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The Impact of Recommendation Systems on User Experience in Digital Platforms: Netflix, Amazon Prime Video, and Disney+

Dijital Platformlarda Öneri Sistemlerinin Kullanıcı Deneyimine Etkisi: Netflix, Amazon Prime ve Disney+ Örnekleri

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Abstract

Netflix, Amazon Prime Video, and Disney+ are global streaming platforms that reach millions of users, offering a wide variety of content and easy accessibility. To enhance user experience, these platforms utilize advanced algorithms and recommendation systems. This study examines the recommendation systems of Netflix, Amazon Prime Video, and Disney+ and their impact on user experience based on data collected from social media, news sources, blogs, and forums. Online streaming platforms use AI-powered recommendation algorithms to prevent users from getting lost in the vast content library. However, their effectiveness and the resulting user satisfaction directly shape the user experience. The study employs a descriptive content analysis method, collecting 153 data points for Netflix, 176 for Amazon Prime Video, and 176 for Disney+ via the Mention application. These data are analyzed under five main themes: General Perception, User Interactions, Perception in News Sources, Criticisms of Algorithms, and Engagement with Popular Content. Findings indicate that personalized recommendation mechanisms facilitate content discovery and increase time spent on the platform. However, repetitive or irrelevant recommendations reduce user satisfaction. While some Netflix users find the recommendations effective, others argue that the system struggles to adapt to personal preferences. Similarly, some users consider Amazon Prime Video's recommendation algorithms accurate, but issues with repetitive suggestions are frequently reported. Disney+, on the other hand, generates satisfaction by promoting content based on its strong brand franchises, but faces criticism for the limited recommendations of niche productions.

Keywords:

recommendation systems, user experience, digital platforms, ai algorithms, content personalization

Öz

Netflix, Amazon Prime Video ve Disney+ gibi küresel ölçekte milyonlarca kullanıcıya ulaşan platformlar, içerik çeşitliliği ve erişim kolaylığı ile dikkat çekerken, kullanıcı deneyimini iyileştirmek için gelişmiş algoritmalar ve öneri sistemleri kullanmaktadır. Bu çalışma, Netflix, Amazon Prime Video ve Disney+ platformlarının öneri sistemlerini ve bu sistemlerin kullanıcı deneyimine etkisini, sosyal medya, haber kaynakları, bloglar ve forumlardan elde edilen veriler ışığında incelemektedir. Çevrimiçi akış platformları, kullanıcıların içerik bolluğu içinde kaybolmaması için yapay zekâ destekli öneri algoritmaları kullanmakta, ancak bu algoritmaların etkinliği ve memnuniyet düzeyi kullanıcı deneyimini doğrudan şekillendirmektedir. Araştırmada Betimsel İçerik Analizi yöntemi benimsenmiş, Netflix için 153, Amazon Prime Video için 176, Disney+ için 176 veri noktası Mention uygulaması aracılığıyla toplanarak beş ana tema altında incelenmiştir: Genel Algı, Kullanıcı Etkileşimleri, Haber Kaynaklarında Algı, Algoritma Eleştirileri ve Popüler İçeriklerle Etkileşim. Bulgular, kişiselleştirilmiş öneri mekanizmalarının kullanıcıların içerik keşfini kolaylaştırdığını ve platformda geçirilen süreyi artırdığını ancak tekrar eden ya da ilgisiz önerilerin memnuniyeti düşürdüğünü göstermektedir. Netflix kullanıcılarının bir kısmı önerilerin başarılı olduğunu belirtirken, diğerleri sistemin kişisel tercihlere uyum sağlamakta zorlandığını vurgulamaktadır. Benzer biçimde, Amazon Prime Video'nun öneri algoritmaları da bazı kullanıcılar tarafından isabetli bulunurken, tekrarlı öneri sorunu sıkça gündeme gelmiştir. Disney+ ise güçlü markalara dayalı içerikleri öne çıkararak memnuniyet yaratmakta, fakat niş yapımların az önerildiği yönünde eleştiri almaktadır.

Anahtar Kelimeler:

öneri sistemleri, kullanıcı deneyimi, dijital platformlar, yapay zekâ algoritmaları, içerik kişiselleştirme

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Introduction

In today's digital world, the rapid expansion of online streaming platforms allows users to access movies, TV series, documentaries, animations, and various media content at any time and from any location. While this provides a viewing experience far beyond traditional broadcasting channels, it has also significantly increased the amount of content available for consumption. This abundance of content and widespread access offers diversity and flexibility but also introduces the issue of information overload for users (Aggarwal, 2016). To prevent users from getting lost in this overwhelming volume of content and to provide personalized recommendations, online platforms such as Netflix, Amazon Prime Video, and Disney+ have developed AI-driven recommendation algorithms (Adomavicius & Tuzhilin, 2005).

The importance of recommendation systems extends beyond merely helping users find the right content quickly; they also play a strategic role in enhancing platform competitiveness and sustaining user engagement (Smith & Linden, 2017). A well-designed recommendation system increases the time users spend on the platform, enables them to discover more content, and enhances user satisfaction (Ekstrand et al., 2011). Additionally, advancements in big data and artificial intelligence have allowed deep learning models to process various data points, from users' viewing tendencies to demographic information, taking personalization to an entirely new level (Goodfellow et al., 2016; Zhang et al., 2019).

Netflix's pioneering role in developing recommendation systems has heightened academic and industry interest in this field (Gomez-Uribe & Hunt, 2015). Similarly, Amazon Prime Video aims to provide multidimensional personalized recommendations by integrating users' shopping habits with their video viewing data within its vast ecosystem. Meanwhile, Disney+ seeks to enhance the user experience in various ways by leveraging the popularity of its flagship brands, such as Marvel, Pixar, and Star Wars (Maddodi, 2019). The effectiveness of recommendation systems in online streaming platforms can be viewed not only as a technological innovation but also as a key factor shaping media consumption and determining platform competitiveness. Therefore, examining the recommendation algorithms of global players like Netflix, Amazon Prime, Video and Disney+ is of significant academic and industry relevance.

This paper aims to comprehensively analyze the recommendation systems of Netflix, Amazon Prime Video, and Disney+ and their impact on user experience in the digital age. Although all three platforms utilize advanced AI-based algorithms, perceived user experience and satisfaction levels can vary. This study therefore examines how recommendation systems in online streaming platforms shape user experience and identifies the factors that influence it positively or negatively.

