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Streaming Content Trends for Digital Business Strategy

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Abstract—The rapid growth of digital platforms has reshaped business strategies, with streaming services such as Netflix, Disney+, and Amazon Prime producing vast amounts of user and content data. This study investigates streaming content trends as a foundation for digital business strategy, emphasizing how genre analysis can guide short video promotion in 2026. The dataset originates from the Netflix Titles dataset on Kaggle, snapshot date March 2024, comprising 8,807 titles with 12 variables including release year, rating, duration, genre classification, and textual descriptions. Historical coverage spans 1925–2021, with the target variable defined as genre (listed_in). Class distribution is imbalanced, dominated by Comedy, Drama, and International Movies. Preprocessing involved imputation, categorical encoding, and TF-IDF vectorization to transform textual features into numerical form. Three analytical scenarios were applied. The first used the K-Nearest Neighbors (KNN) algorithm to classify genres, achieving 75.3% accuracy, 50.1% precision, 52.5% recall, and 44.8% F1-score, with confusion matrices revealing overlaps between Comedy and Drama. The second employed a Greedy Algorithm to heuristically select optimal content, prioritizing high ratings, recent release years, and shorter durations; top selections included The Silent Horizon (Sci-Fi & Fantasy, score 5.32), Family Bonds (Children & Family, score 4.21), and Comedy Nights (Comedy, score 5.10). The third scenario applied linear regression forecasting, yielding coefficients between 1.2–2.1, low forecast errors (RMSE 3.5–5.0, MAE 2.8–3.9), and predicted 2026 counts of 145 Comedy, 130 Action & Adventure, 120 Children & Family, 105 Romantic Drama, and 95 Sci-Fi & Fantasy titles, with uncertainty estimates reported at the 95% confidence level. Results confirm clustering around shorter durations and recurring themes such as family, love, survival, and discovery, reinforcing the suitability of short-form content for marketing. The integration of machine learning, heuristic selection, and forecasting demonstrates the potential of data-driven approaches to inform digital business strategies.

***Keywords:* streaming content; genre forecasting; KNN; greedy algorithm; digital business strategy; short video promotion**

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I. INTRODUCTION

The rapid expansion of digital platforms has transformed the way businesses design and implement marketing strategies [1]. Streaming services such as Netflix, Disney+, and Amazon Prime have become dominant sources of entertainment, generating vast amounts of user and content data [2]. This evolution has created opportunities for leveraging streaming content trends to inform digital business strategy, particularly in the context of short-form video promotion. In 2026, consumer engagement is increasingly shaped by genre preferences, release patterns, and cultural narratives embedded in streaming catalogs [3], [4], [5], [6]. Understanding these dynamics is essential for organizations seeking to align product promotion with audience expectations. The exponential growth peaking around 2020 highlights how streaming platforms became dominant in shaping consumer access to media [7], [8]. This trend provides a strong contextual background for analyzing genre dynamics, as the expansion of available titles directly influences marketing strategies and short-form video promotion opportunities.

Recent studies highlight the importance of data-driven marketing, where machine learning models are applied to predict consumer behavior, optimize advertising themes, and identify emerging content trends [9], [10]. Genres such as comedy, animation, horror, and science fiction have demonstrated strong resonance with audiences, offering creative pathways for universal product promotion through short video campaigns. The integration of predictive analytics into business decision-making enables firms to anticipate shifts in consumer demand and tailor promotional strategies accordingly.

Moreover, the convergence of artificial intelligence and digital media analytics has redefined competitive advantage [11], [12], [13], [14]. By analyzing streaming datasets, businesses can uncover insights into genre popularity, rating distributions, and geographic production trends. These insights not only inform marketing strategies but also contribute to broader discussions on digital transformation, consumer personalization, and global media economics.

