Algorithmic Curation and Adolescents' Media Consumption

By

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ABSTRACT

This thesis investigates the relationship between algorithmic design, monetization strategies, and bias exposure in adolescent-facing media across TikTok, YouTube, and Netflix. Drawing on Algorithmic Personalization Theory, Algorithmic Bias and Fairness Theory, and Critical Media Literacy and Algorithmic Governance, the study examines how platform architecture influences content repetition, diversity, engagement, and representational equity. Data was collected manually over six weeks using simulated adolescent user profiles with varied engagement levels. A sample of 427 recommended media cases was documented and coded for repetition, diversity, monetization, and bias indicators. Analyses were conducted using descriptive statistics, chi-square tests, and correlation analyses in SPSS. Findings reveal that monetization was positively correlated with repetition and negatively correlated with diversity, suggesting that commercial optimization may contribute to narrower content exposure. Higher engagement was associated with lower diversity, consistent with personalization-feedback loops. Bias was present across all platforms, with TikTok exhibiting the highest concentration, Netflix showing bias within entertainment formats, and YouTube selectively amplifying bias through advertisement and creator ecosystems. These results highlight governance gaps and ethical concerns in algorithmic curation, particularly for adolescent audiences. Practical implications include the need for fairness-aware recommendation systems, transparent personalization logic, and critical media literacy interventions.

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INTRODUCTION

The increasing reliance on algorithmic personalization in digital media platforms has transformed adolescents' media consumption patterns, content preferences, and information exposure (Cotter and Reisdorf 2020). Recommendation systems on platforms such as Netflix, TikTok, and YouTube curate personalized media experiences by analyzing user engagement and behavioral data (Covington et al. 2016; Gomez-Uribe et al. 2016; Zeng et al. 2021). These systems continuously adapt to user behavior, prioritizing engagement maximization, user retention, and monetization (Cotter and Reisdorf 2020; Turner Lee 2018; Levido et al. 2025).

Recommendation systems utilize machine learning algorithms to predict user preferences and deliver content through predictive modeling, tailoring recommendations based on prior interactions, viewing habits, and engagement levels (Turner Lee 2018). Although these systems are often described as driven by artificial intelligence, they may be more accurately understood as examples of narrow artificial intelligence. These are applications designed to perform specific tasks using data-driven optimization techniques (Floridi and Cowls 2019). While they are distinct from large language models or autonomous artificial intelligence systems, algorithmic recommendation engines nonetheless raise key ethical concerns about fairness, transparency, and user autonomy (Taddeo and Floridi 2018).

While personalization enhances accessibility and user satisfaction, concerns arise regarding algorithmic bias, engagement-driven filtering, and profit incentives, which may limit content diversity and reinforce ideological or commercial priorities (Cotter and Reisdorf 2020; Levido et al. 2025). Given the widespread adoption of these platforms by adolescents aged thirteen to seventeen, it is critical to examine how algorithmically curated recommendations shape their media engagement, potentially reinforcing consumption patterns, ideological

viewpoints, or limiting access to diverse content ecosystems. This study situates content personalization systems within the broader field of algorithmic governance, examining how their operation may shape adolescent experiences in digital media environments.

This research originated as a classroom project in which I observed my son's use of YouTube Kids. The project involved coding the videos he encountered and conducting pre- and post-engagement interviews to assess how the platform's recommendations evolved in response to his viewing behavior. This early exploration revealed patterns of algorithmic inference, emotional framing, and content repetition that raised broader questions about how digital platforms construct user identity. These observations served as the foundation for this comparative study of algorithmic personalization across multiple platforms and engagement profiles.

This study examines the nature and ethical implications of algorithmic personalization in adolescents' digital media environments, focusing on bias detection, engagement strategies, and monetization practices. By systematically analyzing content recommendations across Netflix, TikTok, and YouTube, this research identifies patterns of algorithmic reinforcement and exclusion, evaluating how data-driven recommendation systems may shape adolescent media exposure. This study applies a structured coding framework to assess content categorization, algorithmic repetition and diversity trends, bias indicators, and monetization impact, providing empirical insights into algorithmic governance and the ethical dimensions of platform-based personalization technologies.

This study contributes to ongoing interdisciplinary examinations of algorithmic governance, digital media, and the ethics of new technologies. By documenting how recommendation systems may shape adolescent identity toward commercial aims, this research

offers empirical insights into algorithmic processes that platforms strive to make invisible. Algorithmic machinations must be uncovered so we may grasp the broader implications of algorithmic personalization for adolescents' digital engagement, cognitive development, and access to diverse media ecosystems.

LITERATURE REVIEW

Importance of Algorithmic Personalization in Shaping Media Consumption Habits

Algorithmic personalization plays a pivotal role in structuring adolescents' digital experiences. It determines the quality, quantity, and variety of content exposure, reinforces or challenges specific narratives, and influences long-term media consumption patterns (Cotter and Reisdorf 2020). Recommendation systems refine suggestions through behavioral tracking and engagement metrics, often resulting in personalized media environments that prioritize content designed to maximize user engagement (Turner Lee 2018). These filtered media ecosystems can contribute to selective exposure, where adolescents receive content that aligns with prior interactions rather than diverse perspectives (Levido et al. 2025). While personalization enhances user experiences, it also raises ethical concerns about content reinforcement, algorithmic bias, and commercial prioritization (Mehrabi et al. 2019; Noble 2018). Understanding the impacts of these recommendation mechanisms is essential for evaluating broader implications on digital literacy, autonomy, and cognitive development.

Foundations and Mechanisms

Algorithmic personalization and adolescents' digital media exposure. Recommendation algorithms have become central to shaping adolescents' engagement with digital media by curating content based on individual behavioral data (Metzler and Garcia 2024). Platforms such as YouTube, TikTok, and Netflix use personalized algorithmic feeds to optimize engagement,

tailoring suggestions to individual users. Research indicates that algorithmic curation plays a central role in shaping adolescents' exposure to digital content, often reinforcing personalized media “bubbles” that limit exposure to diverse perspectives (Swart 2021).

Studies analyzing algorithmic influence on user engagement patterns emphasize how media recommendation loops reinforce viewing behaviors, gradually shaping digital media exposure (Oeldorf-Hirsch and Neubaum 2023). For example, Netflix’s genre-based content clustering emphasizes continuity with prior preferences (Gomez-Uribe et al. 2016), whereas TikTok’s adaptive feedback loop prioritizes real-time behavioral data to recalibrate recommendations more dynamically (Zeng et al. 2021). These differing algorithmic strategies have implications for how adolescents encounter repetition, novelty, or ideological variance in their digital media ecosystems.

Levido et al. (2025) explore how algorithmic literacy can be developed through curatorship, emphasizing the importance of media literacy education in helping adolescents critically engage with recommendation systems. Their study highlights how curatorship and non-digital media production activities can foster critical reflection on algorithmic filtering, providing adolescents with tools to more effectively navigate personalized environments on various media platforms. Media literacy education, in this view, becomes a crucial tool for strengthening digital agency and reducing the opacity of algorithmic influence among adolescent users.

Bioethics and algorithmic governance. Floridi and Cowls (2019) propose a unified framework for ethical algorithm design, emphasizing human autonomy, justice, beneficence, and non-maleficence. These values serve as foundational guidelines for governing the societal impact of narrow artificial intelligence systems, including personalization technologies embedded in digital platforms. Jobin, Ienca, and Vayena (2019) further analyze global AI ethics guidelines,

highlighting how these core values shape regulatory approaches to algorithmic decision-making and personalized media exposure.

As recommendation systems increasingly dictate digital content exposure, scholars emphasize the importance of transparent governance frameworks that safeguard adolescent autonomy and mitigate algorithmic bias (Taddeo and Floridi 2018). Rahwan et al. (2019) explore machine behavior dynamics, underscoring the necessity of ethical oversight in data-driven personalization systems, particularly in platforms that shape adolescent media consumption. Additionally, Binns (2017) applies principles of fairness from political philosophy to machine learning, reinforcing the argument that adolescents should have greater control over their digital exposure to ensure recommendation systems personalization does not compromise cognitive development or reinforce harmful consumption patterns.

Algorithmic bias and representation in digital media. Personalization algorithms are designed to maximize user engagement, but they may unintentionally reproduce biases embedded in training data and user behavior patterns (Swart 2020). Research has documented disparities in algorithmic recommendations, particularly in news selection and content representation, revealing that platform algorithms frequently amplify pre-existing biases, favoring dominant cultural narratives and commercial interests over diverse representation (Mehrabi et al. 2019).

TikTok's engagement-based recommendation system raises concerns about algorithmic amplification of homogenized trends, as studies indicate that content similarity and engagement-driven filtering contribute to skewed cultural representation (Anonymous 2024; Lu 2024). TikTok's content delivery model dynamically amplifies viral content, reinforcing short-form

repetition patterns that favor high-engagement creators, often limiting exposure to underrepresented voices (Anonymous 2024).

In contrast, YouTube's monetization-driven curation system prioritizes monetized creators and mainstream narratives, affecting content diversity in adolescent media consumption (Valor 2025). As YouTube relies heavily on advertising-driven personalization, algorithmic curation tends to optimize visibility of advertiser-friendly content, further influencing what adolescent users are exposed to (Miller 2025). Research suggests that monetization influences recommendation patterns, leading to preferential promotion of revenue-generating creators while limiting organic content visibility (Valor 2025).

User engagement and algorithmic responsiveness. User interaction plays a crucial role in shaping algorithmic recommendations, with passive consumption and active engagement influencing personalization differently. Passive consumption, characterized by minimal interaction, often leads to content stagnation, where users receive repetitive suggestions based on previous behaviors. In contrast, active engagement (e.g., clicking, liking, sharing) allows algorithms to dynamically adjust recommendations, introducing greater variation over time (Oeldorf-Hirsch and Neubaum 2023). Studies on algorithmic engagement models highlight that TikTok's engagement-based recommendation system adapts faster than Netflix's, as Netflix relies on static user history, whereas TikTok continuously refines recommendations based on short-term behavioral cues (MIT Open Access Articles 2023). Swart (2021) examines how adolescents perceive and engage with algorithmic news selection, finding that algorithmic literacy varies significantly based on user experience and exposure to personalization cues. Their study highlights the importance of transparency in algorithmic filtering, as many adolescents struggle to articulate how algorithms shape their media consumption.

Monetization strategies and commercial influence on content curation. Beyond engagement metrics, monetization strategies significantly shape algorithmic recommendation systems. Platforms integrate commercial incentives, including ad placements, sponsored content, and influencer-driven promotions, directly into algorithmic curation models. Research has found that highly monetized profiles receive a disproportionate number of commercially driven recommendations, subtly influencing adolescents' media consumption patterns toward branded content (Oeldorf-Hirsch and Neubaum 2023). Studies evaluating the intersection of advertising and recommendation algorithms reveal that monetization-driven filtering mechanisms optimize commercial visibility over organic engagement (Wang et al. 2025). These systems prioritize revenue-generating content, reinforcing commercial biases across digital media spaces. Pasquale (2015) explores the concept of the "black box society," arguing that opaque algorithmic decision-making processes shape digital consumption patterns in ways that favor corporate interests over user autonomy. Their study highlights the need for regulatory oversight to ensure fairness and accountability in monetization-driven personalization models.