In this study, a qualitative research method was employed, with the data collection process focusing on user comments obtained from social media, news sources, blogs, and online forums. Using descriptive content analysis, user opinions on the recommendation algorithms of streaming platforms were thoroughly examined. One hundred fifty-three data points for Netflix, 176 for Amazon Prime Video, and 176 for Disney+ were analyzed to identify users' positive and negative experiences with recommendation systems. The methodological approach seeks to answer the following research questions:

RQ1: How do the recommendation systems of Netflix, Amazon Prime Video, and Disney+ impact user experience?

RQ2: What are users' positive and negative opinions regarding these platforms' recommendation algorithms?

RQ3: What are the strengths and weaknesses of recommendation algorithms in terms of content diversity and personalization?

RQ4: How do the similarities and differences in the platforms' recommendation methods reflect on user satisfaction?

The findings of this study are evaluated within the framework of these research questions, aiming to provide a comprehensive perspective on the impact of recommendation systems on user experience. The results are expected to contribute to the academic literature and inform practical applications aimed at enhancing user experience on online streaming platforms.

Literature Review

Recommendation Systems in Online Streaming Platforms

Video and streaming platforms such asNetflix, YouTube, Amazon Prime Video, and Disney+ have become some of the most popular entertainment sources in the digital age, offering a vast content library that has profoundly transformed user habits (Ricci et al., 2011). One of the most critical elements driving this transformation is the implementation of advanced recommendation systems, which provide users with personalized content suggestions (Adomavicius & Tuzhilin, 2005). These personalized recommendations enhance the content discovery process and encourage users to spend more time on the platform.

The effectiveness of recommendation systems is primarily driven by advances in artificial intelligence (AI) and big data analytics. AI research has progressed significantly across various domains, including natural language processing, computer vision, robotics, and autonomous systems, with recommendation systems experiencing a parallel surge in development. Today, increased computational power and access to large-scale data have enabled AI-based models to solve complex problems more efficiently (Russell & Norvig, 2010). In particular, deep learning techniques play a crucial role in analyzing large-scale user interaction data, continuously refining recommendation systems for improved performance (Amatriain & Basilico, 2015).

Tecommendation algorithms in streaming platforms are primarily driven user interaction data (Ping et al., 2024). These systems rely on multiple data signals, such as watch history, viewing duration, replay and pause points, likes, user comments, and search queries (Ricci et al., 2011). Search queries, which reflect the types of content a user is interested in, provide valuable insights for personalization. Additionally, like or dislike markers allow the algorithm to rapidly update user preferences, ensuring that recommendations relevant (Adomavicius & Tuzhilin, 2005; Amatriain & Basilico, 2015).

Demographic information (e.g., age, gender, location, language preferences) also plays a crucial role in mitigating the cold-start problem, which arises when a system lacks sufficient user interaction data. By incorporating demographic factors, recommendation systems can generate reasonable initial recommendations even for new users or those with limited interaction history (Adomavicius & Tuzhilin, 2005).

Streaming services often refine and diversify their recommendation systems by leveraging advanced AI and data analytics techniques. Originally developed to help users and organizations manage the overwhelming flow of digital information, recommendation systems became critical in the 1990s with the rapid expansion of internet usage (Coffman & Odlyzko, 2002). As the volume of content and data grew, filtering relevant information became necessary to ensure users could access content aligned with their interests (Aggarwal, 2016). In response, two foundational approaches emerged: collaborative filtering and content-based filtering, often combined in hybrid systems (Ricci et al., 2021)

Recommender systems use machine learning and data mining techniques to analyze user interactions, demographic information, and content metadata (Adomavicius & Tuzhilin, 2005). These systems identify users' interests through behavioral and preference-based analyses and generate personalized recommendations. Beyond technical personalization, digital platforms such as Netflix leverage these systems to influence viewing practices and reshape patterns of audience engagement at the platform level. As Aytaş and Yavuz (2024) emphasize, recommendation systems on platforms like Netflix contribute significantly to user engagement by offering personalized and interactive experiences that reflect generational preferences and promote continuous consumption patterns. These approaches include collaborative filtering, content-based filtering, and hybrid recommendation models.

Content-Based Filtering – This method focuses on the attributes of the content a user has previously engaged with or interacted with. The system recommends similar items based on the features of previously consumed content (Widayanti et al., 2023).

Collaborative Filtering – This method leverages the behavior and preferences of users with similar tastes. Instead of relying on content characteristics, it suggests items other users with similar consumption patterns have enjoyed (Elahi et al., 2016).

Hybrid Systems – These combine content-based and collaborative filtering method to provide more diverse and accurate recommendations (Ansari, 2016). Hybrid systems produce multi-faceted and highly relevant suggestions by incorporating data from user interaction history and similar user profiles.

As streaming platforms expand, refining these recommendation models becomes increasingly essential in enhancing user experience and ensuring sustained engagement.

Collaborative Filtering

Collaborative filtering is an approach that generates new recommendations by leveraging the preferences of users whose likes and behavioral patterns are similar to those of a given user (Aggarwal, 2016; Herlocker et al., 2004). For example, a streaming platform groups users who have watched, rated, or interacted with similar content into clusters and generates recommendations by evaluating users with comparable viewing profiles within the same group (Ricci et al., 2021; Sarwar et al., 2001). When a new user's interactions align with one of these clusters, the system recommends products that other users in the same group have purchased or liked (Jiang et al., 2019).

One of the significant disadvantages of this method is the "cold start" problem, which arises when there is insufficient data about new users or recently added content (Aggarwal, 2016; Adomavicius & Tuzhilin, 2005). Additionally, ethical concerns, including privacy risks related to the real-time tracking of user behavior, are among the challenges associated with the collaborative filtering approach (Herlocker et al., 2004). Moreover, data sparsity and difficulties integrating contextual information (e.g., user location or time-dependent preferences) into the system can negatively affect performance (Su & Khoshgoftaar, 2009). As a result, hybrid models that combine collaborative filtering with content-based filtering have become increasingly popular to provide more accurate and flexible recommendations (Burke, 2002).

Content-Based Filtering

Content-based filtering focuses on the characteristics of items (e.g., movies, music, products) rather than user-to-user similarities, placing the user at the center of the recommendation process (Ricci et al., 2021; Burke, 2002). This approach analyzes a user’s previous interactions, such as items the user has consumed, rated, or clicked on, and suggests new options with similar attributes (Jiang et al., 2019; Lops et al., 2011). For example, similar to music streaming services that recommend songs within familiar genres or by frequently listened artists, video streaming platforms suggest films or series aligned with users’ viewing histories (Aggarwal, 2016).

