

Platform-Based Strategy and Ecosystem Competition in the Digital Economy

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Abstract. The rapid growth in the number of digital platforms has made competition in the streaming services industry intense, and firms now differentiate their business practices through content and integration strategies. This paper analyzes the differences in the content structures of two major firms, Netflix and Amazon Prime Video. Using public datasets, it examines the types of content offered, the genres offered, the geography covered, and growth over time. Machine learning models for clustering and classification were used to segment the content of both firms and to relate genres to content types. The results show that Netflix follows a content-led strategy with greater diversification and a fast-growing content portfolio, while Prime Video follows an ecosystem-integration strategy with less diversification and stable growth.

Keywords. Platform strategy; ecosystem competition; digital economy; content diversity; streaming platforms; machine learning; clustering; content analysis; Netflix; Amazon Prime Video

I. INTRODUCTION

Growth in the digital age has changed the dynamics of competition in the economy, especially among streaming platforms. Besides competing on content, digital platforms today compete on their overall strategy and on their integration into ecosystems [1]. Leading streaming companies compete in several ways, and the rivalry between Netflix and Amazon Prime Video is one example. Netflix can be described as a content platform, while Amazon Prime Video is part of a service ecosystem that includes streaming [2]-[4].

II. LITERATURE REVIEW

The emergence of digital platforms has brought attention to platform strategy and ecosystem competition. Previous literature shows that competition between digital platforms rests not only on the product or service but also on the strength of the ecosystem and the engagement model used [5]. For streaming services, content holds a special place in drawing users to the platform.

Studies of Netflix focus on the company's content-centric method, which includes investment in varied and innovative content to promote customer loyalty and international expansion. Research on Amazon Prime Video, on the other

hand, focuses on the integration of video streaming into a larger network of services [6].

Previous literature has concentrated mainly on business model strategies, and little quantitative, data-driven evidence exists on how content characteristics vary across platforms [7].

III. DATASET DESCRIPTION

Two datasets containing the content of Netflix and Amazon Prime Video were used in this research. Both datasets list movies and TV shows with their features, such as content type, genre, country, and release year.

The two datasets have a similar format, which makes their features comparable. The Netflix dataset covers content from more countries, while the Prime Video dataset has a higher proportion of movies and missing country information for some titles. These datasets provide the basis for analyzing content strategy, diversity, and platform competition.

IV. METHODOLOGY

This research uses a data-driven approach to examine strategy and ecosystem competition between Netflix and Amazon Prime Video. The methodology has three steps: data

preprocessing, exploratory data analysis, and machine learning analysis [8].

A. Data Preprocessing

Missing values in important features such as country, genre (the “listed in” field), and content type were handled by imputation, which mostly involved assigning an “Unknown” category to the feature [9].

The genre field, which holds several genres in one row, was restructured into a list so that the data could be analyzed easily. This helped in organizing and encoding genre information in the later steps [10].

Irrelevant variables, for example incomplete date fields, were also screened out to ensure consistency. The cleaned datasets had a consistent format and content across both platforms for comparison [11].

B. Exploratory Data Analysis

The exploratory data analysis (EDA) stage looked for patterns in content distribution and platform strategy. Four attributes were considered.

Distribution of content types: The distribution of movies and TV shows was explored to identify the focus of each platform [12].

Genre distribution: The genre distribution was checked to examine variety and specialization in genre selection.

Geographical distribution: The distribution of countries was measured using the country attribute.

Trends by year: The temporal distribution of content was analyzed by release year to track trends and expansion plans.

C. Machine Learning Analysis

Machine learning algorithms were used for deeper analysis by detecting core patterns within the content strategies [13], [14].

Clustering (K-means): K-means clustering was performed on genre features after the data were converted into numerical form by multi-label encoding. This method segmented the content into clusters based on genre similarity. The clusters identified content groups such as those dominated by drama, crime, and family titles, which gives information on the content segmentation of both platforms.

Classification (logistic regression): A classifier was built on the genre attributes to predict whether a title is a movie or a TV show. Logistic regression was selected for its transparency and its suitability for classification tasks. The model was used less for precise prediction than to inspect how genre composition influences content type. The feature importance generated by the model showed which genres are associated more with TV shows than with movies.

V. RESULTS AND DISCUSSION

This section discusses the results of the comparison of content on the two platforms.

A. Content Type Distribution

The distribution of content types shows a distinct structure that differentiates the content strategies of the two firms. Fig. 1 presents the distribution of the content of Netflix and Amazon Prime Video, with differences in the proportions of

movies and TV shows. The difference reflects different strategic orientations. Netflix maintains a more balanced content library, with a sizable proportion of TV shows, which keeps the audience engaged through episodic content. Amazon Prime Video's library, on the other hand, is skewed toward movies.