Platform-specific algorithmic architectures. Digital platforms deploy distinct algorithmic architectures to personalize content delivery, each shaped by unique engagement priorities, data inputs, and optimization strategies (Anonymous 2024; Covington et al. 2016; Steck et al. 2021). Understanding these differences is essential for evaluating how adolescents encounter repetition, novelty, and ideological framing across media ecosystems (Bhandari and Bimo 2022; Cakmak et al. 2024; Lu 2024; Siles et al. 2019).

Netflix employs a hybrid recommendation system that integrates collaborative filtering, deep learning, and contextual bandits to optimize content relevance across user segments. Steck et al. (2021) detail how Netflix applies deep learning models to support multiple

recommendation tasks, including personalized ranking and homepage curation. Siles et al. (2019) explore the co-adaptive relationship between users and Netflix's algorithm, describing a process of "mutual domestication" that reinforces genre loyalty and narrows exposure to unfamiliar content.

TikTok relies on a dynamic feedback loop driven by short-form engagement metrics such as watch time, replays, likes, and shares. Its algorithm recalibrates recommendations in real time, amplifying viral trends and optimizing for immediate affective engagement. Bhandari and Bimo (2022) describe TikTok's personalization system as constructing an "algorithmized self," where user identity is shaped through behavioral capture and performance-based feedback. This architecture favors content similarity and repetition, often reinforcing homogenized cultural narratives and limiting representational diversity.

YouTube integrates deep neural networks with monetization logic, combining user behavior data with advertiser-friendly filters. Covington et al. (2016) describe YouTube's large-scale recommendation system, which uses candidate generation and ranking models to optimize click-through rates and watch time. Cakmak et al. (2024) highlight how YouTube's algorithmic drift can lead to narrative narrowing, privileging monetized creators and mainstream content over organic diversity. This architecture embeds commercial prioritization into personalization, shaping adolescent exposure through visibility metrics and revenue optimization.

These platform-specific architectures reveal that algorithmic personalization is not a uniform process, but is shaped by engagement goals and commercial imperatives. For adolescents, these differences influence the emotional tone, thematic elasticity, and ideological range of recommended content. Comparative analysis of these systems is essential for

understanding how digital platforms construct identity, reinforce consumption patterns, and mediate access to diverse media experiences.

Governance and Policy Contexts

Governance and ethical considerations in algorithmic media curation. The increasing reliance on algorithmic personalization in adolescent media consumption necessitates robust governance mechanisms to ensure fairness, accountability, and ethical oversight. As recommendation systems dictate content exposure and engagement patterns, concerns regarding algorithmic bias, data privacy, and user autonomy have prompted scholars and policymakers to advocate comprehensive regulatory frameworks (Shouli et al. 2025). Research highlights that personalization mechanisms can exacerbate existing societal biases, reinforce racial disparities, and perpetuate content inequalities unless systematically assessed through bias detection methodologies (Turner Lee 2018).

Among the proposed interventions, algorithm auditing serves as a crucial mechanism for assessing bias and representation, ensuring that recommendation systems do not disproportionately favor dominant cultural narratives or commercialized content (Swart 2021). Regular audits of algorithmic filtering and recommendation transparency can help mitigate reinforcement loops that contribute to content homogenization and exclusionary exposure patterns (Nechushtai et al. 2024).

Additionally, parental mediation frameworks have been suggested to support content oversight, allowing caregivers to engage in active mediation strategies that enhance adolescents' algorithmic literacy and critical consumption skills (Levido et al. 2025). Research highlights the importance of equipping adolescents with tools to navigate personalization systems, fostering cognitive resilience against algorithmically amplified biases (Shouli et al. 2025).

Beyond content regulation, industry-wide transparency requirements aim to standardize ethical practices, calling for platform accountability in algorithmic design, content moderation policies, and monetization influences on recommendation engines. Furthermore, the intersection of corporate governance and algorithmic ethics raises concerns about advertiser influence on recommendation structures, prompting discussions on whether commercial optimization strategies should be separated from content recommendation algorithms (Turner Lee 2018). As platforms continue to function as algorithmic gatekeepers, interdisciplinary research is essential to assess how governance interventions can balance personalization benefits with ethical safeguards, ensuring content diversity, equitable representation, and autonomy for adolescent users.

Emerging policies in algorithmic governance. In the United States, existing frameworks such as the *Children's Online Privacy Protection Act* (COPPA) offer protections for children under thirteen but leave adolescents aged thirteen to seventeen largely unprotected (Federal Trade Commission 2023). The *Federal Trade Commission Act* prohibits unfair or deceptive practices in commerce and has been used to investigate platforms for misleading personalization and opaque data practices (Federal Trade Commission n.d.). Proposed legislation such as the *Algorithmic Accountability Act* would require companies to assess the impact of automated decision systems on fairness, bias, and discrimination (U.S. Congress 2025). The *American Data Privacy and Protection Act* (ADPPA) seeks to establish comprehensive federal data privacy rights, including provisions for algorithmic transparency and youth protections (Congressional Research Service 2025).

Recent updates to COPPA regulations emphasize stricter parental consent requirements and limits on data retention for adolescent users. The amended COPPA Rule, finalized by the

Federal Trade Commission (FTC) in April 2025, introduces expanded definitions of personal information, including biometric identifiers and government-issued identifiers, to better protect children's privacy online (Federal Trade Commission 2025). Additionally, the rule strengthens parental notice and consent requirements, ensuring that platforms provide clear disclosures on data collection, retention, and third-party sharing practices. These amendments reflect growing concerns about adolescent digital exposure, reinforcing the need for greater transparency in platform-based personalization practices.

Similarly, the European Union's *General Data Protection Regulation* (GDPR) and *Artificial Intelligence Act* (AI Act) aim to increase the transparency and accountability of algorithmic content curation. The AI Act, which went into effect in August 2024, mandates strict transparency requirements for AI systems, particularly those classified as high-risk AI models, including those used in content moderation and recommendation systems (European Commission 2024). These provisions require platforms to disclose how personalization mechanisms operate, ensuring that users understand how their data influences recommendation algorithms. Additionally, the AI Act introduces bias detection mechanisms, allowing regulators to audit systems for discriminatory patterns in content curation (European Commission 202; Hacker 2023).

Beer (2022) examines the tensions of algorithmic thinking, exploring how automation and predictive logic shape decision-making across digital infrastructures. Their study highlights the political dimensions of algorithmic governance, emphasizing the need for ethical oversight in systems that influence media exposure. As algorithmic recommendation systems become a dominant force in adolescent media consumption, scholars and policymakers advocate for greater regulatory intervention, ensuring that personalization technologies align with principles

of fairness, autonomy, and democratic accountability (Kiesse Bahangulu and Owusu-Berko 2025).

Comparative international governance models. As algorithmic systems increasingly shape digital experiences, international governance models have emerged to regulate their development, deployment, and societal impact. These models vary in scope, enforcement, and philosophical orientation, reflecting distinct national priorities around innovation, risk mitigation, and ethical safeguards. Understanding these frameworks is essential for evaluating how adolescents encounter algorithmic personalization across geopolitical contexts and for informing educational and policy interventions (Nemitz 2018; Floridi et al. 2018).

The European Union's AI Act represents one of the most comprehensive and binding regulatory frameworks to date. It adopts a horizontal, risk-tiered approach that classifies AI systems into four categories of risk: unacceptable, high, limited, and minimal (Madiega 2024). Systems deemed unacceptable, such as those involving manipulative or exploitative profiling, are prohibited outright. High-risk systems, including those used in education and biometric identification, are subject to strict transparency, documentation, and oversight requirements (Future of Life Institute 2024; Trilateral Research 2025). The European Union's emphasis on human rights, algorithmic accountability, and cross-sectoral enforcement positions it as a global leader in ethical AI governance (Yadav 2025).

In contrast, the United States has adopted a sector-specific and innovation-driven model. Regulatory efforts are fragmented across agencies such as the Federal Trade Commission and the Department of Education, with a focus on consumer protection, data privacy, and algorithmic fairness (FTC 2025; U.S. Department of Education 2025). While federal legislation remains limited, state-level initiatives and voluntary frameworks, such as the Blueprint for an AI Bill of

Rights, offer guidance on transparency, accessibility, and non-discrimination (White House 2025). This decentralized approach reflects a broader cultural emphasis on market flexibility and technological entrepreneurship (Shouli et al. 2025).

China's governance model prioritizes state oversight and strategic control. The country's AI regulations emphasize national security, social stability, and ideological alignment, with strict content moderation and data localization requirements (Zou and Zhang 2025). Algorithmic systems used in education and media are subject to real-time monitoring and censorship, particularly when targeting youth audiences (Wang 2024). While China's model ensures centralized enforcement, it raises concerns about surveillance, autonomy, and freedom of expression (Sheehan 2024).

Other nations, including Japan, Canada, and the United Kingdom, have adopted hybrid models that balance innovation with ethical safeguards. Japan's *AI Promotion Act* emphasizes voluntary cooperation, sandbox testing, and public-private collaboration to foster responsible development (Lölfing and Saito 2025). Canada's Digital Charter and proposed bill C-27 prioritize youth protection, data transparency, and algorithmic accountability (Beauvais and Shade 2022; UNICEF Canada 2023). The United Kingdom's regulatory strategy focuses on adaptive risk assessment and algorithmic auditing, particularly in education and health sectors (Information Commissioner's Office 2025; Nasar, Sloan, and O'Neill 2024).

These comparative models reveal divergent approaches to algorithmic governance, each with implications for adolescent media engagement. The European Union's rights-based framework offers robust protections against algorithmic bias and exclusion, while the United States' model relies on civic literacy and institutional accountability. China's centralized control

limits youth autonomy but enforces strict content boundaries. Hybrid models seek to balance ethical oversight with developmental flexibility.

Human Impact and Educational Response

Adolescent cognitive development and media influence. Adolescence is a critical period of neurodevelopment characterized by heightened sensitivity to social feedback, novelty, and emotional salience. During this stage, the prefrontal cortex, which governs executive function and impulse control, is still maturing. In contrast, subcortical regions associated with reward processing are highly active. This developmental imbalance increases adolescents' susceptibility to algorithmically curated media environments that prioritize engagement over cognitive resilience (Marciano et al. 2024).

Digital media platforms are designed to exploit these sensitivities by delivering personalized content that emphasizes emotional arousal and social validation. Beginning around age ten, children experience a neurobiological shift that intensifies their drive for peer approval and social rewards. These stimuli are amplified by algorithmic feeds on platforms such as TikTok, YouTube, and Instagram (Abrams 2023). Recommendation systems reinforce behavioral loops through repetition and feedback, shaping identity performance and media preferences in ways that may limit critical reflection and exposure to diverse content.

A systematic review by Naik et al. (2025) found that prolonged social media exposure is associated with changes in attention, memory, and executive function among adolescents. The review emphasizes how algorithmic repetition and emotionally charged content can disrupt cognitive control processes, particularly in youth with high screen time or limited parental mediation. These findings support the need for media literacy interventions that strengthen adolescents' ability to recognize and resist algorithmic influence.