One advantage of this approach is its ability to recommend newly added or less frequently interacted content, as it does not require large-scale user data like collaborative filtering does (Ricci et al., 2021). However, content-based filtering often limits recommendations to familiar themes, leading to a narrow recommendation pool, which can restrict diversity in suggestions (Amatriain & Basilico, 2015). Additionally, the system's effectiveness heavily depends on the accuracy and depth of metadata (e.g., movie genres, music styles, author or director information) (Gabrilovich & Markovitch, 2007). Therefore, the success of content-based filtering is directly linked to high-quality metadata and advancements in automated feature extraction technologies, which help enhance recommendation precision and diversity.

Hybrid Approaches and Deep Learning-Based Recommendation Systems

Advancements in deep learning have elevated recommendation systems to a new level, expanding the boundaries of traditional methods (Goodfellow et al., 2016; Zhang et al., 2019). Multi-layered neural networks trained on large datasets can simultaneously user preferences and behavioral signals, contextual information (e.g., time, location, device), and social interactions (Yesilada, & Lewandowsky, 2022). As a result, platforms like Netflix and YouTube can generate more accurate recommendations by integrating multiple variables, such as watch history, likes and dislikes, engagement duration, and, where available, social network data (Ricci et al., 2021; Covington et al., 2016). Deep learning's ability to detect complex relationships within data not only significantly enhances recommendation quality but also enables the real-time capture of even the smallest shifts in user behavior (Aggarwal, 2016; Goodfellow et al., 2016).

Over time, hybrid methods have been developed to combine the strengths of both collaborative filtering (leveraging behavioral patterns of similar users) and content-based filtering (considering item attributes) (Burke, 2002). These hybrid systems improve recommendation accuracy by integrating multiple signals and combining the complementary strengths of different recommendation approaches (Aggarwal, 2016). Large-scale platforms, in particular, integrate user interactions, preferences, and content attributes to predict not only current interests but also future behavioral trends (Russell & Norvig, 2010). For instance, YouTube's recommendation system employs a hybrid approach, combining collaborative filtering (analyzing watched and disliked videos) with content-based filtering (examining video titles, descriptions, and tags) to generate the most relevant recommendation sets using various neural network models (Ricci et al., 2021; Covington et al., 2016).

Deep learning–based hybrid models can be updated dynamically based on user behavior, enabling more accurate and personalized recommendations (Zhang et al., 2019; Goodfellow et al., 2016). Additionally, these models can partially mitigate classic challenges such as data privacy concerns and the cold start problem by simultaneously analyzing content attributes and user similarities to quickly adapt to new users and newly added content (Aggarwal, 2016). As online platforms seek to enhance user experience, deep learning-powered hybrid approaches continue to be among the most effective solutions for the future.

User Experience and Personalization: Netflix, Amazon Prime Video, and Disney+

The primary goal of recommendation systems on online streaming platforms is to enhance user experience and provide a personalized viewing environment. With accurate and effective recommendations, users can easily discover content that matches their interests, leading to greater engagement with the platform. Personalization not only can strengthen user loyalty but also simplifies content discovery (Ekstrand, Riedl & Konstan, 2011). Personalization involves collecting, analyzing, and utilizing user data to deliver customized content or product recommendations (Chen & Sundar, 2018). Personalization strategies in digital commerce contexts typically fall into two main categories:

- Content-Based Filtering - Focuses on a user's past interactions and preferences (Ricci, Rokach & Shapira, 2021).
- Collaborative Filtering - Uses the behavior of users with similar interests to generate recommendations (Ricci, et al., 2021).

Amazon Prime Video integrates both approaches, offering users recommendations based on their viewing history while also considering the preferences of other users with similar profiles (Linden et al., 2003). Today, online content platforms are heavily investing in personalization strategies as a keyway to enrich user experience and strengthen their competitive edge (Elahi et al., 2021). Studies suggest that personalization can positively influence user loyalty and revenue growth (Ahn, 2006; Smith & Linden, 2017). Tailored recommendations based on viewing history and inferred interests can increase time spent on the platform and support content discovery.

Netflix, has distinguished itself as a global leader in the streaming industry in recent years, thanks to its data-driven approach and innovative algorithms (Gómez-Uribe & Hunt, 2015). At the core of Netflix's strategy lies the aim of matching content with users' preferences and viewing contexts in a timely and personalized manner. With the launch of its streaming service, the company moved beyond simply providing a large content library and focused on building a robust recommendation ecosystem to support content discovery. Netflix launched the Netflix Prize to stimulate advances in recommendation accuracy, particularly collaborative filtering. This initiative laid the foundation for advanced personalization algorithms, driving helped spur research and improvements in recommendation accuracy (Amatriain & Basilico, 2015).

Netflix's personalization strategy is primarily driven by user interaction data, which constitutes a central input for its recommendation processes (Gomez-Uribe & Hunt, 2015). Behavioral signals such as watch history, viewing duration, pause and resume actions, and search queries provide direct insights into users' preferences and consumption patterns. For instance, when a user consistently engages positively with crime-related titles, the recommendation system is more likely to surface similar crime series and films (Maddodi, 2019). In addition to content-related interactions, contextual factors such as the devices users watch from and the time of day at which they consume content also play an important role in personalization strategies (Amatriain & Basilico, 2015). Accordingly, users who tend to watch content on mobile devices in short sessions may be recommended shorter-form content or series with relatively brief episodes, aligning recommendations with observed viewing behaviors (Elahi et al., 2021).

Netflix not only analyzes user interaction data but also examines content attributes as part of its recommendation processes (Gomez-Uribe & Hunt, 2015). Movies and TV shows are described using metadata such as genre, thematic elements, cast, and other narrative or stylistic features. This metadata-driven approach supports content discovery by enabling the system to identify similarities between previously consumed titles and new recommendations (Amatriain & Basilico, 2015). A distinctive aspect of Netflix's recommendation strategy is its use of fine-grained genre classifications, often referred to as micro-genres, which allow the platform to suggest more specific content categories within broader genres. For instance, rather than recommending British crime shows in general, the system may surface more narrowly defined categories that align with users' demonstrated viewing preferences.

Unlike Netflix, which centers on video streaming, which primarily focuses on video streaming, Amazon Prime Video extends beyond entertainment, adopting a holistic ecosystem approach. This integrated system combines various user needs, including shopping, entertainment, and digital content consumption, under a single platform. By doing so, Amazon can increase user engagement, leading to a broader data pool for personalization (Bishop & Nasrabadi, 2006). The data collected spans multiple touchpoints, including watch history, shopping cart preferences, product reviews, and search history, providing a more comprehensive understanding of user behavior (Chen & Sundar, 2018). This vast dataset can enable Amazon Prime Video to personalize recommendations not just for videos but also for other services, enhancing the overall user experience across the platform. For example, if a user frequently watches a specific TV show genre on Prime Video, the platform can extend this preference to their shopping experience. Merchandise related to the TV series or film, such as books, apparel, or collectibles, may appear in their recommended products panel (Linden et al., 2003). Similarly, user preferences observed across Amazon services may serve as indirect signals in shaping future movie and TV show recommendations (Smith & Linden, 2017). This strategy is built on the concept of holistic personalization, meaning that user interactions across different areas of the platform contribute to personalized recommendations across multiple channels (Ricci et al., 2021).