B. Genre and Content Diversity

The genre distribution on the two platforms shows clear differences in content diversity and specialization. Fig. 2 presents the leading genres on Netflix and Prime Video. Netflix carries a large number of genre categories, including international movies, dramas, and comedies. This variety can be linked to the inclusion of both international and TV genres in the collection.

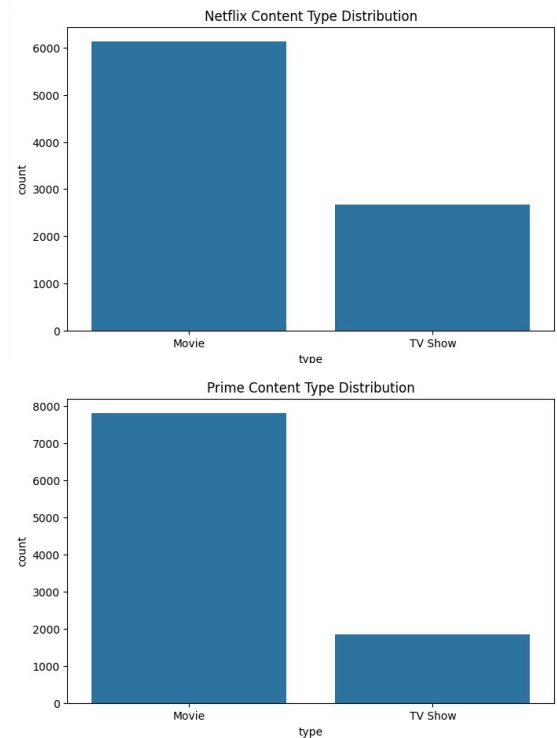


Fig. 1. Content type distribution of Netflix (top) and Prime Video (bottom).

Amazon Prime Video shows a relatively narrow distribution of genres that includes drama, comedy, action, and suspense, among others. Its genre distribution is much more compact than that of Netflix.

These results indicate that Netflix follows a content diversification strategy, using various genres to attract different audience segments in different parts of the world. Prime Video, in contrast, follows an intensive content strategy that targets the most popular genres without emphasizing diversification.

C. Geographical Distribution

The country-wise distribution of content shows significant differences in global reach and regional concentration between the two platforms, as illustrated in Fig. 3. Netflix shows geographical diversity, with content sourced from many nations such as the United States, India, the United Kingdom, and Canada.

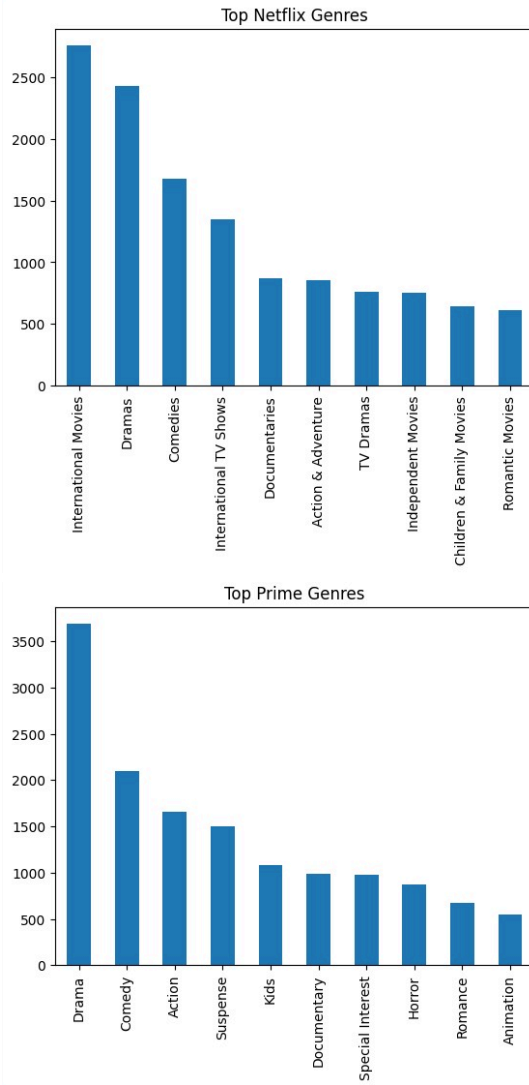


Fig. 2. Top genre distribution of Netflix (top) and Prime Video (bottom).