Furthermore, Costello et al. (2023) present an interdisciplinary study linking algorithmic amplification to increased risks of anxiety, poor body image, and disordered eating behaviors. Their research highlights how opaque personalization systems may exacerbate mental health vulnerabilities by reinforcing emotionally charged or socially comparative content without adequate safeguards. The authors advocate state-level policy interventions to protect youth from the psychological harms of algorithmically driven social media environments.

Understanding adolescent cognitive development is essential for evaluating the ethical implications of algorithmic personalization. As recommendation systems increasingly shape digital exposure, governance frameworks must account for developmental susceptibility. Personalization technologies should support, rather than undermine, adolescent autonomy, resilience, and cognitive growth.

Intersectionality and algorithmic identity construction. Algorithmic personalization systems are not neutral mechanisms. They are embedded within broader cultural, economic, and historical structures that shape how identity is constructed, represented, and reinforced in digital environments (Noble 2018; Gillespie 2018; Pasquale 2015). These systems reflect and reproduce existing power dynamics through data-driven processes that often privilege dominant social norms while marginalizing others (Turner Lee 2018; Cotter and Reisdorf 2020). Intersectionality, a framework introduced by Crenshaw (1989) to examine how overlapping systems of oppression affect individuals differently based on race, gender, class, and other social categories, offers a critical lens for analyzing how algorithmic systems mediate adolescent identity formation (Glatt 2022; Willson 2019).

Recommendation algorithms are trained on behavioral data and historical content patterns that often reflect dominant cultural norms (Cotter and Reisdorf 2020; Gillespie 2018; Kitchin

2017). As a result, these systems may amplify existing inequalities by disproportionately promoting content aligned with hegemonic identities while marginalizing underrepresented voices (Swart 2020; Glatt 2022; Cakmak et al. 2024). Noble (2018) documents how search algorithms reinforce racial and gender stereotypes, revealing how algorithmic infrastructures reproduce systemic bias under the guise of neutrality. Turner Lee (2018) further emphasizes that algorithmic bias is not merely a technical flaw but a reflection of broader social inequities embedded in data collection and model design.

In adolescent media ecosystems, such biases shape how youth encounter representations of race, gender, sexuality, and ability, influencing their sense of self and social belonging (Willson 2019; Swart 2021; Glatt 2022; Levido et al. 2025). Bhandari and Bimo (2022) describe how TikTok's algorithmic logic encourages performance-based identity construction, rewarding users who conform to dominant aesthetic and behavioral norms. Glatt (2022) provides an ethnographic account of YouTube's influencer ecosystem, illustrating how creators experience precarity, discrimination, and algorithmic invisibility. Their study reveals how algorithmic infrastructures reinforce racialized and gendered hierarchies, shaping which identities are amplified and which are suppressed.

Moreover, algorithmic identity construction is not solely a matter of representation but also of behavioral shaping (Bhandari and Bimo 2022; Willson 2019). Platforms push users to perform identities that fit algorithmic preferences, rewarding conformity with visibility (Glatt 2022; Swart 2021). Adolescents may feel pressured to present themselves in ways that hide intersectional identities or reinforce commodified versions of self (Levido et al. 2025; Noble 2018). Willson (2019) argues that algorithmic quantification contributes to the construction of the "ideal adolescent," shaping expectations around behavior, appearance, and social value.

Intersectional analysis reveals that algorithmic personalization is not equally experienced by all users (Crenshaw 1989; Noble 2018). Adolescents at the intersections of marginalized identities may face compounded harms, including misrepresentation, erasure, and algorithmic exclusion (Glatt 2022; Turner Lee 2018; Swart 2021). These dynamics underscore the need for inclusive algorithmic design, participatory governance, and critical media literacy that equips youth to recognize and resist the subtle ways in which algorithms shape identity and access to cultural visibility (Levido et al. 2025; Cotter and Reisdorf 2020; Oxford AI in Society 2023).

Educational implications and classroom integration. The sociotechnical dynamics of algorithmic personalization present significant implications for educational practice, particularly in relation to adolescent identity development, media literacy, and civic engagement. As digital platforms increasingly mediate how youth encounter information, representation, and social norms, educators must address the pedagogical challenges and opportunities posed by algorithmic systems (Livingstone et al. 2021; Marciano et al. 2024).

The prevalence of algorithmically curated content necessitates a shift from traditional media literacy toward algorithmic literacy, which includes the ability to critically interpret, interrogate, and navigate personalization systems (Bulger and Davison 2018). Levido et al. (2025) propose a curatorship-based model of media literacy, wherein students actively engage with platform mechanics to understand how content is selected, framed, and circulated. This approach enables adolescents to recognize patterns of repetition, ideological framing, and commercial prioritization, thereby fostering critical awareness of how algorithms shape their digital environments.

The behavioral and representational pressures exerted by recommendation systems underscore the need for identity-conscious pedagogy. Adolescents are often incentivized to

perform identity in ways that align with algorithmic preferences, which may obscure intersectional identities or reinforce commodified self-expression (Glatt 2022; Willson 2019). Harrell-Levy and Kerpelman (2010) emphasize that educators can serve as co-constructors of adolescent identity by fostering collaborative learning environments that support critical reflection on the sociotechnical forces shaping self-presentation.

The ethical and governance dimensions of algorithmic bias invite participatory learning models that position students as co-investigators of digital systems. Cotter and Reisdorf (2020) highlight the knowledge gaps and asymmetries that characterize platform-user relationships, particularly among marginalized youth. Participatory pedagogies, including project-based inquiry and scenario analysis, have been shown to support civic reasoning and ethical engagement with algorithmic systems (Sáez-López et al. 2020). These methods align with emerging frameworks for digital civics and youth empowerment, encouraging students to explore the implications of algorithmic decision-making, data profiling, and content moderation (Livingstone et al. 2012).

Classroom integration of algorithmic critique must also be developmentally attuned. Research on adolescent cognitive vulnerability suggests that youth are particularly susceptible to persuasive design, algorithmic nudging, and emotionally manipulative content (Marciano et al. 2024; Nesi et al. 2022). Educators must scaffold discussions around algorithmic influence with attention to emotional resilience, peer dynamics, and contextual relevance. Narrative-driven pedagogy, including roleplay and game-based inquiry, has been shown to support engagement while grounding abstract concepts in lived experience (Harrell-Levy and Kerpelman 2010).

Synthesis of Gaps in Current Research

The preceding literature review reveals a rapidly evolving field at the intersection of algorithmic personalization, adolescent development, and digital governance. While scholars have made significant strides in mapping the technical, ethical, and pedagogical dimensions of algorithmic systems, several critical gaps remain. These gaps span conceptual clarity, empirical scope, methodological transparency, and educational application, particularly in relation to adolescent users navigating personalized media environments.

First, although algorithmic personalization has been extensively theorized in terms of engagement optimization and content curation (Covington et al. 2016; Steck et al. 2021), few studies examine how adolescents interpret and respond to these systems in real time. Studies often portray youth as passive, rather than as active agents negotiating visibility, identity, and autonomy (Cotter and Reisdorf 2020; Glatt 2022). This limits understanding of how adolescents perceive algorithmic logic, adapt their behavior, or resist platform incentives.

Second, while algorithmic bias and representational inequality have been documented across race, gender, and sexuality (Noble 2018; Benjamin 2019), there is a lack of intersectional analyses that center adolescent experiences. Most studies focus on adult users or aggregate demographic trends, overlooking how identity construction unfolds within youth-specific algorithmic ecologies such as TikTok's "For You" feed or YouTube Shorts (Bishop 2021; Ionescu and Licu 2023). This gap constrains the development of inclusive media literacy frameworks that address the compounded effects of algorithmic profiling on marginalized youth.

Third, the literature on governance and policy remains fragmented across jurisdictions and disciplines. Although the European Union's AI Act and the United

States' Blueprint for an AI Bill of Rights have received scholarly attention (Madiega 2024; Shouli et al. 2025), comparative analyses often neglect how these frameworks address adolescent-specific risks, such as persuasive design, data commodification, and emotional manipulation (Livingstone et al. 2012; Marciano et al. 2024). Moreover, few studies evaluate how regulatory models translate into platform accountability or user empowerment at the classroom level.

Fourth, educational responses to algorithmic systems remain underdeveloped. While scholars have proposed algorithmic literacy as a pedagogical goal (Pangrazio and Selwyn 2018; Kong and Zhang 2024), there is limited empirical research on how such literacies are cultivated in secondary education settings. Existing interventions often emphasize technical comprehension over ethical reasoning, identity reflection, or civic engagement (Levido et al. 2025). Furthermore, few studies integrate adolescent developmental psychology with participatory pedagogy to scaffold critical inquiry into algorithmic systems.

Fifth, methodological transparency remains a persistent challenge. Studies of platform algorithms frequently rely on reverse engineering, scraped data, or researcher-created accounts, which may not capture the lived experiences of adolescent users (Bodo et al. 2017; Hastuti et al. 2025). Ethical constraints around data access, consent, and platform terms of service further limit the scope of empirical inquiry. As a result, there is a need for reflexive, participatory, and ethically grounded methodologies that center youth perspectives while navigating platform opacity.

THEORETICAL FRAMEWORK

Algorithmic Personalization Theory

Algorithmic personalization theory explores how recommendation systems shape digital content exposure, tailoring suggestions based on user behaviors, engagement patterns, and predictive modeling. Cotter and Reisdorf (2020) emphasize that personalization algorithms reinforce consumption habits, generating digital media bubbles that limit user exposure to diverse content. This theory provides a foundation for analyzing how platforms like YouTube, TikTok, and Netflix curate adolescent media consumption through adaptive filtering mechanisms, prioritizing high-engagement content over exploratory or diverse recommendations. While personalization enhances user retention, it also introduces concerns regarding algorithmic bias and representation, necessitating further exploration through Algorithmic Bias and Fairness Theory.

Algorithmic Bias and Fairness Theory

Bias detection in algorithmic personalization examines how recommendation algorithms amplify pre-existing inequalities, often reinforcing dominant cultural narratives at the expense of marginalized perspectives. The risks of algorithmic bias within digital platforms are significant, as personalization models disproportionately filter content based on engagement metrics rather than equitable representation (Turner Lee 2018). Building on Algorithmic Personalization Theory, this perspective addresses how recommendation engines unintentionally limit content diversity, influencing adolescent perceptions of media. As recommendation engines continuously refine suggestions, the lack of bias auditing mechanisms may exacerbate exclusionary recommendation patterns, reinforcing ideological, cultural, or commercial dominance. To counter these biases, scholars advocate for Critical Media Literacy and Algorithmic Governance,

equipping adolescents with the tools needed to navigate algorithmic recommendation systems in media landscapes.

