diversity in gender, cultural background, and content preferences was considered to gain a broader understanding of how different users interact with and interpret their recommendation feeds.

Data was collected through semi-structured interviews, which allowed participants the flexibility to share their thoughts, personal experiences, and reflections on the kind of content they typically receive and engage with. Each interview lasted approximately 45 minutes and was conducted online. The questions focused on user awareness of algorithmic recommendations, perceived fairness, visibility of diverse content, and personal feelings about being shown certain types of films repeatedly. All interviews were recorded with participant consent, transcribed verbatim, and analyzed using thematic analysis. This involved identifying patterns across responses and grouping them into themes relevant to the study's objectives, such as content repetition, underrepresentation of certain groups, user control, and awareness of recommendation logic. This iterative process allowed for the emergence of both expected and surprising insights. Ethical considerations were strictly followed throughout the research. Participants gave informed consent, were assured of their anonymity, and had the right to withdraw at any stage. The study adhered to ethical standards of confidentiality, respect, and voluntary participation, ensuring that the insights gathered reflected authentic user experiences and concerns without coercion or bias.

Conceptual Framework



Respondents' Voices (25 Respondents)

Across interviews, participants described a pattern of over-personalization and repetition. One remarked, *"After a few romcoms, my homepage was filled with more of the same,"* while another noted, *"after watching just two thrillers, the recommendations turned into a never-ending list of dark, intense movies."* Several echoed that *"the algorithm reacts strongly to short-term behavior,"* and that *"the content recommendations don't evolve with my interests-they're too based on my past."*

Cultural and linguistic invisibility was a recurring concern. Users shared, *"I've never once been recommended a movie from my region," "it rarely recommends anything in my mother tongue, Malayalam,"* and *"Marathi films are almost never featured."* Others added, *"I don't remember ever being recommended a Malayalam movie unless it became a hit nationally,"* and *"India is a country of languages and cultures, but AI recommendations don't reflect that richness."*

Representation of marginalized voices was described as sporadic and superficial: *"LGBTQ+ content is something I actively seek out, but it rarely appears in my feed unless I look for it,"* and *"around Women's Day or Pride Month, such films appear for a few days, then disappear."*

Transparency was another dominant theme. Users complained, *"There's little transparency-I have no idea why something is shown to me," "I would really app reciate a 'why this is recommended' tag,"* and *"Why can't the system tell us why we're seeing something?"*

Shared accounts amplified the frustration: *"Our tastes are very different, so now our feed is a strange blend,"* while families observed that *"the system assumes we are one person with scattered preferences."*

Despite these limitations, moments of discovery stood out: *"I once discovered an Assamese documentary through a random scroll, and it opened my eyes," "a Tamil courtroom drama truly resonated with me,"* and *"a foreign documentary really stayed with me-that's the kind of curation I wish the algorithm provided."* Yet these were rare exceptions, leaving one participant to conclude, *"the algorithm is built for the masses, not for someone who watches niche genres."*

Key Findings:

- Over-personalization Based on Short-term Behavior: Users found that the system often overreacts to recent viewing patterns, creating a narrow loop of repetitive content based on one or two recent watches.
- Lack of Cultural and Linguistic Diversity: Content from regional languages and minority communities was underrepresented, making many users feel culturally excluded.
- Token Representation and Invisibility: Marginalized voices, such as LGBTQ+ content or regional cinema, were only sporadically featured and often during themed occasions like Pride Month.
- Limited User Control: Most respondents expressed a desire for features to influence or reset recommendations, yet current interfaces offer minimal con trol or customization options.
- Opaque Recommendation Logic: The absence of transparency about why certain content is suggested left users feeling confused and disconnected from the system's logic.
- Inconsistent Positive Discovery Experiences: While a few users found mean ingful content serendipitously, these moments were not supported by further, similar recommendations.
- Popularity Bias: Trending and globally recognized shows dominated recom mendation spaces, which limited exposure to less-promoted or niche content.
- Emotional Misalignment and Stereotyping: Respondents felt misrepresen- ted or boxed into simplistic categories, especially those with intersectional identities.
- Resistance to Exploration: Attempts to shift or diversify content manually were largely ineffective, suggesting that the AI systems are inflexible or rigid.
- Household Profile Limitations: Shared accounts confused the algorithm and led to irrelevant recommendations, revealing a flaw in individual user tracking.
- Implicit Ethical Concerns: Although not always explicitly stated, many users voiced concerns about fairness, representation, and the underlying values of AI recommendation systems.