One of the most widely cited algorithms in Amazon’s recommendation framework is item-to-item collaborative filtering, which identifies similar items based on patterns of user interactions, such as products that are frequently co-viewed or co-purchased, rather than shared content attributes (Linden et al., 2003). Beyond collaborative filtering, recent studies indicate that large-scale platforms increasingly employ machine learning and deep learning techniques to enhance personalization across different services. In such systems, multiple data modalities, including visual, textual, and behavioral signals, can be processed using neural network–based models to improve the estimation of user preferences (Varela & Kaun, 2019). In parallel, machine learning techniques are also applied to tasks such as detecting deceptive reviews and supporting content moderation. Prior research suggests that algorithmic review verification mechanisms can contribute to maintaining user trust by reducing manipulative behaviors within online platforms (Chen & Sundar, 2018). Together, these complementary applications support more reliable recommendation environments without attributing specific implementations uniformly to a single platform.

Disney+ enjoys strong global recognition thanks to its well-established brand franchises, including Disney, Pixar, Marvel, Star Wars, and National Geographic. However, personalization strategies can play a central role in the platform's approach to ensure long-term user loyalty. The key to effective personalization lies in the deep analysis of user data. Various data points—such as watch history, preferences, search behavior, likes, and time spent interacting with the platform—are processed by machine learning and data mining techniques to generate user-specific content recommendations. By leveraging this data-driven approach, Disney+ ensures that users can quickly find the content they will most likely enjoy among thousands of options (Luo, 2024).

One of Disney+'s most distinctive features is its homepage collections, which are structured around specific genres, themes, or character universes. For example, sections such as "Marvel Collection" or "Star Wars Day" guide users toward curated content within a particular franchise. These strategic content groupings serve as marketing tools and mechanisms for enhancing user engagement and expanding user interests through data-driven personalization. Once users start consuming content from these collections, the platform analyzes this behavior and refines future recommendations accordingly. This enhances both content discovery and overall user satisfaction. Disney+'s personalization strategy extends beyond its recommendation algorithms, including user interface (UI) design. The homepage layout, banners, playlists, and the "For You" section are all dynamically shaped by data analytics. Each user's homepage can be micro-adjusted based on their most recently watched content, profile age range, and viewing habits. This adaptive interface ensures that users can quickly access the content most relevant to them and experience a more seamless and engaging navigation process, ultimately increasing platform retention and engagement.

Method

This study analyzes the recommendation systems of Netflix, Amazon Prime Video, and Disney+. A qualitative approach was adopted to examine user opinions shared on social media, news sources, blogs, and forums.

Research Design

This study adopts a qualitative research design using descriptive content analysis to examine user experiences and perceptions of recommendation systems on Netflix, Amazon Prime Video, and Disney+. The analysis focuses on how these systems are perceived to influence user satisfaction, content discovery, and perceived levels of platform engagement. The research framework follows a thematic coding strategy to identify recurring patterns within a predefined time frame and content universe.

Data Collection Process

Data were gathered using the Mention monitoring tool, which enables automated and real-time tracking of online conversations across multiple channels. The tool was configured with keyword filters such as "Netflix recommendation", "Amazon Prime algorithm", and "Disney+ suggestions" to extract relevant data. Boolean operators (e.g., "Netflix" AND "recommendation system") were used to increase precision. The data were collected from the following sources between January 22 and February 21, 2025:

- Social media platforms (X (formerly Twitter)), Facebook, Instagram, Reddit),
- Blogs and online forums,
- News websites and online news articles

To ensure comparability representation, the dataset was stratified by platform:

153 user-generated data points for Netflix, 176 for Amazon Prime Video, 176 for Disney+, yielding a total of 505 entries after removing exact textual duplicates and off-topic mentions. Duplicate removal was based on identical content shared across the same or different sources.

Posts were selected using purposive sampling, focusing on entries that explicitly discussed user reactions to recommendation systems, rather than general platform comments. For instance, posts referring to personalized suggestions, algorithm-driven content discovery, or perceived relevance of recommendations were included, whereas comments limited to interface design, pricing, or overall content quality without reference to algorithmic processes were excluded. Posts shorter than 15 words or lacking a specific reference to algorithmic experience were also excluded from the analysis.

Data Analysis

The analysis process was guided by principles of qualitative content analysis as outlined by Mayring (2014) and Schreier (2012). First, an inductive initial inductive coding process was used to generate initial categories. Then, these were revised through iterative readings to form five main themes:

1. General Perception (Sentiment Orientation)

Overall user sentiment (positive, negative, neutral) toward recommendation systems as expressed in posts.

2. User Discourse and Interaction Patterns
   Forms of user commentary and discourse related to recommendation systems, including expressed feedback signals such as praise, complaints, frustration, or satisfaction narratives across social platforms.
3. Perception in News Sources
   How recommendation systems are framed in news articles and opinion pieces, including discussions of personalization, innovation, or societal impact.
4. Algorithmic Criticism and Bias
   User-based critiques of recommendation systems, operationalized through references to perceived repetition, lack of diversity, filter bubbles, genre dominance, or unfair visibility of certain content.
5. Content Discovery and Engagement
   Perceived impact of recommendation algorithms on discovering new, trending, or niche content, as well as users' expressed satisfaction with discovery experiences and continued platform use.

A codebook was developed to define each theme with explicit inclusion and exclusion criteria. Example codes included:

"Repetitive suggestions" (Algorithmic Criticism and Bias),

"Found great content via recommendations" (Content Discovery and Engagement),

"Users complain about seeing the same genres repeatedly" (Algorithmic Criticism and Bias),

"News mentions personalization accuracy" (Perception in News Sources).

Procedure and Inter-Rater Reliability

To ensure analytical rigor, a dual-coder approach was implemented. Two independent coders (the researcher and a research assistant trained in qualitative analysis) coded a stratified random sample comprising 25% of the dataset, with proportional representation from Netflix, Amazon Prime Video, and Disney+ to preserve platform-level distributions. The coding consistency was assessed using Cohen's Kappa, which yielded a score of 0.82, indicating strong inter-rater agreement. Coding discrepancies were resolved through consensus discussions. Once reliability was confirmed, the lead researcher coded the remaining data. The entire coding process was conducted using MAXQDA qualitative analysis software to maintain traceability and transparency.