Critical Media Literacy and Algorithmic Governance

Critical media literacy theory underscores the importance of user awareness in digital consumption, arguing that adolescents must be actively engaged in understanding algorithmic filtering to resist passive consumption patterns. Levido et al. (2025) explore how algorithmic literacy enables resistance to hyper-personalized filtering, fostering greater critical engagement with digital content. To support this perspective Livingstone and Blum-Ross (2020) emphasize the role of algorithmic governance in ensuring transparency and accountability, advocating for public oversight measures, ethical data guidelines, and educational frameworks that empower adolescent users. As Algorithmic Bias and Fairness Theory reveals hidden inequalities, Critical Media Literacy and Governance Theory provides solutions by equipping users with cognitive resilience against biased personalization models. However, beyond user empowerment, broader ethical considerations must guide the design and regulation of recommendation systems, necessitating deeper exploration into Ethical AI and Responsible Personalization.

Ethical AI and Responsible Personalization

Ethical governance frameworks integrate autonomy, justice, and non-maleficence to ensure responsible personalization systems (Floridi and Cowls 2019). This perspective recognizes the power asymmetry between algorithmic decision-making and user autonomy, reinforcing the necessity for transparent regulatory frameworks that prevent unethical content manipulation. Building upon Algorithmic Governance Theory, the European Commission (2024) introduces regulatory measures under the AI Act, mandating that personalization platforms disclose data handling mechanisms and bias mitigation strategies. These guidelines align with

Critical Media Literacy, ensuring that adolescent users are not only educated on algorithmic processes but also protected from harmful personalization loops that may influence cognitive development.

Current Research

This study investigates how algorithmic personalization systems may shape adolescent media engagement across Netflix, TikTok, and YouTube. It focuses on the mechanisms through which recommendation algorithms construct educational and entertainment user profiles, particularly in relation to bias emergence, engagement responsiveness, and profit incentives. The research questions are as follows:

1. How might algorithmic recommendation systems on YouTube, TikTok, and Netflix shape the media engagement patterns of adolescents aged thirteen to seventeen?
2. Do algorithmic recommendations on these platforms encourage content diversity among adolescents or limit their exposure?
3. What role does user engagement play in shaping algorithmically curated content on these platforms?
4. What influence might profit incentives have on these platforms' content curation aimed at adolescents?

METHODOLOGY

To answer these questions, this study employs a comparative content analysis approach to examine algorithmic curation, bias detection, and commercialization in adolescent media across Netflix, TikTok, and YouTube. Integrating structured coding frameworks and descriptive statistical analyses using SPSS, I systematically categorized algorithmically recommended content in relation to user engagement patterns.

Data Collection

I gathered data manually from Netflix, TikTok, and YouTube using newly created accounts or profiles designed to simulate three distinct adolescent media consumption patterns: a user interested in education who prioritized STEM, documentaries, and learning materials; a user interested in entertainment who engaged with content related to cartoons, gaming, and popular culture; and a user interested in a mix of education and entertainment who interacted with all types of content listed above. Each profile operated within controlled conditions to enable the observation of algorithmic recommendations across varying levels of user engagement.

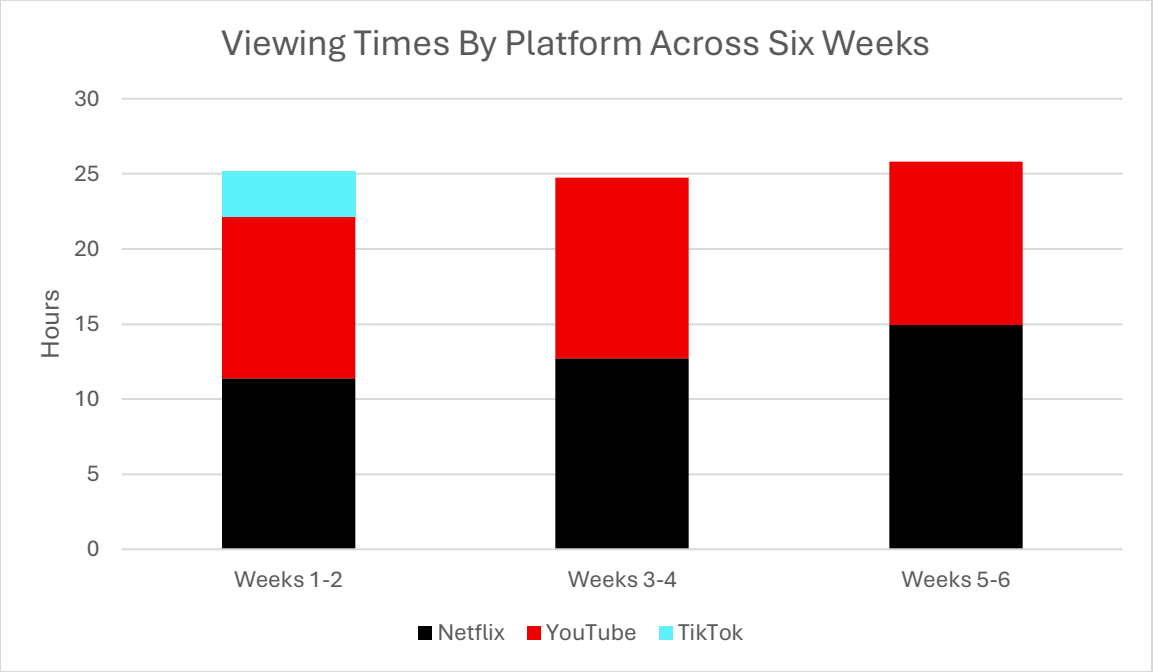
Because user engagement patterns influence algorithmic personalization, I systematically varied user engagement levels across each profile over time. For the first week of data collection for each user profile, I prioritized low user engagement or minimal interaction with content on the platform, merely scrolling and viewing videos without clicking, liking, commenting on, or sharing them. For the second week of data collection for each user profile, I prioritized high user engagement by liking, sharing, commenting on, and actively selecting content, as each platform allowed.

I used private internet browsers to ensure consistency across sessions and to minimize residual algorithmic influence. Netflix data were gathered using newly created user profiles with no prior viewing history, while a new email address and corresponding user profile were created for YouTube and TikTok each week. This approach minimized the influence of prior user history, allowing for clearer observation of recommendation shifts based on controlled interaction patterns.

I documented a total of 427 recommended videos across all platforms during the six-week study period. Of these, 280 were collected from TikTok, 103 from YouTube, and 44 from

Netflix. TikTok data collection was limited to the first two weeks of the study because the platform flagged my account as a bot, likely due to the absence of geographic data and search history, which disrupted recommendation functionality. I viewed a total of 75 hours, 41 minutes, and 34 seconds of content across platforms.

Figure 1.



For each video I watched, I collected the following information: time watched, platform, content creator, content title, video duration, publication date, and, if applicable, the number of views. I also generated data related to video content, repetition, diversity, monetization indicators, user engagement, and interpretive notes. Screenshots were captured to archive the platforms' recommendation interfaces and visual metadata. Publication dates were examined to determine the recency and relevance of each video, and I made note of whether the content appeared to reflect current sociopolitical, cultural, or trending developments.

Data Analysis

Coding. Recommended content was classified into four main categories: education (EDU), entertainment (ENT), advertisement (AD), and mixed (MIX). I tracked the repetition and diversity of algorithmic recommendations for each user profile each week, assigning a label of high, medium, or low for each variable. Recommended content was also analyzed for bias patterns. Bias was initially coded using three primary indicators: demographic bias (BIA-D), content Bias (BIA-C), and no observable bias (BIA-N). As the study progressed, the coding framework was expanded to include linguistic bias (BIA-L), body normativity (BIA-B), sexualization (BIA-S), promotion of risky behaviors (BIA-RB), political bias (BIA-G), and religious bias (BIA-RI). These indicators were applied to recommended content that reflected implicit or explicit reinforcement of normative assumptions, exclusionary representations, or disproportionate emphasis on specific identity traits, behaviors, or ideologies. Monetization of content was coded as either low (MON-L), indicating minimal profit motives, moderate (MON-M), indicating some profit motives, or high (MON-H), high profit motives. These indicators were applied to recommended content based on visual cues, verbal disclosures, and platform-specific monetization structures.

Statistical analyses. Quantitative analysis was conducted using IBM SPSS Statistics Version 31 to evaluate content frequency, category distribution, engagement influence, and bias presence across platforms. To facilitate analysis, several variables were transformed into binary or ordinal formats. Platform affiliation was dummy coded into three binary variables: *Platform: Netflix*, *Platform: YouTube*, and *Platform: TikTok* (1 = affiliated, 0 = not affiliated). Monetization level was recoded into a binary variable (*Medium or High Monetization*; 1 = medium or high, 0 = none or low). Bias presence was coded as a binary variable (*Any Bias*

Present; 1 = yes, 0 = no). Three algorithmic traits (*Engagement*, *Repetition*, and *Diversity*) were transformed into ordinal scales (1 = low, 2 = medium, 3 = high) to capture gradations in user interaction intensity, content recurrence, and representational variety.

Descriptive statistics were used to quantify the occurrence of specific content categories, enabling identification of dominant trends in personalized recommendations. Category distribution analysis compared exposure patterns across engagement levels and user profiles, providing insight into algorithmic filtering behavior. The influence of user engagement on algorithmic recommendation patterns was assessed through Pearson correlation tests. To examine potential associations between bias patterns and platforms, chi-square tests of independence were conducted.

Ethical Considerations

Ethical integrity and platform compliance are central to this study, guiding all aspects of data collection, analysis, and interpretation. I adhered strictly to the terms of service for YouTube, TikTok, and Netflix. Platform-specific compliance procedures introduced additional ethical complexities. For YouTube, account creation required a Gmail address. During setup, Gmail presented an option to restrict data sharing between Gmail and YouTube. However, upon activating the YouTube account, platform terms mandated data integration, overriding the initial privacy setting. Users must manually revisit Gmail settings to disable cross-platform data sharing. This process illustrates the opacity of consent mechanisms and the structural challenges of maintaining user autonomy within algorithmically governed ecosystems.

FINDINGS

Content Distribution Across Profiles and Platforms

This section presents a comparative analysis of recommended content across the three types of user profiles: education, entertainment, and mixed. Due to platform restrictions, TikTok data were collected only from an education user profile and only during the first two weeks of the study. As a result, TikTok findings reflect a limited engagement scope and should be interpreted with caution when compared to YouTube and Netflix.

Distribution by user profile. Education profiles recommended a higher proportion of entertainment content across all platforms, particularly during periods of low-engagement data collection. On YouTube, 68 percent of recommendations for education user profiles were educational, followed by 54 percent on Netflix and 42 percent on TikTok. During periods of high-engagement data collection, the proportion of educational content recommended to these user profiles declined on TikTok and YouTube, corresponding with an increase in entertainment and advertisement content.

User profiles focused on entertainment were recommended mostly entertainment content across YouTube and Netflix. YouTube presented 76 percent of recommendations classified as entertainment, while Netflix presented 61 percent. During periods of high-engagement data collection, 19 percent of recommended content for entertainment user profiles on YouTube was classified as advertisement, frequently embedded within branded content or influencers' videos.

Mixed user profiles received the most balanced distribution of content recommendations. On Netflix, mixed profiles received 48 percent of education and 45 percent of entertainment content. YouTube recommended content that was 52 percent entertainment and 41 percent education.