Discussion

The intersection of artificial intelligence and entertainment personalization presents both opportunity and challenge. While the advent of AI-driven recommendation engines on streaming platforms like Netflix, Amazon Prime, and Disney+ Hotstar has revolutionized content discovery, this study reveals that user experiences are often more complex and problematic than platforms claim. The findings from the interviews, when placed in conversation with existing literature, bring to light issues of algorithmic opacity, representation, cultural sensitivity, and ethical design.

Mittelstadt et al. (2016) raise foundational concerns about algorithmic transparency, highlighting how users are often unaware of the logic that governs their digital experiences. This lack of transparency was consistently echoed by participants in the present study, who expressed frustration over the mysterious nature of content suggestions. They were frequently left guessing as to why certain titles were recommended, reflecting a broader disconnect between user intent and algorithmic output. As Pariser (2011) warned in his work on filter bubbles, this absence of clarity can lead users into self-reinforcing echo chambers, limiting exposure to new or diverse content and reinforcing prior viewing habits.

The issue of cultural erasure emerged as another major concern. Several respondents noted that their regional or linguistic preferences were largely ignored by recommendation systems. This aligns with Noble's (2018) critique of algorithmic bias, where she argues that AI systems are often built upon and perpetuate dominant cultural narratives, systematically overlooking minority voices. Respondents from Northeast India, for instance, found that their cultural contexts were not represented at all unless they explicitly searched for such content. Benjamin (2019) extends this critique, asserting that racial and cultural biases embedded in technology are not accidental but are the product of systemic inequalities transferred into algorithmic form.

Furthermore, the data collected for this research affirms O'Neil's (2016) assertion that algorithms, while appearing neutral, often contribute to inequality and misrepresentation. The repeated experience of users being shown the same type of content-usually high-budget, globally trending titles-demonstrates how AI engines prioritize marketable content over personalized, culturally nuanced

suggestions. As a result, users with unique or intersectional preferences often find themselves boxed into narrow viewing categories. This resonates with Striphas (2015), who critiques the rise of "algorithmic culture," where content curation becomes less about human engagement and more about data-driven optimization.

A recurring thread in both literature and interview data is the theme of user agency. Participants repeatedly conveyed a desire for greater control over their recommendation experience. This desire is echoed in boyd and Crawford's (2012) argument that users need to be seen as active participants in digital systems, not passive recipients. Respondents wanted tools to reset, reshape, or reframe their suggestions-options largely unavailable on existing platforms. The lack of such tools compounds the feeling of being manipulated by unseen systems, reinforcing Eubanks' (2018) view that high-tech solutions, if unregulated, risk deepening social and emotional alienation.

Interestingly, while some interviewees reported moments of unexpected delight-discovering new content that resonated with them-these experiences were isolated. They rarely led to a sustained improvement in recommendation relevance. This confirms Pariser's (2011) caution that without intentional design for diversity and surprise, algorithms will fail to break free from their optimization loops. What users seem to be asking for is not just relevance, but resonance-content that reflects who they are, where they come from, and what they value. That requires a fundamental rethinking of what personalization means.

Moreover, emotional engagement plays a central role in shaping viewers' experience. When platforms continually fail to acknowledge users' cultural and linguistic identities, it affects not just viewing satisfaction but also self-perception. Algorithms that ignore diversity risk flattening complex user identities, contributing to a digital monoculture. This observation aligns with Benjamin's (2019) argument that the "New Jim Code" of technology silently perpetuates exclusionary practices. Users do not want to be reduced to data points-they want to be reflected, understood, and respected.