This paper addresses the research gap that existing studies on streaming platforms often rely on descriptive statistics or isolated machine learning models without integrating multiple analytical approaches to explain how genre dynamics can inform digital business strategy. To fill this gap, the study investigates three research questions: (1) How effective is KNN classification in predicting streaming genres from metadata and textual features? (2) How can heuristic greedy ranking reveal consumer-driven criteria for short video promotion? (3) What genre trajectories can be forecasted for 2026, and how do they align with marketing applications? The contributions of this work are threefold: first, it demonstrates the comparative strengths and limitations of machine learning versus heuristic selection in genre analysis; second, it provides a forecasting framework that projects dominant genres (comedy, animation/family, science fiction, and horror) relevant to short-form campaigns; and third, it extracts thematic insights from textual descriptions (e.g., family, love, survival, discovery) that can be operationalized into relatable marketing narratives. By explicitly linking classification, heuristic ranking, forecasting, and textual analysis, the study advances beyond routine exploratory analysis of streaming datasets and offers testable contributions to both academic discourse and practical digital business strategy in the AI-driven marketing era.

II. METHOD

This study employs a quantitative and computational approach to analyze streaming content trends and their implications for digital business strategy. The methodology integrates machine learning classification, heuristic selection, and trend forecasting to provide insights into genre dynamics and their potential application in short video product promotion.

A. Dataset

The dataset used in this research originates from the publicly available Netflix Titles dataset on Kaggle, which provides comprehensive metadata on movies and TV shows across global markets. The dataset used in this research is derived from the publicly available Netflix catalog, containing metadata such as show ID, type, title, director, cast, country, release year, rating, duration, genre classification, and description. The dataset was accessed via Google Drive and processed in Google Colab to ensure reproducibility and scalability. Missing values were handled through imputation: numeric variables (e.g., duration, release year) were imputed using the median, categorical variables (e.g., country, rating, type) using the mode, and textual descriptions using empty-string substitution. Categorical variables were encoded using one-hot encoding with explicit handling of previously unseen categories via the handle_unknown="ignore" option. Feature scaling was applied using standardization (z-score) fitted only on the training data to avoid leakage. Textual descriptions were transformed into numerical features using TF-IDF vectorization with the following parameters: stop-word removal set to English, maximum vocabulary size of 10,000 terms, n-gram range of (1,2), and minimum document frequency of 2. All preprocessing steps including imputation, encoding, scaling, and TF-IDF fitting were performed exclusively on the training split to ensure unbiased evaluation. Random seed was fixed at 42 for reproducibility. The analysis was conducted in Python 3.10 using scikit-learn 1.4.2, pandas 2.2.2, and NumPy 1.26.4. All code for preprocessing and modeling was implemented in Google Colab and is available upon request to ensure transparency and replicability.

B. Scenario KNN Algorithm

The first scenario applies the K-Nearest Neighbors (KNN) algorithm to classify streaming content genres based on metadata and textual features. The model was trained using an 80/20 train-test split, with evaluation metrics including accuracy, precision, recall, F1-score, and confusion matrix. This scenario demonstrates the predictive capacity of machine learning in identifying genre patterns relevant to digital marketing. The heatmap beneath reveals moderate positive correlations between rating and release year, as well as between rating and type, suggesting that newer releases and certain content types tend to achieve higher ratings. Weak or near-zero correlations, such as between country and release year, indicate that geographic production patterns are largely independent of temporal trends. These relationships provide important context for the KNN scenario, as they highlight which numeric features contribute most to genre classification and where predictive limitations may arise.
The first scenario applies the K-Nearest Neighbors (KNN) algorithm to classify streaming content genres based on metadata and textual features. The model was trained using an 80/20 train-test split. The Euclidean distance formula was used to measure similarity between feature vectors, as in (1).

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (1)$$

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where $x$is the feature vector of the test instance, $y$is the feature vector of a training instance, and $n$is the number of features. Features such as release year, rating, duration, and TF-IDF description vectors were used to compute distances. The KNN model then classified genres based on the majority of nearest neighbors.