Distribution by platform. Netflix's algorithmic recommendations remained the most stable, with minimal responsiveness to shifts in user engagement. Education user profiles were typically recommended documentary-style content with low monetization and limited content diversity. Entertainment user profiles were typically recommended serialized dramas made for young audiences, often anchored by Netflix-produced titles such as *Wednesday* and *KPop Demon Hunters*. Mixed user profiles revealed minimal algorithmic support for educational content, which was treated as occasional rather than essential within recommendation systems. Across all conditions, recommended content on Netflix maintained low monetization and moderate repetition. Bias was consistently identified throughout the Netflix cases, with 32.4% of sessions containing at least one coded indicator. The most frequent types included body normativity bias (8.1%), risk behavior bias (8.1%), religious ideology bias (5.4%), and governmental bias (5.4%), with several sessions exhibiting overlapping bias categories.

YouTube demonstrated the most dynamic content distribution. Education user profiles received a wide range of recommended content, including introductory science modules, philosophical commentaries, and socio-political analyses. Entertainment user profiles were saturated with eye-catching creator videos, sponsored corporate content, and content shaped by gender roles. Mixed user profiles blended learning with emotional content, surfacing both educational and entertainment content. Monetization on YouTube ranged from moderate to high, with frequent embedded advertisements and sponsor integrations. Bias appeared consistently throughout the six-week YouTube dataset, with 35.1% of sessions containing at least one coded indicator. The most frequent types included sexualization bias (6.2%), risk behavior bias (5.2%), and religious ideology bias (1.0%), along with isolated instances of body normativity bias (1.0%) and governmental bias (1.0%). Content bias appeared in 4.1% of sessions, and several entries

featured overlapping bias categories, contributing to a layered and persistent bias profile. YouTube's algorithm adapted fluidly to user engagement, building viewer identities through popular creators and changing content styles.

TikTok data collection was limited to education user profiles due to platform restrictions. Across two weeks of data collection, TikTok's algorithm consistently recommended highly monetized content. Bias indicators appeared in 19.9% of cases overall, with content bias present in 6.8%, language bias in 5.1%, and demographic bias in 4.0%, including several instances of overlapping categories. The recommendation algorithm seemed to rapidly infer user traits such as financial precarity, entrepreneurial ambition, and cultural affiliation, shaping a "For You" feed that was emotionally charged and commercially saturated. Repetition increased with user engagement, while diversity remained moderate due to high creator turnover, though content maintained a narrow thematic range.

Overall, Netflix maintained genre stability and promotional anchors, resisting thematic expansion even in periods of high user engagement. YouTube adjusted to user engagement and profile traits, shaping complex viewer identities through popular creators and varied content. TikTok, despite limited data collection, revealed aggressive monetization and emotional profiling, shaping the "For You" feed through commercial logic and cultural inference. These patterns demonstrate that content distribution is not merely reactive to user engagement but actively shaped by platform priorities, profit incentives, and representational norms.

User Engagement's Influence on Recommendation Diversity

This section examines how user engagement levels influenced the diversity and repetition of recommended content across YouTube, TikTok, and Netflix.

Effects by platform. Netflix demonstrated the least responsiveness to changes in engagement. During periods of low-engagement data collection, recommendations included mostly documentaries intended for adults, with low diversity and minimal repetition. During periods of high-engagement data collection, algorithmic recommendations reinforced previously liked content but did not expand different themes. Even when users consistently watched educational content, Netflix kept promoting familiar genres and shows, suggesting its recommendations aim to keep viewing habits steady rather than broaden them. Repetition increased slightly in periods of high user engagement, but diversity remained low. Netflix treated educational videos as isolated cases, not as a way to tailor future recommendations.

YouTube exhibited the most dynamic response to user engagement. Periods of low-engagement data collection began with recommendations of education content, but recommendations gradually shifted toward entertainment. High levels of user engagement significantly increased content diversity, with recommended content spanning science, ethics, media literacy, and creator ecosystems. Repetition remained moderate, often tied to creator visibility rather than thematic redundancy. YouTube adapted smoothly to user engagement, shaping complex viewer profiles through shifts in tone, educational content, and entertainment videos.

TikTok, which was limited to education user profiles, revealed high sensitivity to user engagement. During periods of low-engagement data collection, recommendations included monetized education content with moderate diversity and low repetition. Periods of high engagement were associated with greater repetition and a narrowed thematic range, despite high creator turnover. Diversity declined, and the “For You” feed became saturated with financial advice, lifestyle routines, and emotionally framed content. TikTok inferred user identity rapidly,

reinforcing traits such as entrepreneurial ambition and cultural affiliation based on minimal input.

Effects by profile. Recommendation algorithms responded differently to education user profiles across platforms. On Netflix, education-related user engagement reinforced stable, adult-oriented content with minimal expansion. On YouTube, it triggered thematic exploration and intellectual depth. On TikTok, it surfaced emotionally charged, monetized advice, often framed through cultural and linguistic bias.

Entertainment user profiles were linked with algorithmic recommendations that revealed genre loyalty and bias amplification. Netflix leaned into serialized dramas made for young audiences, while YouTube prioritized flashy creator content and normative gender portrayals. High levels of user engagement intensified recommendations of content with emotional tone and bias visibility, particularly body normativity, sexualization, and risk behavior.

Mixed user profiles showed the most complex engagement patterns. When engagement was low, platforms repeated promotional content and adjusted emotionally. When engagement was high, YouTube offered a wider mix of topics, while Netflix leaned heavily into belief-based content. These mixed profiles revealed the broadest range of bias and monetized content, suggesting that engaging with different types of media leads algorithms to blend recommendations instead of fine-tuning them.

Overall, when users were highly engaged, Netflix and TikTok repeated similar content, while YouTube offered a wider mix of topics. Low engagement was correlated with stable and familiar recommendations, especially on Netflix, which maintained the same genres and promotions. YouTube responded to user behavior by shaping viewer identities through creators and emotional content. TikTok quickly identified user traits and reinforced them with emotional

and monetized videos. Netflix avoided variety and kept viewing habits consistent. Users with mixed interests triggered the most flexible and intense recommendation patterns, revealing how each platform responds when engagement is unclear.

Biases in Algorithmic Curation

This section presents findings related to the presence and progression of bias in algorithmically curated content across Netflix, YouTube, and TikTok.

Biases by platform. TikTok exhibited consistent bias in recommended content despite data collection being limited to education user profiles. Content bias, linguistic bias, and demographic bias appeared in periods of both low- and high-engagement data collection, often embedded in monetized advice content and emotionally charged narratives. This suggests that bias on TikTok may be embedded in the platform's recommendation algorithms.

YouTube demonstrated progressive bias diversification. Early data collection revealed demographic and content bias in recommended content, while later data collection introduced sexualization, promotion of risky behavior, body normativity, and religious bias in recommended content. Religious bias appeared most frequently in recommendations for mixed user profiles during periods of high user engagement, indicating that hybrid interaction patterns may trigger exposure to ideologically framed content.

Netflix presented a slower but cumulative bias trajectory. Initial data collection revealed demographic bias in recommended content, while later data collection introduced body normativity, promotion of risky behavior, religious bias, and political bias. These findings suggest that Netflix's editorial curation does not fully insulate users from biased content, particularly under entertainment and mixed engagement conditions.

Figure 2.

Week	Engagement Type	Netflix	YouTube	TikTok
1	Passive Educational	Demographic bias; documentaries framing identity and social roles	Demographic and content bias; location targeting, paranoia themes	Demographic, content, and language bias; career gatekeeping, cultural stereotypes
2	Active Educational	No observable bias	No observable bias	Demographic, content, and language bias; monetized educational content with cultural and language targeting
3	Passive Entertainment	Demographic, reckless behavior, and sexualization bias; serialized dramas glamorizing risky behavior	Demographic, reckless behavior, sexualization bias; Gender stereotypes	—
4	Active Entertainment	Body normativity, reckless behavior, and sexualization bias	Body normativity, reckless behavior, religious bias, and sexualization	—
5	Passive Mixed	Body normativity, demographic, reckless behavior, and sexualization bias; promotional content reinforcing cultural norms and ideals	Religious ideology bias; vigilante-style and morally charged content	—
6	Active Mixed	Body normativity, government, reckless behavior, religious ideology, and sexualization bias; political critique blended with stylized or educational content	Religious ideology bias in historical and scientific content	—

Biases by profile. Periods of high-engagement data collection consistently increased the diversity and intensity of bias in recommended content. Entertainment user profiles received the widest range of bias in recommended content, particularly on YouTube and Netflix. Mixed user profiles received the most complex bias exposure, with religious and political bias appearing only during periods of high-engagement data collection. Education user profiles on TikTok encountered multiple bias types in recommended content, underscoring the platform's limited differentiation between user intent and content prioritization.

Overall, bias expanded from three to seven categories over the course of the study, reflecting increased complexity in algorithmic curation. TikTok surfaced consistent bias in recommended content even within education user profiles, particularly content bias, linguistic bias, and demographic bias. YouTube demonstrated progressive bias diversification, with religious bias appearing in recommended content for mixed user profiles during periods of high user engagement. Netflix exhibited cumulative bias exposure, with political and religious bias emerging in later periods of data collection. High user engagement amplified bias diversity and frequency across all platforms. Mixed user profiles triggered the most ideologically complex recommendations.

Monetization Patterns

This section analyzes the presence, frequency, and prioritization of monetized content across YouTube, TikTok, and Netflix.

Monetization trends by platform. TikTok surfaced the highest proportion of highly monetized content, despite data collection being limited to education user profiles during the first two weeks of the study. Of the 280 TikTok videos analyzed, sixty percent were coded as highly monetized, often featuring product endorsements by influencers, corporations, and affiliate links.

These videos appeared even for education-focused users suggesting that profit incentives are embedded in algorithmic recommendations across user profile types and are not limited to entertainment content.

YouTube presented a stratified monetization landscape. Across the six-week data collection period, content ranged from lightly monetized educational explainers to heavily monetized branded entertainment. Highly monetized content included sponsored challenges, product integrations, and direct advertisements embedded within creator ecosystems. Moderately monetized content often featured subtle brand affiliations or channel partnerships. Educational user profiles received recommendations for less monetized content, while entertainment and mixed user profiles more often encountered highly monetized material.

Netflix exhibited no obviously monetized content across the 44 videos analyzed. This reflects the platform's subscription-based profit model and editorial curation, which limits intrusive advertising and product placement. However, the persistent promotion of proprietary content and algorithmic prioritization of Netflix-produced series may constitute a form of monetization. Promotional anchors such as *Wednesday*, *Stranger Things*, and *KPop Demon Hunters* were recommended repeatedly across user profiles, suggesting that Netflix leverages its own content catalog to keep stabilize viewers' habits and interests.

Monetization trends by user profile and engagement. High user engagement consistently increased recommendations of highly monetized content on YouTube and TikTok. On TikTok, high engagement by the education user profile intensified the presence of branded advice, financial tools, and lifestyle promotions. On YouTube, high user engagement triggered recommendations of a blend of educational and entertainment content, with creator ecosystems serving as vehicles for embedded advertising and product sponsorship. Monetization was not

limited to entertainment user profiles; even education and mixed user profiles encountered monetized content when sustaining a high level of user engagement.