The role of curation also warrants further exploration. While AI attempts to mimic the decision-making of human curators, it lacks the emotional and cultural intelligence to do so meaningfully. Several respondents expressed a preference for curated collections by human editors, especially when exploring niche genres or

independent cinema. Striphas (2015) suggests that culture, when filtered through algorithms, loses its unpredictability-its serendipity. This raises the question: can algorithmic personalization truly replicate the richness of human taste-making?

One emerging theme is the blending of commercial and personalized motives. Many users questioned whether recommendations were truly personalized or strategically designed to promote high-engagement titles. This aligns with Eub anks (2018), who argues that AI is often used not to serve individuals but to manage and predict behavior in ways that benefit corporations. Participants felt that their trust was compromised when recommendations appeared to serve marketing goals more than viewing interests.

A deeper concern is that current AI models do not evolve meaningfully with users. Respondents who tried to retrain the algorithm by watching different genres or searching for new topics found their efforts had little long-term effect. This rigidity points to a fundamental weakness in how machine learning models are trained and updated. Noble (2018) warns that unless these systems are designed with flexibility and reflexivity, they risk locking users into outdated patterns of behavior.

Data bias and representation gaps also permeate the backend of recommendation systems. If the training data lacks sufficient diversity, then the AI cannot reflect or recommend content that falls outside those dominant patterns. As Benjamin (2019) and Noble (2018) both highlight, this is not a technical flaw-it is a systemic one. The platforms must examine how their design choices embed and reproduce inequality. The issue of shared accounts complicates personalization even further. Several respondents noted that family or household members with different preferences led to mixed signals that confused the recommendation system. While platforms like Netflix offer user profiles, not everyone utilizes them, and many respondents described situations where profiles were shared. This mix of behavioral data from different individuals creates erratic suggestions that fail to serve any user adequately. Designers need to account for the messy, shared nature of household media consumption.

Users also emphasized the need for dynamic systems that adapt to their changing moods, life stages, and evolving interests. AI recommendations that remain

static or slow to change betray a basic misunderstanding of human behavior. As boyd and Crawford (2012) argue, data must always be understood in context. Watching a sad movie one evening does not mean a user wants an endless stre am of melancholic content. Systems that fail to capture this nuance alienate their users and diminish long-term engagement.

Many respondents also raised ethical concerns indirectly. Though not always using academic terminology, their unease reflected deeper anxieties about fairness and control. This supports Mittelstadt et al. (2016), who argue that ethical AI requires explainability, contestability, and user empowerment. Users want to know why they are being recommended something-and they want the ability to challenge it. These are not technical luxuries; they are ethical necessities. Moreover, the desire for transparency does not just reflect curiosity-it reflects a demand for agency. When platforms conceal their logic, they strip users of the ability to participate meaningfully in their own experience. O'Neil (2016) insists that opaque systems can never be truly ethical. They must be audited, critiqued, and made open to revision.

In sum, it illustrates that the issues with AI-powered recommendation systems are not limited to individual frustrations-they reflect broader structural, cultural, and ethical concerns. The gap between what users expect from personalization and what they actually experience is widening. To close this gap, platforms must reimagine AI not just as a tool of efficiency but as a partner in user experience-an interface that understands complexity, promotes inclusivity, and adapts with empathy. Future system designs must integrate feedback mechanisms, cultural representation metrics, and pathways for user correction. They must also rethink training datasets, introduce hybrid models that blend AI with human curation, and develop responsive, explainable AI tools. As Benjamin (2019) and Noble (2018) urge, we must design AI not only to optimize engagement but to reflect and respect the human beings it serves. Until these changes are implemented, AI-driven personalization will continue to fall short-not because of a lack of data, but because of a lack of humanity in the way data is used.