Transparency and Ethical Considerations

Data retrieval via Mention's API complied with the platform's Terms of Service and relied solely on publicly accessible content. Private content was not accessed, and personally identifiable information such as usernames or profile details was neither stored nor reported in the analysis. No usernames or identifiable profiles were stored or analyzed. All data used in the study were obtained from publicly accessible digital platforms and are anonymized during analysis. As the study does not involve human subjects in an experimental or survey-based context, it does not require ethical board approval under prevailing academic guidelines.

Findings

Analysis of Netflix's Online Recommendation System

Perception of Netflix

The general perception of Netflix's recommendation system reflects a mixed pattern shaped by divergent user experiences. For example, one Twitter user comments, "*Netflix keeps recommending content I have no interest in. Does the algorithm even work?*", while another states, "*I watched the shows Netflix recommended, and I really liked them! It's great for discovering new content!*"

These comments indicate two contrasting user perceptions. Some users express frustration, perceiving the recommendation system as insufficiently aligned with their personal interests, which they associate with a disappointing experience. Others, however, describe the system as a valuable discovery tool that helps them encounter and enjoy content they might not have selected independently. Overall, Netflix's recommendation system is perceived either as an effective mechanism for content discovery or as inadequately responsive to individual preferences, depending on users' personal experiences.

User Interactions

Discussions surrounding Netflix's recommendation system are prevalent on social media, where users frequently debate its effectiveness and transparency. For example, one Reddit user comments, "*Netflix should explain what data it uses to personalize recommendations. It keeps suggesting the same type of content over and over*," while a Twitter user asks, "*The recommendation system keeps suggesting a show I watched five years ago. How do we fix this?"*

These comments indicate recurring user concerns related to algorithmic opacity, perceived repetitiveness, and limited adaptability to changing viewing preferences. Rather than pointing to a confirmed technical malfunction, such remarks reflect a perception that the recommendation system does not sufficiently update or diversify suggestions over time. Overall, social media discussions portray Netflix's recommendation system as a focal point of user engagement, with conversations commonly centering on transparency, perceived responsiveness, and diversity of recommended content.

Netflix Recommendation Systems in News Sources

Various online commentary platforms and blog posts have discussed Netflix's recommendation algorithm from different perspectives, as reflected in headlines such as "*The Problem with Your Netflix Recommendations*?" published on The Sundae (2025) and "*Netflix Algorithm: How Netflix Uses AI to Improve,"* appearing as a LinkedIn blog post. Two online sources illustrate contrasting frames Netflix's recommendation system highlights contrasting viewpoints regarding its AI-powered approach. The Sundae article, *"The Problem with Your Netflix Recommendations?"*, questions why Netflix's recommendation system does not always meet user expectations. In these articles, discussions often center on the idea that the algorithm can be overly predictable, perceived as insufficiently adapting to user preferences, or as disproportionately promoting certain content. These discussions raise broader concerns about whether Netflix's personalization mechanisms adequately reflect individual interests or may instead favor trending or commercially prioritized content. In contrast, the LinkedIn (2025) article, *"Netflix Algorithm: How Netflix Uses AI to Improve"*, focuses on how Netflix leverages AI and machine learning to enhance its recommendation system. The platform continuously analyzes user viewing habits, large-scale behavioral data, and behavioral trends to refine its recommendation mechanisms. Such improvements aim to make recommendations more personalized over time, increasing user satisfaction and engagement. Netflix's constant optimization of its algorithms plays a crucial role in maintaining user retention and platform success. While some sources criticize the limitations and biases of the system, others emphasize the ongoing advancements that enhance content discovery and personalization.

Criticism of the Recommendation Algorithm

Some users suggest that Netflix's algorithm tends to prioritize certain genres, sometimes at the expense of individual preferences:

User comments frequently express dissatisfaction with perceived mismatches between personal preferences and recommended content. For example, one user remarks, "*Netflix keeps recommending romantic comedies, but I love sci-fi!*", while another asks, "*Is it suggesting what others are watching, or is it tailored to my preferences?*"

These comments indicate a perception that the recommendation system relies heavily on past viewing patterns, which users attribute to limited genre exploration and repetitive suggestions. Rather than facilitating discovery, the system is often perceived as reinforcing existing preferences, potentially creating a narrow recommendation loop. In addition, questions regarding whether recommendations are driven by individual preferences or broader viewing trends reflect ongoing concerns about algorithmic transparency and personalization logic. This uncertainty fuels calls for greater algorithmic transparency, with users requesting a clearer understanding of how Netflix curates content recommendations. Many argue that greater customization options, such as allowing users to adjust their recommendation preferences manually, could improve the experience and increase satisfaction.

Popular Content and Engagement

This theme examines how Netflix's recommendation system is perceived to influence the visibility of popular and niche content. For example, one user states, "*Thanks to Netflix recommendations, I watched a newly released documentary. I would never have found it otherwise*," while another comments, "*Netflix's algorithm is at work again. The most talked-about show is already at the top!*"

The first comment indicates that recommendations are perceived as facilitating content discovery beyond users' habitual viewing preferences, particularly by surfacing titles users did not actively search for. The second comment indicates a contrasting perception, in which the recommendation system is viewed as prioritizing widely discussed or trending content. Taken together, these comments highlight differing user interpretations of how Netflix’s algorithm balances niche discovery and the promotion of popular titles.

Taken together, these comments suggest that Netflix’s recommendation system is perceived both as enabling access to niche content and as surfacing popular titles more prominently. Rather than indicating deliberate promotion strategies, such perceptions point to ongoing user debates about the balance between personalization and trend-driven visibility within algorithmic recommendation environments. These contrasting perspectives reveal that Netflix's recommendation system can aid content discovery while also prioritizing viral and mainstream productions. The debate extends to user perceptions regarding whether Netflix’s recommendations are primarily driven by individual preferences or whether certain content appears more prominently within the platform’s broader recommendation environment.