Entertainment user profiles were most saturated with highly monetized content, particularly on YouTube. Mixed user profiles encountered a broader range of monetization levels, with recommendations often blending educational content with branded spectacle. Education user profiles on TikTok and YouTube still received substantial amounts of moderately and highly monetized content, indicating that platform monetization strategies are not sensitive to user intent or developmental appropriateness.

Overall, TikTok surfaced a high volume of highly monetized content, even within education user profiles, and increased monetization during periods of high-engagement data collection. YouTube displayed a full spectrum of monetization, with recommendations of moderately and highly monetized content prevalent across all user profiles and engagement levels. Netflix exhibited no obviously monetized content, though internal promotion of proprietary content was persistent. High levels of user engagement consistently increased recommendations of monetized content on TikTok and YouTube. Entertainment and mixed profiles were most susceptible to commercial saturation, but education profiles were not exempt from monetization logic.

Statistical Findings

This section presents the results of Pearson correlation analyses, Spearman's rho correlations, and chi-square tests. Results highlight platform-specific patterns in bias exposure, algorithmic traits, and monetization relevant to adolescents' digital media engagement.

Correlations. Spearman's rho correlations revealed a statistically significant negative association between medium/high monetization and content diversity ($\rho = -.229$, $p < .001$),

indicating that more monetized recommendations tended to be less diverse. A statistically significant positive association was observed between monetization and repetition (ρ = .137, p = .007), suggesting that commercially saturated content was more frequently re-recommended.

Figure 3.

Correlations[c]

			Medium or High Monetization	Engagement	Repetition	Diversity
Spearman's rho	Medium or High Monetization	Correlation Coefficient	1.000	.009	.137**	-.229**
		Sig. (2-tailed)	.	.862	.005	<.001
	Engagement	Correlation Coefficient	.009	1.000	.017	-.106*
		Sig. (2-tailed)	.862	.	.729	.031
	Repetition	Correlation Coefficient	.137**	.017	1.000	-.448**
		Sig. (2-tailed)	.005	.729	.	<.001
	Diversity	Correlation Coefficient	-.229**	-.106*	-.448**	1.000
		Sig. (2-tailed)	<.001	.031	<.001	.

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

c. Listwise N = 414

Pearson correlations further demonstrated that medium/high monetization was statistically significantly positively associated with number of video views (r = .217, $p < .001$), suggesting that content with higher view counts was associated with high levels of monetization.

Figure 4.

Correlations

		Medium or High Monetization	Any Bias Present (1=Yes, 0=No)	Video Views
Medium or High Monetization	Pearson Correlation	1	.071	.217**
	Sig. (2-tailed)		.142	<.001
	N	427	427	383
Any Bias Present (1=Yes, 0=No)	Pearson Correlation	.071	1	-.091
	Sig. (2-tailed)	.142		.076
	N	427	427	383
Video Views	Pearson Correlation	.217**	-.091	1
	Sig. (2-tailed)	<.001	.076	
	N	383	383	383

**. Correlation is significant at the 0.01 level (2-tailed).

A strong statistically significant negative correlation was found between repetition and diversity (r = –.420, $p < .001$), indicating that content with higher repetition scores tended to exhibit lower diversity. Engagement was statistically significantly positively correlated with repetition (r = .147, $p = .002$) and statistically significantly negatively correlated with diversity (r = –.420, $p < .001$).

Figure 5.

Correlations

		Repetition	Diversity
Repetition	Pearson Correlation	1	-.420**
	Sig. (2-tailed)		<.001
	N	414	414
Diversity	Pearson Correlation	-.420**	1
	Sig. (2-tailed)	<.001	
	N	414	414

**. Correlation is significant at the 0.01 level (2-tailed).

Platform-specific patterns were also evident. Bias was statistically significantly positively correlated with TikTok content (r = .225, $p < .001$) and negatively correlated with YouTube content (r = –.244, $p < .001$), while Netflix showed no statistically significant association (r = –.017, $p = .730$).

Figure 6.

Correlations

		Platform: Netflix	Platform: YouTube	Platform: TikTok	Any Bias Present (1=Yes, 0=No)
Platform: Netflix	Pearson Correlation	1	-.180**	-.490**	-.017
	Sig. (2-tailed)		<.001	<.001	.730
	N	427	427	427	427
Platform: YouTube	Pearson Correlation	-.180**	1	-.769**	-.242**
	Sig. (2-tailed)	<.001		<.001	<.001
	N	427	427	427	427
Platform: TikTok	Pearson Correlation	-.490**	-.769**	1	.225**
	Sig. (2-tailed)	<.001	<.001		<.001
	N	427	427	427	427
Any Bias Present (1=Yes, 0=No)	Pearson Correlation	-.017	-.242**	.225**	1
	Sig. (2-tailed)	.730	<.001	<.001	
	N	427	427	427	427

**. Correlation is significant at the 0.01 level (2-tailed).

Medium/high monetization was positively associated with YouTube (ρ = .484, $p < .001$) and negatively associated with Netflix (ρ = –.163, $p < .001$). Netflix correlated positively with repetition (ρ = .463, $p < .001$) but negatively with diversity (ρ = –.249, $p < .001$), YouTube showed moderate repetition (ρ = .265, $p < .001$) and reduced diversity (ρ = –.536, $p < .001$), while TikTok was negatively associated with repetition (ρ = –.529, $p < .001$) and positively associated with diversity (ρ = .632, $p < .001$).

Figure 7.

Correlations

			Platform: Netflix	Platform: YouTube	Platform: TikTok	Medium or High Monetization	Engagement	Repetition	Diversity
Spearman's rho	Platform: Netflix	Correlation Coefficient	1.000	-.180	-.490	-.163	.019	.463	-.249
		Sig. (2-tailed)	.	<.001	<.001	<.001	.690	<.001	<.001
		N	427	427	427	427	427	414	414
	Platform: YouTube	Correlation Coefficient	-.180	1.000	-.769	.484	-.039	.265	-.536
		Sig. (2-tailed)	<.001	.	<.001	<.001	.422	<.001	<.001
		N	427	427	427	427	427	414	414
	Platform: TikTok	Correlation Coefficient	-.490	-.769	1.000	-.323	.022	-.529	.632
		Sig. (2-tailed)	<.001	<.001	.	<.001	.651	<.001	<.001
		N	427	427	427	427	427	414	414
	Medium or High Monetization	Correlation Coefficient	-.163	.484	-.323	1.000	.018	.137	-.229
		Sig. (2-tailed)	<.001	<.001	<.001	.	.716	.005	<.001
		N	427	427	427	427	427	414	414
	Engagement	Correlation Coefficient	.019	-.039	.022	.018	1.000	.017	-.106
		Sig. (2-tailed)	.690	.422	.651	.716	.	.729	.031
		N	427	427	427	427	427	414	414
	Repetition	Correlation Coefficient	.463	.265	-.529	.137	.017	1.000	-.448
		Sig. (2-tailed)	<.001	<.001	<.001	.005	.729	.	<.001
		N	414	414	414	414	414	414	414
	Diversity	Correlation Coefficient	-.249	-.536	.632	-.229	-.106	-.448	1.000
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.031	<.001	.
		N	414	414	414	414	414	414	414

Content platform analyses revealed monetization level was positively associated with YouTube (ρ = .071, $p = .131$) and TikTok (ρ = .052, $p = .266$) and significantly negatively associated with Netflix (ρ = −.118, $p < .001$). Repetition and engagement were positively correlated with monetization (ρ = .012 and .132, respectively), while diversity was negatively associated (ρ = .044). TikTok displayed the strongest positive correlations with repetition (ρ = .221, $p < .001$) and diversity (ρ = .379, $p < .001$).

Figure 8.

Correlations

		Content: Education	Content: Entertainment	Content: Advertisement	Content: Mixture	MH Monetization	Repetition	Diversity
Content: Education	Pearson Correlation	1	-.799**	-.497**	-.140**	-.462**	-.280**	.299**
	Sig. (2-tailed)		<.001	<.001	.004	<.001	<.001	<.001
	N	427	427	427	427	427	414	414
Content: Entertainment	Pearson Correlation	-.799**	1	-.096*	-.027	.217**	.391**	-.395**
	Sig. (2-tailed)	<.001		.048	.579	<.001	<.001	<.001
	N	427	427	427	427	427	414	414
Content: Advertisement	Pearson Correlation	-.497**	-.096*	1	-.017	.456**	-.084	.070
	Sig. (2-tailed)	<.001	.048		.730	<.001	.087	.155
	N	427	427	427	427	427	414	414
Content: Mixture	Pearson Correlation	-.140**	-.027	-.017	1	.055	-.017	-.039
	Sig. (2-tailed)	.004	.579	.730		.257	.735	.434
	N	427	427	427	427	427	414	414
MH Monetization	Pearson Correlation	-.462**	.217**	.456**	.055	1	.098*	-.200**
	Sig. (2-tailed)	<.001	<.001	<.001	.257		.047	<.001
	N	427	427	427	427	427	414	414
Repetition	Pearson Correlation	-.280**	.391**	-.084	-.017	.098*	1	-.420**
	Sig. (2-tailed)	<.001	<.001	.087	.735	.047		<.001
	N	414	414	414	414	414	414	414
Diversity	Pearson Correlation	.299**	-.395**	.070	-.039	-.200**	-.420**	1
	Sig. (2-tailed)	<.001	<.001	.155	.434	<.001	<.001	
	N	414	414	414	414	414	414	414

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Chi-square tests. According to chi-square analyses, bias was significantly less likely to appear in YouTube content ($\chi^2(1) = 24.986$, $p < .001$) and significantly more likely to appear in TikTok content ($\chi^2(1) = 21.656$, $p < .001$). No significant association was found for Netflix ($\chi^2(1) = 0.120$, $p = .729$).

DISCUSSION

The results of this study suggest that content monetization and user engagement are associated with algorithmic processes that prioritize repetition and reduce diversity. Monetized content receives greater visibility and is significantly more likely to contain bias. Platform affiliation influences bias exposure, with TikTok showing elevated risk and Netflix maintaining neutrality. Educational content resists commercial amplification, suggesting ethical resilience. These findings support the thesis that algorithmic architecture and monetization strategies shape adolescent media engagement and bias exposure.

The findings align with prior research on algorithmic amplification and commercial bias. Kitchin (2017) and Zuboff (2019) describe platforms as behavioral infrastructures that optimize for engagement through repetitive and emotionally resonant content. The repetition-diversity tradeoff and monetization-driven visibility observed in this study reflect these dynamics.

Benjamin (2019) and Noble (2018) document how commercial algorithms encode and amplify racial and gendered biases. Bahangulu and Owusu-Berko (2025) emphasize the importance of fairness and transparency in AI-powered systems. The significant link between monetization and bias presence supports these concerns.

Adolescent vulnerability to algorithmic influence has been widely documented. Abrams (2023), Marciano et al. (2024), and Naik et al. (2025) highlight the neurological and cognitive sensitivity of youth to emotionally charged and repetitive media. Willson (2019) explores how adolescents engage with and resist algorithmic curation, underscoring the need for agency and critical awareness.