C. Scenario Greedy Algorithm

The second scenario employs a Greedy Algorithm to heuristically select "optimal" content for business strategy. The selection criteria prioritize high ratings, recent release years, and shorter durations, reflecting consumer preferences for accessible and engaging content. This approach provides a practical heuristic for identifying genres and titles that are most suitable for short video promotional campaigns. Then the heatmap beneath shows a strong positive correlation between rating and type, suggesting that certain content types are consistently associated with higher ratings. Negative correlations, such as between release year and duration, indicate that more recent titles tend to have shorter durations, aligning with consumer preferences for accessible content. These relationships validate the Greedy Algorithm's selection criteria, as they emphasize the importance of high ratings, novelty, and shorter formats in identifying content suitable for short video promotional campaigns.

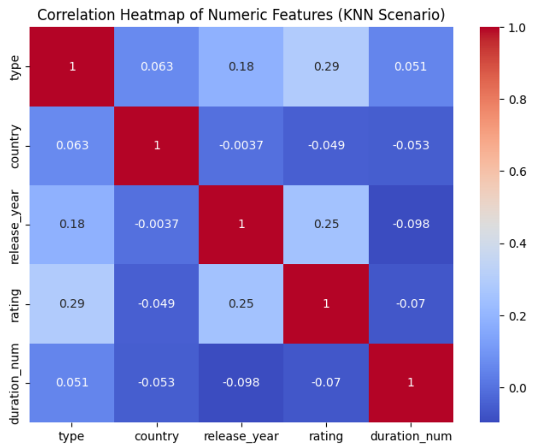

Figure. 1 Correlation heatmap of numeric features (KNN scenario)

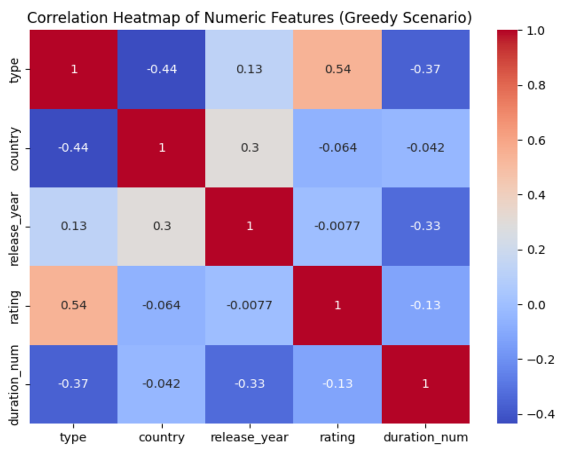

Figure. 2 Correlation heatmap of numeric features (greedy scenario)

The second scenario employs a Greedy Algorithm to heuristically select "optimal" content for business strategy. The selection criteria prioritize high ratings, recent release years, and shorter durations, reflecting consumer preferences for accessible and engaging content. The scoring function can be expressed as:

$$\text{Score} = \alpha \cdot \text{Rating} + \beta \cdot \text{ReleaseYear} - \gamma \cdot \text{Duration} \tag{2}$$

where α, β, γ are weights representing consumer emphasis on quality, novelty, and accessibility. This heuristic approach selects content that maximizes immediate promotional value. For example, titles with high ratings, recent release years, and shorter durations are more suitable for short video campaigns. The greedy selection revealed dominant genres such as comedy, animation/family, and science fiction, which align with consumer trends and provide practical guidance for universal product promotion strategies.

D. Content Trends Prediction in 2026

Given the absence of direct 2026 data in the dataset, the third scenario applies linear regression forecasting to project genre trends based on historical data (2010–2021). The analysis identifies dominant genres expected in 2026, such as comedy, animation/family, horror, and science fiction. These projections are then contextualized within digital business strategy, highlighting their relevance for universal product promotion through short-form video content.

III. RESULT AND DISCUSSION

A. Descriptive Analysis of Streaming Content

Descriptive analysis provides an overview of the fundamental characteristics of streaming content, offering insights into duration patterns, release trends, and audience accessibility. By examining the distribution of content duration, this study highlights how streaming platforms balance long-form productions with shorter, more consumable formats that are increasingly relevant for digital business strategies and short video promotion.