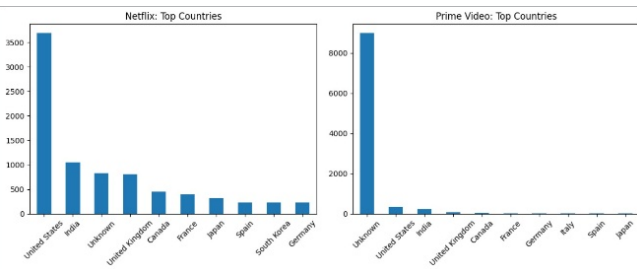


Fig. 3. Country-wise content distribution of Netflix and Prime Video.

Prime Video, however, shows a high concentration in the “Unknown” category, with smaller contributions from individual nations. Even among the recognized countries, the contributions from the United States and India are relatively small.

D. Clustering Analysis

K-means clustering was applied to organize content by genre similarity, and it revealed distinct content segments within the dataset. Fig. 4 shows the five genre-based clusters. The distribution is uneven, which suggests that content is concentrated around specific genre combinations. The larger clusters represent the dominant content categories, while the smaller clusters indicate niche segments. This

points to an organized content segmentation strategy in which platforms prioritize in-demand genres while keeping selective diversity.

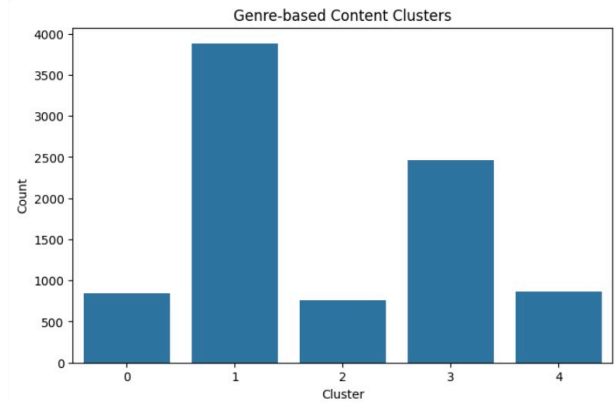


Fig. 4. Genre-based content clusters.

E. Temporal Content Trends

The yearly analysis of content brings out the growth patterns of both platforms over time. Fig. 5 presents the growth of content by year and shows the different strategic approaches of the two platforms. The rapid growth seen for Netflix shows the importance it places on expanding the content available. The slower and steadier growth seen for Prime Video indicates a more selective approach to content, supported by its place within a larger system.

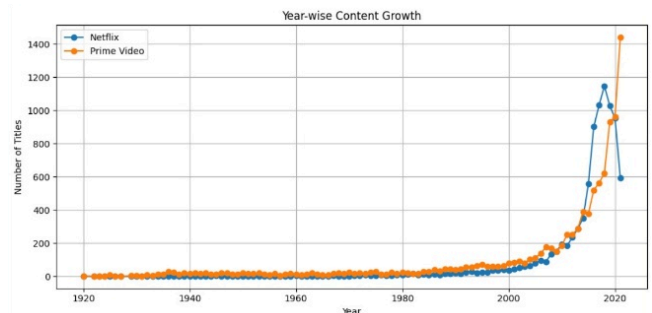


Fig. 5. Year-wise content growth of Netflix and Prime Video.

F. Key Findings

The results show a clear distinction between the content strategies of Netflix and Amazon Prime Video. Netflix focuses on diversified genres, global reach, accelerated growth of content production, and content categorization. Amazon Prime Video offers content that is more concentrated, both by genre and geographically, and grows steadily. This suggests that Prime Video follows a less content-driven approach, focused instead on system integration and the ecosystem.

VI. CONCLUSION

This research examined platform strategy and ecosystem competition by analyzing the strategies of Netflix and Amazon Prime Video at the content level. The results show that Netflix uses a content strategy defined by a wide range of genres, broad international coverage, and fast growth in the number of titles. Prime Video uses an ecosystem strategy with a more limited content range and consistent growth, so its competitive advantage comes not only from content but

also from its services ecosystem. In platform strategy terms, the content diversification strategy of Netflix and the ecosystem integration model of Amazon Prime Video are different ways of competing.

The results also suggest that content diversity and segmentation play an important part in the engagement strategy of content-heavy platforms, while ecosystem integration may reduce reliance on the scale of content, so that platforms such as Prime Video can compete even with limited content diversification. Future research could extend the analysis to AI-driven recommendation, user engagement analytics, and personalization strategies, which would help describe the role of platform strategy in user retention and content consumption behavior.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and preparation of this work and approved the final version of the manuscript.

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DECLARATION OF GENERATIVE AI USE

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript. The authors take full responsibility for the content of the publication.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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