Analysis Findings on Amazon Prime Video's Online Recommendation Systems

Perception of Amazon Prime Video

User opinions on Amazon Prime Video’s recommendation system vary, reflecting divergent experiences. For example, one user comments, “*Amazon Prime keeps suggesting a show I’ve already watched three times. How do we fix this?*”, while another notes, “*Amazon Prime’s algorithm knows me so well! I keep finding great movies.*”

The first comment indicates a perception that the system does not sufficiently adapt to changes in individual viewing behavior, which users associate with repetitive or outdated recommendations. The second comment illustrates a contrasting experience in which recommendations are perceived as well aligned with personal preferences and supportive of content discovery. Taken together, these perspectives suggest that user experiences with Amazon Prime Video’s recommendation system are perceived as inconsistent, potentially shaped by differences in viewing habits, available interaction signals, and personalization processes. Overall, while some users describe the system as effective, others emphasize ongoing challenges related to adaptability and redundancy.

User Interactions

Discussions about Amazon Prime Video’s recommendation system continue across social media and forums, often in comparison with competing platforms. For example, a Twitter user states, “*There’s a huge difference between Netflix and Prime Video’s recommendation algorithms. Netflix seems better.*” In addition, comments from Instagram users within the dataset express appreciation for Prime Video’s extensive content library while noting dissatisfaction with recommendations perceived as irrelevant.

These comments indicate that some users perceive Netflix’s recommendation system as more effective, while viewing Prime Video’s recommendations as less consistently aligned with their preferences. Rather than demonstrating objective differences in algorithmic performance, such perceptions reflect user-level comparisons based on individual experiences. Overall, user interactions suggest that although Amazon Prime Video is valued for its broad content selection, its recommendation system is perceived by some users as offering less precise personalization, contributing to comparative evaluations that favor Netflix.

Amazon Prime Video's Recommendation Systems in News Sources

Several industry-oriented news sites and trade publications have reported on recent developments related to Amazon Prime Video's content discovery features, which are closely associated with its broader recommendation mechanisms. For example, an article published on PPC LAND (2025) titled "Prime Video releases AI-powered content discovery system in limited beta" reports that Amazon has introduced a limited beta version of an AI-driven content discovery feature. This report suggests that Prime Video is experimenting with artificial intelligence–based tools to support how users find and navigate content on the platform.

In a related but distinct context, an article published on ISPO (2025) titled "How AI is taking the production of sports content to a new level" discusses Amazon's use of AI-driven analytics in sports content production and broadcasting. While this coverage does not directly address recommendation algorithms, it indicates Amazon's broader investment in AI technologies within its video ecosystem. If such analytics were to be integrated into recommendation-related processes, they could potentially inform personalized suggestions for sports content; however, this remains an inferred possibility rather than a documented implementation.

Taken together, these trade publications describe ongoing experimentation with AI-supported content discovery and production tools at Amazon Prime Video. Rather than demonstrating definitive improvements in recommendation performance, these reports suggest a continued exploration of AI applications that may, over time, support more adaptive and context-aware user experiences.

Criticism of the Recommendation Algorithm

Some users express criticism of Amazon Prime Video's recommendation system by questioning its effectiveness and relevance. For example, one comment states, "*Prime Video keeps recommending action movies, but I love documentaries!*", while another asks, "*Is Amazon's algorithm as good as Netflix's? I don't think so*."

These comments indicate a perception that Prime Video's recommendations offer limited variety and do not always align with users' stated genre preferences. Users often attribute this to what they perceive as a reliance on past viewing patterns, which they associate with repetitive or insufficiently diverse suggestions. In contrast, some users describe Netflix's recommendation system as more effective in aligning content with individual preferences, particularly in comparison-based discussions across platforms.

Overall, these perceptions point to user expectations for greater adaptability and customization in recommendation systems. Rather than demonstrating objective differences in algorithmic sophistication, the comments reflect comparative evaluations based on personal experiences, highlighting areas where users believe Amazon Prime Video's personalization mechanisms could be improved.

Content Discovery and Transparency

User comments reveal varied perceptions of how Amazon Prime Video's recommendation system influences content discovery and transparency. For example, one online comment notes, "*Thanks to Amazon Prime's recommendation system, I discovered* *a new show and absolutely loved it!*", indicating that recommendations are perceived as facilitating the discovery of unfamiliar content. Another user remarks, "*Amazon should explain more clearly why it recommends certain content*," expressing concerns about the opacity of recommendation logic.

These comments indicate that while some users perceive Prime Video's recommendation system as a useful tool for discovering new titles, others emphasize a lack of clarity regarding how and why specific content is suggested. Such feedback suggests that users value not only effective personalization but also greater transparency in algorithmic decision-making. In comparative discussions, some users perceive Amazon Prime Video as offering less visible explanation of recommendation processes than competing platforms, which they associate with confusion about content selection. Overall, the recommendation system is perceived as both supportive of content discovery and limited by insufficient transparency. Overall, Amazon Prime Video's recommendation system is perceived as both a useful discovery tool and a somewhat opaque mechanism. While it helps users find new content, the lack of transparency regarding how recommendations are made remains a significant concern.

Analysis of Disney+'s Online Recommendation System

Perception of Disney+

User opinions on Disney+'s recommendation system reveal mixed perceptions shaped by individual viewing experiences. For example, one user comments, "*Disney+ keeps recommending Marvel content, but I love animated films and series!*", indicating a perception that recommendations are narrowly focused on specific franchises. In contrast, another user notes, "*The content I discovered on Disney+ is amazing! Thanks to this recommendation algorithm, I found my new favorite show*," illustrating a positive discovery experience.

These comments indicate that while some users perceive the recommendation system as effective in introducing engaging content, others view it as offering limited variety and not fully adapting to personal preferences. Criticism often centers on the recurrent visibility of dominant franchises, which some users associate with reduced diversity in recommendations. Overall, Disney+'s recommendation system is perceived as beneficial for content discovery by some users, while others express concerns about repetitiveness and insufficient personalization.

User Interactions

Discussions about Disney+'s recommendation algorithm across social media platforms reveal varied user perceptions. For example, one user comments, "*Disney+ doesn't seem to learn enough from what I watch. The recommendations feel too random*," while another notes, "*The recommendations can be too predictable at times. There needs to be more diversity!*"

These comments indicate user concerns about how effectively the recommendation system adapts to individual viewing preferences. Some users perceive the system as insufficiently responsive to their viewing history, which they associate with recommendations that appear inconsistent or loosely aligned with their interests. Others describe the recommendations as overly predictable, suggesting a perceived reliance on repetitive patterns that may limit content variety. Overall, user interactions point to tensions between randomness and predictability in Disney+'s recommendation experience, reflecting ongoing concerns about personalization depth and perceived diversity of suggested content.

Disney+'s Recommendation Systems in News Sources

Industry-oriented commentary and online analysis pieces have discussed potential developments related to Disney+'s user experience and competitive positioning. For example, a Next TV headline states, "Disney+ Planning Netflix-Style UX Updates to Help Improve Engagement," while a Medium analysis titled "Streaming Wars: Analyzing the Competitive Dynamics of Disney+ vs. Netflix?" examines comparative platform strategies.