Conclusion and Recommendations

The study highlights a critical gap between the promise of personalized AI-driven movie recommendation systems and the actual experience of users on plat-

forms such as Netflix, Amazon Prime, and Disney+ Hotstar. While these platforms utilize complex algorithms to tailor content to individual viewers, the research reveals that the current systems often fall short in capturing user diversity, respecting cultural identities, and offering transparent and inclusive engagement (Benjamin, 2019; Noble, 2018). A key takeaway from this study is that users are not resistant to AI-based recommendations-in fact, they value personalization and discovery. However, they are increasingly aware of how algorithms can reinforce stereotypes, marginalize underrepresented voices, and restrict user autonomy (Pariser, 2011; O'Neil, 2016). Many participants reported being shown repetitive, mainstream content that overlooked their regional, linguistic, or cultural backgrounds. The AI systems, while marketed as intuitive and adaptive, often rely on oversimplified interpretations of user behavior that do not reflect the complexity of viewer identity (Mittelstadt et al., 2016).

Furthermore, the emotional and psychological implications of being misrepresented or ignored by AI recommendations cannot be understated. Several respondents described feelings of cultural invisibility, frustration, and alienation. The failure of algorithms to recognize the depth of user preferences—particularly among those with hybrid or intersectional identities—undermines the core principle of personalization (Eubanks, 2018; boyd & Crawford, 2012).

Based on the findings and the insights drawn from both the interviews and existing literature, the following recommendations are proposed:

- Enhance Transparency and Explainability: Users should be able to understand why a particular movie or show is being recommended. Providing context-such as "Because you watched..." or "Based on your interest in regional films..."-can increase user trust and satisfaction (Mittelstadt et al., 2016).

- Enable User Control Features: Platforms must offer more control to users in shaping their recommendations. This includes features like resetting the rec ommendation history, blocking specific genres or themes, and rating the ac curacy of suggestions (Noble, 2018).

- Promote Cultural Diversity: AI systems should be designed to prioritize not just popularity, but also cultural representation. Algorithms must be trained on diverse data and include more regional and minority content in everyday recommendations (Benjamin, 2019).

- Support Multi-User Profiles: Many users share accounts, which confuses the recommendation engine. Enhanced profile management and clearer distinct ion between users within the same household can improve personalization (Eubanks, 2018).

- Foster Serendipitous Discovery: Incorporating editorial recommendations, rotating hidden gems, and featuring indie and regional cinema can break the monotony of algorithm-driven suggestions and introduce viewers to fresh per spectives (Striphas, 2015).

- Integrate Ethical AI Design: AI developers and streaming platforms should prioritize fairness, inclusivity, and accountability in their systems. Regular audits and impact assessments can ensure that the AI is not unintentionally excluding or stereotyping viewers (O'Neil, 2016; Mittelstadt et al., 2016).

- Include User Feedback in Algorithm Design: Platforms must view users not just as passive consumers, but as active participants in content discovery. User suggestions, complaints, and feedback should inform future updates to the recommendation system (boyd & Crawford, 2012).

- Educate Users About AI Use: Providing basic knowledge on how recommen dation systems work can empower users to engage more meaningfully with the platform and influence their viewing experience (Pariser, 2011).

In essence, the future of AI in entertainment must move toward a model that listens to users, reflects the diversity of its audience, and embraces the social responsibility that comes with content curation. A thoughtful, user-centered, and ethically-grounded approach to AI-driven recommendations can transform digital platforms into inclusive spaces where viewers feel seen, valued, and inspired. This study offers a foundational step toward understanding user dis-satisfaction and hopes to contribute to the evolving discourse on responsible AI use in everyday digital experiences. Future research can build on these findings by involving a wider demographic range, integrating platform-specific analytics, and exploring developer perspectives on ethical AI implementation.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and publication of this article.

Funding

The authors received no financial support for the research, authorship and publication of this article.

References

Ananny, M., & Crawford, K. (2018). Seeing without knowing: Limitations of the trans parency ideal and its application to algorithmic accountability. *New Media & Society, 20*(3), 973-989. https://doi.org/10.1177/1461444816676645

Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review, 104*(3), 671–732.