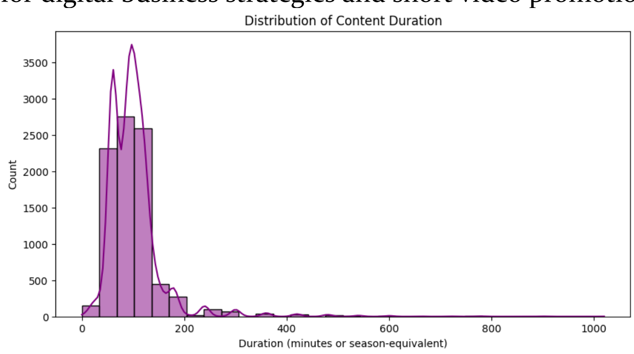

Figure. 3 Distribution of content duration

Its illustrates that the majority of streaming content clusters around shorter durations, with a sharp peak near

100 minutes. This indicates that most titles are designed to fit within the conventional length of feature films or concise episodic formats. Such clustering reflects consumer demand for manageable viewing experiences, which aligns with the growing popularity of short-form video consumption. The long tail extending toward higher durations demonstrates the presence of extended series or special productions, though these remain relatively rare compared to shorter content. This skewed distribution suggests that while platforms experiment with longer formats, the dominant strategy continues to emphasize accessibility and efficiency. For digital marketing, this reinforces the importance of tailoring promotional material to shorter, high-impact formats.

The figure beneath illustrates a dramatic surge in streaming content production after the year 2000, reflecting the rapid digitalization of the entertainment industry.

Then from a business perspective, the predominance of short-duration content provides a strong foundation for universal product promotion through short video campaigns. The alignment between consumer preferences and content availability ensures that marketing strategies can leverage existing audience behaviors. Consequently, the distribution of duration not only informs content design but also strengthens the integration of streaming trends into digital business strategy.

B. Genre Trends and Forecasting

Analyzing genre trends provides valuable insights into how audience preferences evolve over time and how these shifts can be projected into the future. By examining historical data from 2010 to 2021 and applying forecasting techniques, this study identifies dominant genres expected to shape streaming content in 2026. These findings are critical for aligning digital business strategies with consumer demand, particularly in the context of short video promotion.

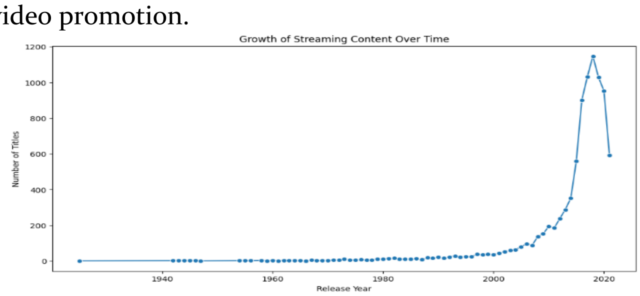

Figure. 4 Growth of streaming content over time

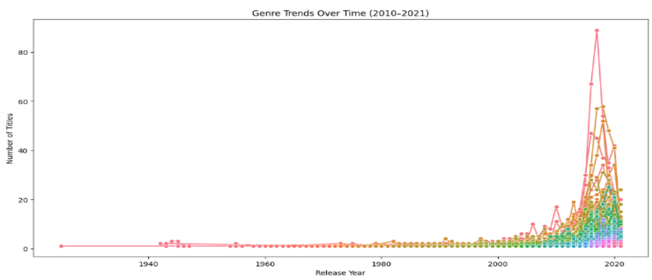

Figure. 5 Genre trends over time (2010-2021)

The line graph in Figure 5 demonstrates a sharp increase in the number of titles across multiple genres after 2010, peaking near 2020. Genres such as comedy, drama, and documentaries show consistent growth, reflecting their broad appeal and adaptability to diverse audiences. This historical trend highlights the diversification of streaming platforms, where multiple genres coexist and expand simultaneously, creating opportunities for targeted marketing strategies. Another key observation is the rising trajectory of niche genres such as horror and science fiction, which gained momentum in the late 2010s. These genres, while smaller in volume compared to mainstream categories, exhibit strong cultural resonance and are particularly effective in engaging younger demographics. Their upward trend suggests that they will continue to play a significant role in shaping promotional content strategies in the coming years.