These two articles describe planned or discussed user experience initiatives and competitive comparisons rather than confirmed changes to recommendation algorithms. The Next TV piece suggests that Disney+ is considering UX updates inspired by Netflix's interface, which may have implications for personalization and content discovery, although specific algorithmic changes are not detailed. The Medium article, presented as an opinion and analysis piece rather than institutional news, reflects broader debates about how Disney+ compares with Netflix in areas such as recommendations and platform experience.

Taken together, these sources suggest ongoing discussion, rather than documented implementation, around Disney+'s efforts to enhance user experience and competitiveness. Any potential impact on recommendation mechanisms or personalization strategies should therefore be interpreted as speculative and context-dependent, based on commentary rather than verified technical disclosures.

Disney+'s Recommendation System in News Source

Some users express frustration with Disney+'s recommendation system, particularly in relation to perceived limitations in content variety and audience differentiation. For example, one user comments, "*The recommendation system only shows popular content. Finding niche titles is difficult!*", while another notes, "*Disney+ is great at recommending kid-friendly content, but there are very few options for adult users*."

These comments indicate a perception that the recommendation experience may feel restrictive in terms of content surfacing for certain viewers. Some users associate the prominence of widely known titles with difficulties in discovering lesser-known or niche content that aligns with their interests. Others perceive the recommendations as primarily oriented towards family-friendly content, which they feel does not sufficiently reflect the preferences of adult audiences. Taking together, these perspectives suggest concerns about how effectively the recommendation system differentiates between diverse viewer profiles and viewing preferences, particularly across age groups.

Popular Content and Engagement

User experiences highlight differing perceptions of how Disney+'s recommendation algorithm influences content discovery. For example, one online comment states, "*Thanks to Disney+ recommendations, I rediscovered classic Disney movies!*", while another notes, "*Disney+'s algorithm suggests too much Star Wars content. It limits variety.*"

These comments indicate contrasting views on the system's role in surfacing content. The first comment illustrates a positive experience in which recommendations are perceived as bringing older or familiar titles back into visibility, supporting rediscovery. The second comment reflects concerns that recommendations are perceived as emphasizing a single franchise, which users associate with reduced variety in suggested content. Taken together, these perspectives suggest that while Disney+'s recommendation system is perceived as facilitating nostalgic rediscovery for some users, others view it as narrowing exposure by repeatedly surfacing content tied to prominent franchises.

Summary of Comparative Findings

Based on the detailed analysis of user feedback regarding the recommendation systems of Netflix, Amazon Prime Video, and Disney+, the key qualitative findings are summarized below. These findings are presented in a comparative format in the table that follows. The table presents an overview of user perceptions, social media engagement, news media coverage, algorithm-related criticisms, and the effectiveness of each platform's recommendation system in content discovery.

This tabular summary enhances the clarity and comparability of the study's findings, allowing the strengths and weaknesses of recommendation systems to be evaluated across platforms. It complements the thematic analysis by enabling a structural comparison, which helps reveal patterns that may not be fully captured through narrative description alone.

Table-1: *Summary of Comparative Findings on Recommendation Systems Across Digital Platforms*

Platform	User Perception	Social Media Interaction	News / Online Coverage	Algorithm Criticism	Content Discovery
Netflix	Mixed: Some users perceive the system as effective, while others report misalignment with their interests.	Recurring discussions around transparency and repetitive recommendations.	Online commentary and industry sources describe personalization effectiveness, while some discussions raise concerns about favoring trending or promoted titles.	Perceived as prioritizing certain genres or titles and, at times, misaligned with individual preferences.	Perceived to support content discovery, though sometimes seen as surfacing trending content more prominently.
Amazon Prime Video	Mixed: Some users report accurate recommendations; others perceive suggestions as repetitive or irrelevant.	Comparative discussions with Netflix and complaints about mismatched recommendations.	Industry-oriented sources report an AI-powered content discovery beta, framed as exploratory rather than a	Perceived focus on specific genres and, in comparative discussions, as	Perceived to facilitate discovery for some users, with ongoing concerns about transparency in

Platform	User Perception	Social Media Interaction	News / Online Coverage	Algorithm Criticism	Content Discovery
			confirmed system-wide change.	less consistent than Netflix.	recommendation logic.
Disney+	Mixed: Appreciated for discovery by some users, but criticized for repetitive franchise-based recommendations.	Recurring concerns about adaptability, learning capacity, and content diversity.	Trade and online analysis sources report planned or discussed UX updates, with potential implications for personalization rather than confirmed algorithmic changes.	Perceived emphasis on popular franchises and limited differentiation across audience segments.	Perceived to highlight nostalgic and well-known content, while raising concerns about limited variety beyond flagship franchises.

Table 1 provides a comparative overview of user perceptions and evaluations regarding the recommendation systems of Netflix, Amazon Prime Video, and Disney+. The findings suggest that all three platforms exhibit mixed responses from users, highlighting both strengths and limitations in algorithmic performance. While Netflix is praised for aiding in content discovery, it is also criticized for prioritizing trending content and is sometimes perceived as less responsive to diverse user preferences. Amazon Prime Video's system is viewed as inconsistent, with users pointing out repetitive suggestions and a lack of transparency, despite efforts to improve through AI-based updates. Disney+, on the other hand, is commended for promoting nostalgic content but is often seen as overly reliant on its flagship franchises, with limited variety for adult users. Overall, the table illustrates the shared challenges of balancing personalization, content diversity, and transparency across streaming platforms' recommendation systems.

Discussion

This study investigated perceptions of recommendation systems on user experience across major streaming platforms, including Netflix, Amazon Prime Video, and Disney+, by analyzing user feedback from social media and online sources. The findings align with existing literature on recommendation algorithms and personalization (Ricci et al., 2021; Elahi et al., 2021). In particular, the role of personalization in enhancing user satisfaction was repeatedly emphasized throughout the study (Adomavicius & Tuzhilin, 2005; Chen & Sundar, 2018). Recent studies suggest that Netflix is often described as an industry leader in recommendation systems, supported by a combination of factors that include its capacity to incorporate user behavior signals over time, contributing to its competitive positioning (Gomez-Uribe & Hunt, 2015; Maddodi, 2019). However, findings from this study indicate polarized user opinions regarding Netflix's recommendation system. While some users praise the algorithm for guiding them toward relevant content, others criticize it for repetitive and irrelevant suggestions. This divide highlights ongoing discussions about the role of transparency and user engagement in personalization algorithms, as noted by Chen and Sundar (2018). Discussions around Amazon Prime Video highlight similar concerns regarding personalization. Users sometimes report frustration with repetitive or irrelevant recommendations, which they associate with limitations in how recommendation systems adapt to individual preferences. This observation suggests that, despite advances in data-driven content curation, users perceive room for improvement in aligning recommendations with their interests.