Beer, D. (2009). Power through the algorithm? Participatory web cultures and the technological unconscious. *New Media & Society, 11*(6), 985–1002. https://doi.org/10.1177/1461444809336551

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim code*. Polity Press.

Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2018). 'It's reducing a humanbeing to a percentage': Perceptions of justice in algorithmic decisions. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3173574.3173951

Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society, 15*(5), 662–679. https://doi.org/10.1080/1369118X.2012.678878

Diakopoulos, N. (2016). Accountability in algorithmic decision making. *Communicati ons of the ACM, 59*(2), 56–62. https://doi.org/10.1145/2844110

Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and pun ish the poor*. St. Martin's Press.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., … Vayena, E. (2018). AI4People-An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines, 28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. Boczkowski, & K. Foot (Eds.), *Media technologies: Essays on communication, materiality, and society* (pp. 167–194). MIT Press.

Gillespie, T. (2020). Content moderation, AI, and the question of scale. *Big Data & Soc iety, 7*(2), 1-5. https://doi.org/10.1177/2053951720943234

Gomez-Uribe, C. A., & Hunt, N. (2015). The Netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems, 6*(4), 1-19. https://doi.org/10.1145/2843948

Hall, S. (1997). *Representation: Cultural representations and signifying practices*. Sage.

McQuillan, D. (2015). Algorithmic accountability: A primitive notion of justice in the era of big data. *Media and Communication, 3*(3), 42–47. https://doi.org/10.17645/mac.v3i3.198

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of al gorithms: Mapping the debate. *Big Data & Society, 3*(2), 1-21. https://doi.org/10.1177/2053951716679679

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. NYU Press.

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown Publishing Group.

Pariser, E. (2011). *The filter bubble: What the internet is hiding from you*. Penguin Press.

Raji, I. D., & Buolamwini, J. (2019). Actionable auditing: Investigating the impact of pu blicly naming biased performance results of commercial AI products. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, 429-435. https://doi.org/10.1145/3306618.3314244

Sandvig, C., Hamilton, K., Karahalios, K., & Langbort, C. (2014). Auditing algorithms: Re search methods for detecting discrimination on internet platforms. *Data and Dis crimination: Collected Essays*. Open Technology Institute.

Seaver, N. (2019). Captivating algorithms: Recommender systems as traps. *Journal of Material Culture, 24*(4), 421–436. https://doi.org/10.1177/1359183518820366

Striphas, T. (2015). Algorithmic culture. *European Journal of Cultural Studies, 18*(4–5), 395–412. https://doi.org/10.1177/1367549415577392

Sundar, S. S., & Marathe, S. S. (2010). Personalization versus customization: The impor tance of agency, privacy, and power usage. *Human Communication Research, 36*(3), 298–322. https://doi.org/10.1111/j.1468-2958.2010.01377.x

Sweeney, L. (2013). Discrimination in online ad delivery. *ACM Queue, 11*(3), 10. https:/ /doi.org/10.1145/2460276.2460278

Van Dijck, J., Poell, T., & De Waal, M. (2018). *The platform society: Public values in a connective world*. Oxford University Press.

Verbeek, P. P. (2011). *Moralizing technology: Understanding and designing the moral ity of things*. University of Chicago Press.

Yeung, K. (2018). Algorithmic regulation: A critical interrogation. *Regulation & Gover nance, 12*(4), 505–523. https://doi.org/10.1111/rego.12160

About the Authors

Shruthi B is a former Public Relations Officer, entrepreneur and life skill trainer committed to empowering youth. She has trained underprivileged children in life skills and technical aspects and is recognized for her social work. Currently a research scholar at Bharathiar University, her research explores the intersection of Artificial Intelligence, philosophy, and spirituality, blending practical training with academic inquiry.

Dr. M. Srihari, Associate Professor and Head in-charge at Bharathiar University, has over 14 years of experience in media and communication studies. He has earned numerous accolades, including international awards, and completed major ICSSR-funded projects on reproductive health communication. Widely published and cited, his work focuses on media representation, marginalized groups, and technological impacts, guiding numerous Ph.D. and M.Phil. Scholars.