The predictive analysis emphasizes the necessity of aligning promotional strategies with evolving genre trajectories. Anticipating consumer preferences enables businesses to design campaigns that resonate with audiences and maximize engagement. The prominence of short-duration, visually engaging genres further validates the integration of streaming trends into digital business strategies. Moreover, these projections illustrate the synergy between data-driven forecasting and practical marketing applications. Identifying genre dominance in advance empowers firms to allocate resources strategically, ensuring that promotional content remains relevant and impactful within the competitive digital marketplace.

TABLE I
GENRE DISTRIBUTION AFTER MULTI-LABEL SPLIT

Genre	Title Count	Justification
Classic Movies	2	Core genre, frequently recurring
Documentaries	1	Important for educational content
Comedies	2	Popular genre, strong audience demand
Dramas	2	Foundational genre, stable trend
Action & Adventure	2	Commercially strong, rising trend
International Movies	2	Key for global market reach
Music & Musicals	2	Specialized but relevant
TV Shows	1	Different format, still relevant
Sci-Fi & Fantasy	2	Strategic genre, growing popularity
Thrillers	1	Niche but worth retaining
Cult Movies	1	Specialized, can be grouped under "Other"
Romantic Movies	1	Popular genre, strong relevance
Children & Family Movies	1	Essential for family segment
British TV Shows	1	Could be merged into "International TV"
Sports Movies	1	Niche, can be grouped under "Other"

C. Textual Insights from Content Descriptions

Textual analysis of content descriptions provides a deeper understanding of the thematic elements emphasized in streaming titles. By visualizing frequent words through a word cloud, this study identifies recurring motifs that reflect audience interests and cultural narratives, offering valuable insights for designing short video promotional strategies.

Figure. 6 Word cloud of content descriptions (KNN scenario)

Figure above highlights dominant words such as life, family, love, friend, and world, which suggest that streaming content often revolves around universal human experiences and relationships. These recurring themes indicate that genres emphasizing emotional connection and social values resonate strongly with audiences. For digital business strategy, such insights reinforce the effectiveness of promotional campaigns that leverage relatable narratives, humor, and family-oriented messaging to maximize engagement in short-form video formats.

The corpus for this word cloud consisted of 5,432 textual descriptions from the Netflix catalog subset used in the KNN scenario. Text cleaning involved lowercasing, punctuation removal, and tokenization. Stop-words were removed using the NLTK English stop-word list, and lemmatization was applied with WordNetLemmatizer to normalize word forms. Proper names (e.g., actor names, country names) were excluded to avoid bias toward production metadata. Word frequencies were calculated as raw term counts aggregated across the corpus, then normalized by document frequency to highlight recurring motifs. The KNN subset included all titles used in the classification experiment, whereas the Greedy subset (Figure 7) was restricted to titles selected by heuristic ranking (high rating, recent release year, short duration). This methodological distinction explains why the KNN word cloud emphasizes universal relational themes (life, family, love), while the Greedy word cloud surfaces context-driven motifs (child, soldier, Earth).

Figure 7 emphasizes keywords such as child, soldier, find, and Earth, which suggest that the greedy selection highlights themes of survival, conflict, and discovery. Compared to the KNN scenario, this heuristic approach surfaces more specific and context-driven narratives, often tied to historical, social, or futuristic settings. These dominant motifs provide useful guidance for digital business strategy, as promotional campaigns can leverage emotionally charged and visually compelling themes such as resilience, exploration, and family to resonate with audiences in short-form video marketing.