Governance implications are supported by policy analyses from the European Commission (2024), Future of Life Institute (2024), and Madiega (2024), which advocate transparency and accountability. Comparative frameworks from Japan, China, and the United States reveal global efforts to address algorithmic harms.

The call for critical media literacy is echoed by Bulger and Davison (2018), Levido et al. (2025), and Bucher (2021), who argue that adolescents must be equipped to decode algorithmic logic and challenge bias. The ethical resilience of educational content in this study supports pedagogical models that prioritize transparency and representational equity.

Governance Gaps and Ethical Implications

This section examines the governance limitations and ethical concerns that emerged from the observed patterns of algorithmic recommendation across YouTube, TikTok, and Netflix. Drawing from coded indicators of bias, monetization, and engagement responsiveness, the findings reveal systemic gaps in platform accountability, transparency, and user protection. These gaps are particularly concerning adolescent users, who navigate digital media ecosystems with limited structural safeguards and uneven access to media literacy education.

Absence of algorithmic transparency. None of the platforms provided visible disclosures regarding how recommendations were generated, ranked, or filtered. Despite significant shifts in content distribution based on engagement level and user profile type, users were not informed of the underlying personalization mechanisms. This lack of transparency restricts users' ability to critically assess the credibility, diversity, or intent of recommended media. For adolescent users, who may not possess advanced media literacy skills, this presents a substantial risk to informed consumption, identity development, and autonomy.

Commercial prioritization over age-appropriateness. YouTube and TikTok demonstrated clear patterns of commercial prioritization, amplifying highly monetized content during high engagement sessions. This occurred even within educational-focused profiles, suggesting that profitability may be prioritized over relevance, diversity, or developmental appropriateness. Netflix, while less overtly monetized, consistently promoted proprietary content through internal recommendation loops. These patterns raise ethical concerns about the commodification of attention and the erosion of content neutrality in environments frequented by young users.

Amplification of social and ideological biases. The presence of bias-coded content, particularly body normativity, sexualization, risk behavior, and religious ideology, indicates that

algorithmic systems may reinforce existing social hierarchies and stereotypes. TikTok frequently amplified emotionally charged and culturally coded content, while YouTube surfaced gendered performance, religious framing, and moral redemption narratives. Netflix, although more curated, exhibited ideological saturation in later sessions. The absence of platform-level safeguards or corrective mechanisms exacerbates these risks, especially for adolescents who are actively forming self-concept and social identity through media exposure.

Lack of developmentally appropriate safeguards. Although all three platforms are widely used by adolescents, none provided age-specific filters, educational framing, or contextual warnings for biased or highly monetized content. Recommendation systems appeared to treat engagement as a universal metric, without regard for developmental stage, informational needs, or emotional vulnerability. This governance gap underscores the ethical imperative for platforms to implement differentiated safeguards, transparency protocols, and participatory oversight mechanisms that prioritize user well-being over engagement metrics.

Recent developments in platform governance further underscore the urgency of these findings. Delta Air Lines has partnered with YouTube to offer creator-driven content, including MrBeast videos, as part of its in-flight entertainment system (Delta Air Lines 2025). This mainstream integration of influencer media illustrates how algorithmically curated content is expanding into physical environments, reinforcing visibility and emotional engagement. YouTube has introduced a “Second Chance” program, allowing previously banned creators to apply for reinstatement after one year, subject to behavioral review (Shapero 2025). This policy shift reflects evolving norms around content moderation and accountability but also raises questions about transparency and ethical boundaries. Meta has updated Instagram’s teen experience by implementing PG-13 content filters, automatically restricting exposure to mature

language, risky stunts, and potentially harmful behaviors (Najib 2025). This intervention aligns adolescent content exposure with cinematic standards and reinforces the need for developmental safeguards in algorithmic environments.

Overall, recommendation systems lacked transparency, preventing users from understanding or challenging algorithmic logic. Commercial prioritization consistently overrode content diversity and developmental relevance, even in educational profiles. Social and ideological biases were amplified through engagement-driven personalization, with no corrective feedback mechanisms in place. Adolescent-specific protections were absent, leaving young users exposed to monetized, biased, and repetitive content without contextual framing.

As algorithmic content curation continues to shape adolescent digital engagement, this research provides valuable insights into algorithmic transparency, ethical governance, and the evolving landscape of media regulation. Findings from this study may inform these regulatory efforts by demonstrating how personalization systems construct adolescent identity through emotional tone, bias saturation, and commercial logic. By evaluating engagement-driven personalization shifts and monetization mechanisms, the research highlights the importance of digital literacy education and policy reform. These interventions can equip users with tools to critically navigate personalized media landscapes and advocate greater oversight of algorithmic systems to ensure fairness, transparency, and user autonomy.

Theoretical Framework

This project is grounded in three complementary frameworks: Algorithmic Personalization Theory (Lury and Day 2019), Algorithmic Bias and Fairness Theory (Barocas et al. 2019), and Critical Media Literacy and Algorithmic Governance (Kellner 2023). Together,

they provide a lens for understanding how recommendation systems shape adolescent identity development through repetition, diversity, monetization, and bias.

Algorithmic Personalization Theory explains the elevated repetition and reduced diversity in high-monetization content because of engagement-maximizing feedback loops. The correlation between monetization and repetition, along with the inverse relationship between diversity and engagement, reflects the logic of algorithmic personalization. Platforms optimize content delivery based on behavioral data and commercial incentives, resulting in feedback loops that prioritize retention over representational breadth. TikTok's repetition-heavy structure and YouTube's monetization-driven visibility exemplify this dynamic. Educational content, which resists these patterns, demonstrates that personalization is not inevitable but contingent on platform design. This study extends personalization theory by showing how repetition and diversity patterns intersect with adolescent identity formation. Personalization is not only a mechanism of engagement optimization but also a process that narrows developmental pathways, reinforcing familiar scripts and limiting exposure to diverse perspectives.

Algorithmic Bias and Fairness Theory contextualizes the selective amplification of sexualization and demographic bias in YouTube content. The significant chi-square association between platform and bias presence ($\chi^2(1) = 24.986$, $p < .001$) indicates that bias is not uniformly distributed but is shaped by monetization architecture and algorithmic design. These findings support the need for fairness-aware systems that audit and mitigate representational harm. This study strengthens fairness theory by providing empirical evidence that bias is patterned by platform architecture and commercial ecosystems. Bias is not random but structured, and the findings highlight the need for platform-specific fairness interventions that address inequities in recommendation systems.

Critical Media Literacy and Algorithmic Governance frameworks emphasize the importance of equipping users, particularly adolescents, with the skills to interrogate algorithmic influence while holding platforms accountable. It shaped the interpretation of findings related to adolescent vulnerability, educational content resilience, and governance gaps. The resilience of educational content in the dataset supports media literacy models that prioritize transparency and equity, while the absence of platform disclosures highlights governance failures. This framework also underpins the study's practical implications, including recommendations for fairness-aware design, transparency protocols, and curriculum integration. This study advances governance theory by empirically validating the resilience of educational content and by proposing actionable recommendations for curriculum integration and transparency protocols. It demonstrates that governance frameworks must evolve to address developmental vulnerabilities in adolescent-facing media.

These frameworks are not abstract lenses but directly embedded in the project's design and analysis. Personalization theory structured the coding of repetition and diversity, bias and fairness theory guided the identification and statistical testing of bias categories, and critical media literacy and governance framed the implications for adolescent autonomy and policy reform. Together, they ensure that the sample is interpreted not only through statistical measures but also through theoretical insights into personalization, fairness, and governance.

Limitations and Methodological Constraints

Several limitations must be acknowledged. The dataset was restricted to 427 media cases across three platforms, which may not capture the full diversity of adolescent media exposure. The study did not include user-level engagement data, which limited the ability to assess individual responsiveness to algorithmic traits. Access to TikTok content was restricted to the

first two weeks of trending media during the data collection period. This constraint may have limited the temporal scope of platform comparison and reduced the visibility of evolving content dynamics. The cross-sectional design does not account for shifts in platform architecture, recommendation logic, or media trends over time.

Additional methodological constraints should also be noted. The study relied on simulated adolescent profiles rather than actual user accounts. This provided ethical safeguards but may not fully replicate lived adolescent experiences. Manual data collection introduced potential observer bias and limited scalability, since automated scraping or application programming interface access was not feasible. Coding categories such as repetition, diversity, monetization, and bias required interpretive judgment, and intercoder reliability was not formally assessed. Statistical analyses identified associations but cannot establish causation, meaning that claims about algorithmic inferences regarding adolescent identity are qualitative interpretations contextualized through theoretical frameworks rather than direct measurements. Finally, the focus on three platforms, TikTok, YouTube, and Netflix, excluded other influential media environments, which limited the generalizability of findings across the broader digital ecosystem.

Suggestions for Future Research

Future research should incorporate longitudinal analysis, user interviews, and platform audits to deepen understanding of algorithmic influence and adolescent media literacy. Expanding the sample to include additional platforms, content types, and timeframes would enhance generalizability and support comparative analysis across governance models.

CONCLUSION

This study examined how algorithmic design, monetization strategies, and bias exposure shape adolescent-facing media across TikTok, YouTube, and Netflix. Drawing on Algorithmic Personalization Theory, Algorithmic Bias and Fairness Theory, and Critical Media Literacy and Algorithmic Governance, the research demonstrated how platform architecture and commercial incentives influence content repetition, diversity, engagement, and identity formation.

Bias was evident across all platforms. TikTok exhibited the highest concentration, Netflix showed bias within entertainment formats, and YouTube selectively amplified bias through creator and advertising ecosystems. These patterns reveal that algorithmic systems, regardless of governance model, can intensify representational harm and reduce user autonomy through opaque recommendation logic and content prioritization.

The repetition and limited diversity in monetized content constrain adolescents' exposure to varied perspectives, reinforcing narrow identity scripts and emotionally charged framing. In contrast, educational content, characterized by lower monetization and higher diversity, offers a model for ethical curation that supports developmental resilience and critical engagement.

These findings underscore the need for stronger media literacy education. Adolescents must be equipped to recognize bias, understand algorithmic influence, and advocate for equitable media systems, while platforms must be held accountable for the cognitive and emotional consequences of their design choices. Although legislation such as the Children's Online Privacy Protection Act, the Algorithmic Accountability Act, and the Digital Platform Commission Act begins to address algorithmic operations, significant gaps remain in protecting adolescent identity development.

Platforms should implement transparency protocols and undergo regular bias audits to ensure fairness in recommendation systems. Educators should integrate algorithmic literacy into curricula, enabling adolescents to critically interrogate their feeds and resist harmful personalization loops. Policymakers must strengthen adolescent protections in existing frameworks and align U.S. standards with international governance models. Technical interventions, such as diversity nudges and limits on monetization saturation in adolescent-facing feeds, can further mitigate risks.

Distinct platform behaviors emerged over six weeks of data collection. Netflix personalized content through familiar genres and consistent emotional tone. YouTube adapted recommendations based on creator popularity and blended thematic elements. TikTok focused on emotional reactions and behavioral profiling to drive monetized content. Each platform constructed identity not only through user behavior but also through internal logic, actively shaping how adolescents are perceived and engaged. For adolescents, whose identities are still developing, this shaping power has profound developmental and ethical consequences. Algorithms do not merely recommend content; they shape identity.