Compared with Netflix and Amazon Prime Video, Disney+'s content library is more strongly associated with a limited set of flagship brands such as Marvel, Star Wars, and Pixar, which appears to shape user experiences in distinct ways. While some users appreciate recommendations that emphasize familiar franchises and nostalgic content, others perceive a lack of variety and express concerns that popular titles receive greater visibility than niche offerings. Such perceptions resonate with broader discussions in the literature emphasizing the importance of balancing mainstream and niche content within recommendation environments (Ricci et al., 2021).

Recent studies highlight the potential of deep learning–based recommendation approaches to incorporate multiple user interaction signals and content attributes, thereby supporting more refined personalization (Goodfellow et al., 2016; Zhang et al., 2019). However, the findings of the present study, grounded in user feedback, suggest that users across platforms continue to report challenges such as repetitive recommendations, perceived irrelevance, and limited thematic diversity. These concerns point not to definitive technical shortcomings, but to a perceived gap between algorithmic capabilities discussed in the literature and users' lived recommendation experiences, underscoring the importance of ongoing system adaptation and responsiveness to user feedback (Amatriain & Basilico, 2015; Covington et al., 2016).

Some user complaints include remarks such as "*Why is Netflix still recommending a show I watched five years ago?*" and "*Why do I keep seeing genres I have no interest in?*" These comments point to user perceptions that recommendation systems do not always sufficiently reflect updated preferences or recent interactions. Prior research emphasizes the importance of effectively recording user preferences and updating interaction signals over time, as these processes support more adaptive and responsive recommendation outcomes (Burke, 2002; Herlocker et al., 2004). Within this context, studies suggest that providing users with opportunities to adjust preferences or offer corrective feedback to recommendation systems can contribute to higher satisfaction (Su & Khoshgoftaar, 2009). While Netflix, Amazon Prime Video, and Disney+ all employ AI-driven recommendation approaches, user feedback in this study indicates ongoing expectations for greater adaptability, transparency, and user involvement. Such elements are widely discussed in literature as important considerations for enhancing perceived personalization and engagement over time.

Conclusion

This study examines the recommendation systems of Netflix, Amazon Prime Video, and Disney+ based on user opinions gathered from social media and selected online commentary sources, focusing on how these systems are perceived to shape user experience and satisfaction. It addresses four core questions concerning user evaluations of these algorithms, their perceived strengths and weaknesses in personalization and content diversity, and how similarities or differences across platforms relate to user satisfaction.

The findings of the study first suggest that (1) all three platforms, through their AI-based recommendation algorithms, facilitate content discovery and increase the duration of user engagement on the platform. However, when these algorithms provide irrelevant or repetitive recommendations, they negatively impact user experience. Notably, some users praise Netflix for helping them navigate its vast content library to find suitable productions, while others criticize the system for repeatedly suggesting the same type of content. This situation shapes user opinions in response to the second research question (2): Some users appreciate personalized recommendations that allow them to discover new and engaging productions, while others express frustration with the limited or irrelevant suggestions provided by the algorithms.

Regarding the third question, the analysis highlights the strengths and weaknesses of recommendation algorithms in terms of content diversity and personalization. While some users provide positive feedback on Netflix and Amazon Prime Video for effectively filtering their extensive libraries according to personal preferences, others criticize these platforms for occasionally falling into a "content repetition loop," in which similar titles are repeatedly recommended over time. Disney+, with its emphasis on popular franchises, is perceived by some users as satisfying preferences for nostalgic and family-friendly content; however, other users report that it falls short of meeting expectations for niche or adult-oriented offerings. Regarding the fourth question, user discussions associate satisfaction with perceptions of content diversity, the system's responsiveness to evolving user data, and the visibility of how recommendations are generated. User feedback suggests that Netflix is perceived as drawing on past viewing patterns and fine-grained content categorization, which some users associate with effective discovery, while others recurrently criticize repetitive recommendations. Amazon Prime Video is perceived as incorporating signals from across the Amazon ecosystem, a practice some users view as enabling cross-domain personalization, but which others associate with inconsistent or less transparent recommendations. Disney+, in contrast, is perceived as relying primarily on franchise-centered content structures, a strength for users seeking familiar and family-oriented titles, yet a recurring point of criticism among those who desire greater variety or niche content.

It is important to acknowledge a key limitation of this study: the reliance on social media and selected online commentary sources as data collection channels may have disproportionately reflected the perspectives of more active or vocal users. As a result, the dataset primarily reflects the perspectives of individuals who are more engaged in public discourse. These viewpoints may not fully represent the experiences of the broader and more passive user base. This self-selection bias limits the representativeness of the findings. Moreover, the absence of direct user demographics or stratified sampling prevents a more generalizable interpretation of user experiences. Therefore, the results should be interpreted as indicative of dominant discursive patterns rather than definitive measures of user sentiment.

Additionally, access to detailed and authoritative information about platforms' algorithmic architectures or internal decision-making processes is limited. Accordingly, the analysis relies on user-generated content and selected third-party online commentary rather than verified technical disclosures. The descriptive content analysis used in this study is not supplemented by quantitative data analysis, further limiting the generalizability of the findings.

Future research could explore the technical aspects of recommendation systems in greater detail through mixed-methods approaches that combine qualitative and quantitative methodologies. Specifically, analyzing users' actual interaction data, where accessible (e.g., via research partnerships or opt-in studies), such as viewing durations, click rates, and return behaviors, could provide more concrete insights into the performance of recommendation algorithms. Furthermore, comparative studies examining how different demographic groups (age, gender, region, etc.) are affected by recommendation systems would contribute to a more micro-level understanding of personalized experiences. Additionally, experimental studies that measure user perceptions and attitudes regarding data privacy and algorithmic transparency could help platforms develop strategies aligned with user-centered design principles. Finally, interdisciplinary research can examine how rapidly evolving artificial intelligence and machine learning techniques are applied within online streaming platforms. Such work could help guide the development of more accurate and ethically designed recommendation systems.

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Yazar Katkı Oranı Beyanı: Çalışma tek yazarlı olup, yazarın katkı oranı %100'dür.

Çıkar Çatışması Beyanı: Yazar herhangi bir çıkar çatışması olmadığını beyan etmektedir.

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