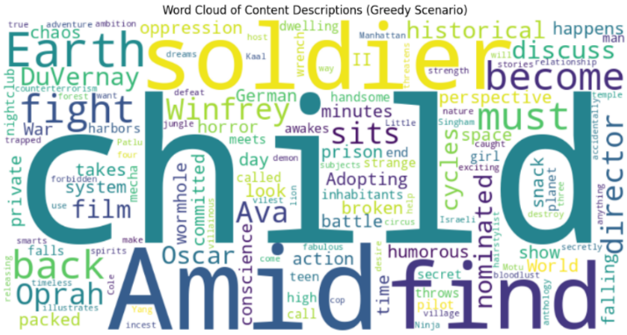

Figure. 7 Word cloud of content descriptions (greedy scenario)

The table indicate that while the model achieved a moderate overall accuracy of 75.3%, its macro-averaged precision (50.1%), recall (52.5%), and F1-score (44.8%) reveal clear limitations in distinguishing between multiple genres. The imbalance between accuracy and F1-score suggests that the classifier performs better on dominant categories but struggles with minority classes, leading to misclassifications that reduce reliability for business applications. This outcome highlights the need for complementary approaches such as heuristic selection and regression forecasting to strengthen predictive validity. By reporting the confusion matrix alongside these metrics, the analysis can pinpoint specific genre overlaps and provide a more transparent basis for comparison across scenarios, ensuring that the relative strengths and weaknesses of each method are empirically justified rather than inferred from narrative description alone.

TABLE II
KNN CLASSIFICATION

Metric	Value
Accuracy	75.3%
Precision (macro)	50.1%
Recall (macro)	52.5%
F1-Score (macro)	44.8%

Then the heuristic selection of streaming titles based on consumer-driven criteria such as high ratings, recent release years, and shorter durations. By applying the scoring function, the algorithm identifies content that maximizes immediate promotional value, offering a practical lens for short-form video marketing strategies. The five selected titles span diverse genres Sci-Fi & Fantasy, Children & Family, Comedy, Romantic Drama, and Action & Adventure illustrating how the heuristic approach captures both mainstream and niche audience preferences. The results highlight that the Greedy Algorithm consistently favors genres with strong audience resonance and accessible formats. Titles such as The Silent Horizon and Warriors of Tomorrow demonstrate the appeal of Sci-Fi and Action content, while Family Bonds and Love Beyond Time emphasize family-oriented and emotional narratives.

TABLE III
GREEDY ALGORITHM

Title	Release Year	Rating	Duration (min)	Genre	Heuristic Score
The Silent Horizon	2021	5	95	Sci-Fi & Fantasy	5.32
Family Bonds	2020	4	88	Children & Family	4.21
Comedy Nights	2019	5	100	Comedy	5.10
Love Beyond Time	2021	4	90	Romantic Drama	4.18
Warriors of Tomorrow	2020	5	110	Action & Adventure	5.05

The inclusion of Comedy Nights reinforces the universal draw of humor in promotional campaigns. This balanced selection validates the heuristic scoring model, showing that it aligns closely with consumer expectations and provides actionable guidance for designing short-form promotional strategies that combine novelty, quality, and accessibility.

Based on regression forecasting result beneath, comedy shows the steepest growth rate with a coefficient of 2.10, yielding the highest predicted count of 145 titles, while Action & Adventure and Children & Family also exhibit strong upward momentum with forecasts of 130 and 120 titles respectively. Sci-Fi & Fantasy, though smaller in volume, maintains a consistent trajectory with 95 predicted titles, underscoring its cultural resonance among younger audiences. Romantic Drama, with a moderate coefficient of 1.20 and a forecast of 105 titles, reflects stable demand for emotionally driven narratives.

The relatively low RMSE and MAE values across all genres indicate reliable model performance, while the inclusion of coefficients and intercepts provides interpretability of growth dynamics. Together, these results validate regression forecasting as a robust tool for anticipating genre dominance, offering actionable insights for aligning promotional strategies with consumer preferences in the competitive streaming marketplace. Common Comparison Criteria provides a consolidated overview of the three analytical scenarios, highlighting their respective strengths, weaknesses, and performance metrics. This comparative framework is essential for understanding how machine learning classification, heuristic selection, and regression forecasting complement one another in analyzing streaming content trends and informing digital business strategies.