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APPENDIX A: CODING FRAMEWORK AND DEFINITIONS

1. Content Category Codes

Code	Label	Definition
EDU	Educational	Content focused on learning, including STEM topics, documentaries, and instructional media.
ENT	Entertainment	Content designed primarily for amusement, including cartoons, gaming, and pop culture.
AD	Advertisement-Driven	Branded content, sponsored videos, or media with overt commercial intent.
MIX	Mixed Content	Content that blends educational and entertainment elements.

2. Repetition and Diversity Codes

Code	Label	Definition
REP-H	High Repetition	Same or similar content types appear frequently with minimal variation.
REP-M	Medium Repetition	Some variation in content but still aligned with previous interactions.
REP-L	Low Repetition	Broad variation in content types beyond prior viewing history.
DVS-H	High Diversity	Recommendations include a wide range of new or unrelated content.
DVS-M	Medium Diversity	Some new content introduced, but mostly familiar or related.
DVS-L	Low Diversity	Recommendations remain narrowly focused on prior content.

3. Bias Codes

Code	Label	Definition
BIA-D	Demographic Bias	Content reflects potential bias toward or against specific gender, racial, or ethnic groups.
BIA-C	Content Bias	Content favors certain themes (e.g., commercial over educational) disproportionately.
BIA-L	Language Bias	Content is in a language other than the viewer's primary language, potentially limiting comprehension or engagement.
BIA-N	No Observable Bias	No significant demographic, thematic, or linguistic bias detected in the recommendation pattern.
BIA-B	Body Normativity Bias	Content promotes narrow physical ideals, marginalizing diverse body types.
BIA-S	Sexualization Bias	Content uses sexualized imagery, especially of women, to attract viewer attention or reinforce gendered norms.
BIA-RB	Risk Behavior Bias	Content normalizes or glamorizes reckless actions (e.g., substance use, violence) without meaningful consequences.
BIA-G	Governmental Form Bias	Content reflects potential bias toward or against specific forms of government (e.g., democracy, authoritarianism, monarchy, theocracy).
BIA-RI	Religious Ideology	Content reflects potential bias toward or against religious belief systems, institutions, or governance models.

4. Monetization Influence Codes

Code	Label	Definition
MON-H	High Monetization	Frequent presence of ads, branded content, or commercial prioritization.
MON-M	Moderate Monetization	Occasional commercial influence observed in recommendations.
MON-L	Low Monetization	Minimal or no commercial influence detected.

5. Engagement Level Codes

Code	Label	Definition
ENG-H	High Engagement	Active user interaction, including likes, shares, comments, or selecting recommended content.
ENG-L	Low Engagement	Passive viewing with minimal or no interaction.

APPENDIX B: SPSS CODE BOOK

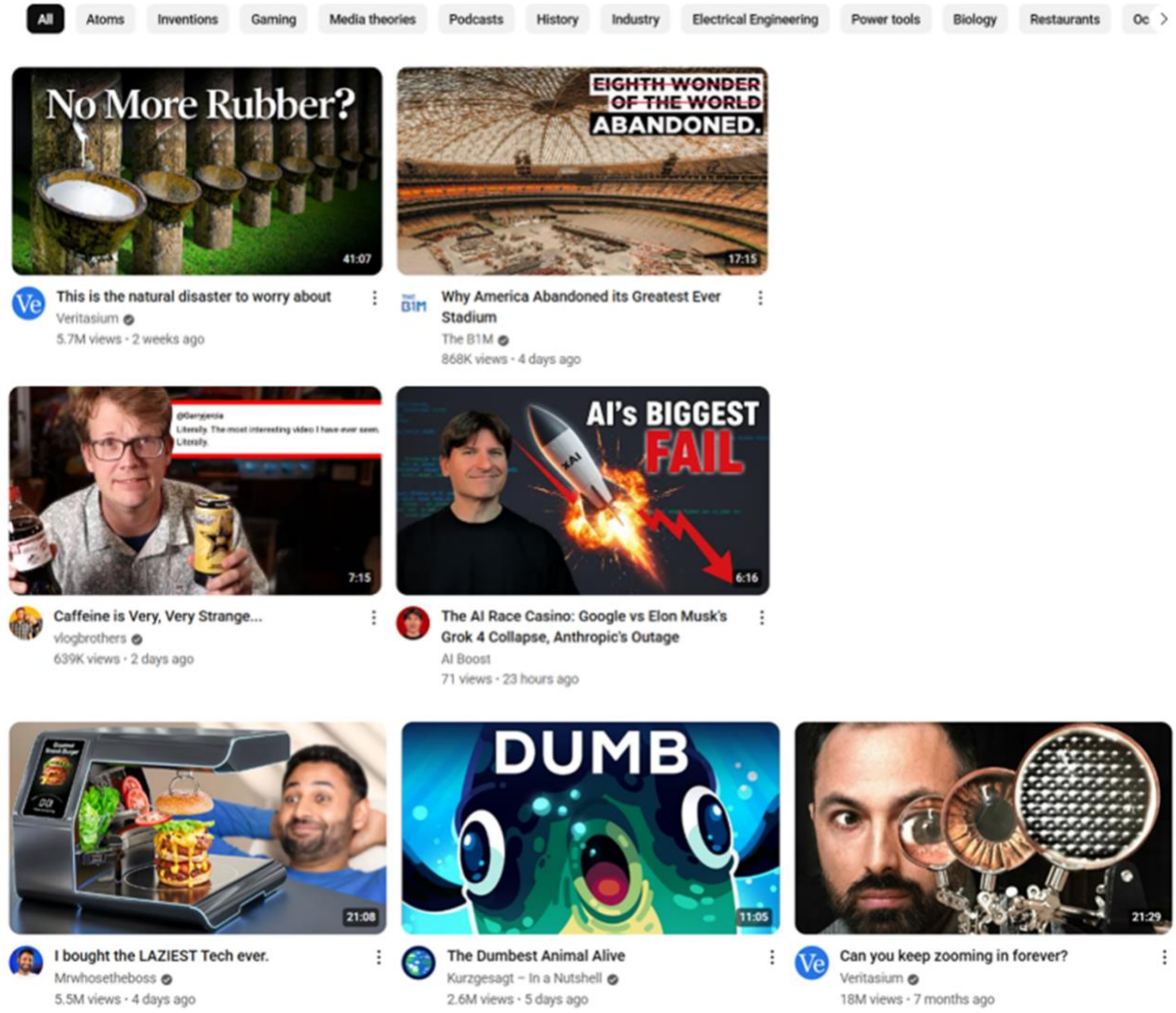
Variable Information

Variable	Position	Label	Measurement Level	Role	Column Width	Alignment	Print Format	Write Format
id	1	Session Number	Scale	Input	12	Right	F4	F4
DV	2	Date Veiwed	Scale	Input	11	Right	DATE11	DATE11
Week	3	Week of research	Ordinal	Input	12	Right	F1	F1
VT	4	View Time	Scale	Input	12	Right	F2	F2
Platform	5	Media Platform	Nominal	Input	12	Right	F2	F2
Dur	6	Duriation	Scale	Input	12	Right	F5	F5
PD	7	Publish Date	Scale	Input	11	Right	DATE11	DATE11
Views	8	Video Views	Scale	Input	8	Right	F8	F8
ConCat	9	Content Category	Nominal	Input	12	Right	F2	F2
B	10	Bias-Body Normativity	Nominal	Input	12	Right	F2	F2
C	11	Bias-Content	Nominal	Input	12	Right	F2	F2
D	12	Bias-Demographic	Nominal	Input	12	Right	F2	F2
G	13	Bias-Government	Nominal	Input	12	Right	F2	F2
L	14	Bias-Language	Nominal	Input	12	Right	F2	F2
N	15	No Bias	Nominal	Input	12	Right	F2	F2
RB	16	Bias-Reckless Behavior	Nominal	Input	12	Right	F2	F2
RI	17	Bias-Religious Ideology	Nominal	Input	12	Right	F2	F2
S	18	Bias-Sexualization	Nominal	Input	12	Right	F2	F2
Mon	19	Monetization	Ordinal	Input	12	Right	F2	F2
Eng	20	Engagement	Ordinal	Input	12	Right	F2	F2
Rep	21	Repetition	Ordinal	Input	12	Right	F2	F2
Div	22	Diversity	Ordinal	Input	12	Right	F2	F2
Bias_Any	23	Any Bias Present (1=Yes, 0=No)	Nominal	Input	10	Right	F8.2	F8.2
CC_EDU	24	Content: Education	Nominal	Input	10	Right	F8.2	F8.2
CC_ENT	25	Content: Entertainment	Nominal	Input	10	Right	F8.2	F8.2
CC_AD	26	Content: Advertisement	Nominal	Input	10	Right	F8.2	F8.2
CC_MIX	27	Content: Mixture	Nominal	Input	10	Right	F8.2	F8.2
Platform_Netflix	28	Platform: Netflix	Nominal	Input	18	Right	F8.2	F8.2
Platform_YouTube	29	Platform: YouTube	Nominal	Input	18	Right	F8.2	F8.2
Platform_TikTok	30	Platform: TikTok	Nominal	Input	17	Right	F8.2	F8.2
MH_Mon	31	MH Monetization	Nominal	Input	10	Right	F8.2	F8.2

Variables in the working file

APPENDIX C: SNAPSHOT EXAMPLE

Homepage:



APPENDIX D: DATA LOG

Researcher: Vaun Baltimore
Date: 07/28/2025

Session Number	View Time	Platform	Content Creator	Content Title	Media Time	Publication Date	Views	Content Category (EDU/ENT/AD/MIX)	Bias Indicator (BIA-B/C/D/L/N/R/S)	Monetization (MON-H/M/L)	Engagement Type (ENG-H/L)	Repetition (REP-H/M/L)	Diversity (DVS-H/M/L)	Notes
27	9:23 AM CST	Netflix	Director: Mor Loushy, Daniel Sivan Executive Producers: Ali Brown, Kerstin Emhoff, Aaron L. Ginsburg, William Green, Floyd Russ,	American Manhunt: Osama bin Laden E1 A New Kind of Enemy	10:57	14-May-25		EDU	D	L	L	H	L	Afghan citizens are authenticity
28	10:55 AM CST	YouTube	Socratica	How to Read a Textbook - Study Tips - Improve Reading Skills	7:42	30-Sep-18	210682	EDU	N	M	L	L	L	
29	11:08 AM CST	YouTube	Strength and Shape	Only 5 Isometric Exercises to Strengthen Your Entire Body – Do Them at Home!	16:24	4-Apr-25	1550792	EDU	N	L	L	L	M	
30	11:23 AM CST	YouTube	PawPrints Daily	If Your Dog Stretches When They See You... This Is What It Really Means	7:36	17-Jul-25	873481	EDU	N	L	L	M	M	
				The Easiest Language to Learn										

Week 1 | Week 2 | Week 3 | Week 4 | Week 5 | Week 6 | +