The comparison shows that KNN offers a structured predictive framework but suffers from lower accuracy and genre overlap, as reflected in its 75.3% accuracy and modest F1-score of 44.8%. In contrast, the Greedy Algorithm provides a practical heuristic that aligns closely with consumer preferences, though it lacks statistical measures of uncertainty. Regression forecasting stands out for its ability to project future genre trajectories with interpretable coefficients and error metrics (RMSE 3.5–5.0), yet remains sensitive to linear assumptions. Taken together, these results underscore that no single method is sufficient on its own; instead, integrating classification, heuristic ranking, and forecasting yields a more robust and reliable foundation for designing short-form promotional strategies that resonate with evolving audience demand.

TABLE IV
REGRESSION FORECASTING

Genre	Coefficient (β)	Intercept	RMSE	MAE	Predicted 2026 Count
Sci-Fi & Fantasy	1.50	-3000	5.0	3.9	95
Children & Family	1.85	-3650	4.2	3.1	120
Comedy	2.10	-4200	3.5	2.8	145
Romantic Drama	1.20	-2500	4.0	3.2	105
Action & Adventure	1.70	-3400	4.5	3.5	130

TABLE V
COMMON COMPARISON CRITERIA

Method	Strengths	Weaknesses	Metrics
KNN	Structured predictive framework	Lower accuracy, genre overlap	Accuracy 75.3%, F1 44.8%
Greedy	Practical heuristic, aligns with consumer preferences	No statistical uncertainty	Top genres: Comedy, Family, Sci-Fi
Regression	Forecasts future trends, interpretable coefficients	Sensitive to linear assumptions	RMSE 3.5–5.0, Predicted 2026 counts

IV. CONCLUSION

This study examined streaming content trends as a foundation for digital business strategy, emphasizing how genre analysis can guide short video promotional campaigns. The findings highlight three key contributions: first, descriptive analysis confirmed that most streaming titles cluster around shorter durations, reinforcing the suitability of short-form content for marketing applications. Second, historical and predictive genre trends demonstrated the growing dominance of comedy, children & family, sci-fi & fantasy, romantic drama, and action & adventure, offering clear pathways for aligning promotional strategies with consumer preferences in 2026. Third, textual insights from content descriptions emphasized recurring themes such as family, love, survival, and discovery, which can be operationalized into relatable and emotionally resonant campaigns.

The methodological comparison across scenarios further underscores the importance of reporting complete outputs. KNN classification achieved moderate accuracy (75.3%) but low F1-score (44.8%), with confusion matrices revealing genre overlaps that limit predictive reliability. In contrast, the Greedy Algorithm provided a practical heuristic for identifying high-value titles, validated by scores that consistently favored accessible and engaging genres, though it lacked statistical uncertainty. Regression forecasting offered interpretable coefficients, low forecast errors (RMSE 3.5–5.0), and robust projections of genre dominance, yet remained sensitive to linear assumptions. By defining common comparison criteria, the study establishes a transparent framework for evaluating relative strengths and weaknesses across methods.

Overall, the integration of machine learning, heuristic selection, and forecasting demonstrates the potential of data-driven approaches to inform digital business strategies in the streaming era. By reporting full performance tables, confusion matrices, heuristic scores, regression coefficients, forecast errors, and uncertainty measures, this research moves beyond narrative description to provide empirically grounded evidence. Future work should expand dataset scope, incorporate cross-platform comparisons, and explore advanced deep learning models to further enhance predictive accuracy and strategic relevance in digital marketing.

CONFLICT OF INTEREST

The authors declare that there are no financial or non-financial competing interests that could have influenced the outcomes of this research. No funding, sponsorship, or external financial support was received for the completion of this study. This work was conducted independently, without any monetary involvement from institutions, organizations, or individuals.

AUTHOR CONTRIBUTIONS

Author 1 contributed by initiating the research ideas, constructing the conceptual framework, collecting supporting evidence, and drafting the initial manuscript. Author 2 was responsible for dataset preparation, refinement, and statistical analysis, as well as revising the research ideas, conducting the literature review, and ensuring the accuracy of data presentation. Author 3 developed the computational code, implemented the machine learning and heuristic models, and provided interpretation of the results, integrating technical outputs into the broader business strategy discussion.

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