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Weekly Ranking Turnover on Netflix Türkiye: A Five-Year Longitudinal Study

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Abstract

Using Netflix's complete country-level Top 10 dataset from 4 July 2021 to 21 June 2026, this study examines the temporal organization of platform-produced visibility in Türkiye. The analysis covers 5,200 ranked observations across 260 weeks, equally divided between films and TV. Visibility is operationalized as an item's recurring presence and relative position within Netflix's publicly disclosed Top 10, rather than as audience size or viewing intensity. The metrics include weekly turnover, item persistence, rank-weighted visibility, and next-week retention. Paired tests compare category churn, and a clustered logistic regression estimates how rank strength, format, and time predict retention. Films showed significantly higher weekly turnover than TV ($M = 4.66$ vs. 3.20 new entries; paired $t(258) = 12.63$, $p < .001$, $d = .78$). TV items appeared for more weeks on average (3.62 vs. 2.35) and had a higher next-week retention rate (68.0% vs. 53.4%). Rank strength was the strongest predictor of retention, with a stronger association for TV. No significant linear trend in turnover was observed over the study period. The findings indicate two temporal regimes within Netflix Türkiye's ranking environment: high-velocity film visibility and comparatively durable television visibility. Because country lists provide ordinal positions rather than audience totals, the results concern platform-produced visibility, not direct measures of national demand or preference.

Keywords: Netflix, Platformed Attention, Ranking Cultures, Streaming Television, Türkiye.

JEL Codes: D83, L82, L86, Z11

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1. Introduction

Subscription video-on-demand services do more than distribute audiovisual content. They organize catalogs, personalize user interfaces, recommend titles, display popularity labels, and selectively disclose audience metrics. These practices make visibility a central resource in platformed cultural distribution. A title may be available in the catalog yet remain difficult to discover, while another may be repeatedly foregrounded through recommendations, promotional artwork, autoplay, or ranked lists. Platform studies therefore treat discoverability and measurement not as neutral technical features but as mechanisms through which cultural goods become more or less visible (Gillespie, 2014; Nieborg & Poell, 2018; van Dijck, Poell & de Waal, 2018). Despite their limitations, Netflix's weekly country-level Top 10 lists offer a useful window into this process. Netflix began publishing weekly ranking data in November 2021 and provides country-level lists retrospectively from July 2021. These files identify the ten highest-ranked films and ten highest-ranked TV titles or seasons each week. Unlike the global lists, however, the country files do not report the number of viewers, hours viewed, or viewing intensity within each market; they provide only ordinal positions. Accordingly, the lists should not be treated as a complete record of national viewing behavior. In this study, they are interpreted as indicators of weekly visibility produced through Netflix's own measurement and reporting system (Netflix, 2021, Perez De Rosso 2021; Scarlata, 2023; Wayne, 2022).

Researchers have used Netflix's ranking and catalogue data to examine transnational circulation, cultural diversity, local content, and the industrial construction of popularity (Lobato, 2018; Lotz, 2021a; Lotz, Eklund & Soroka, 2022; Wayne & Ribke, 2024). Yet relatively little research has examined how a single country's Top 10 changes over an extended period, particularly through a direct comparison of films and TV. A weekly chart is not only a ranking but also a temporal sequence: titles enter, persist, change position, disappear, and sometimes re-enter. These movements create patterns of visibility and attention that may differ by format. Films are generally reported as bounded releases, whereas TV is often reported by season, creating different opportunities for persistence across weeks.

Türkiye provides a relevant case because global streaming services coexist with strong domestic film and television cultures, while Netflix has developed country-specific communication strategies for the Turkish market. Examining eight Netflix commercials produced specifically for Türkiye, Gülmez (2019) identifies localization through character, space, object, language, and music. This work suggests that Netflix's operation in Türkiye involves not only global catalog distribution but also symbolically embedding circulating content within locally familiar frames. The present study does not evaluate these localization strategies, nor does it claim to establish what viewers in Türkiye watched, liked, or demanded. Instead, it examines how Netflix's public ranking system organized the persistence and replacement of visible titles over 260 consecutive weeks. The object of analysis is therefore the ranking environment, not the private behavior of individual subscribers.

Against this background, the study addresses four research questions: (RQ1) How do weekly turnover and persistence differ between films and TV in Netflix Türkiye's Top 10? (RQ2) To what extent do current rank strength and content format predict next-week retention? (RQ3) Which titles or seasons achieved the highest rank-weighted visibility during the observation period? (RQ4) Did weekly turnover change systematically over time? Using official aggregate data, the study provides a replicable design for analyzing platform-produced visibility without relying on user comments or personal data, while keeping interpretation within the limits of ordinal ranking information.

2. Conceptual Framework

2.1. Platformization, Ranking Cultures, and Visibility

Platformization refers to extending platform infrastructures, economic models, and governance arrangements into cultural production and circulation (Nieborg & Poell, 2018; Poell, Nieborg & van Dijck, 2019). In audiovisual media, this transformation affects not only distribution but also how cultural works are categorized, valued, and discovered. Interfaces function as editorial environments in which technical systems and commercial priorities are expressed through rows, badges, thumbnails, recommendations, and charts. These elements shape what users can notice and select. Visibility should therefore be understood not as an automatic consequence of catalog availability but as an infrastructurally organized condition. Bucher (2012, 2018) argues that software architectures produce digital visibility by rendering some objects prominent while making others less perceptible. McKelvey and Hunt (2019) similarly conceptualize discoverability as a form of media power through which platforms coordinate users, content, interfaces, and software. From this perspective, appearing, remaining visible, or disappearing within a platform is inseparable from the technical and institutional organization of choice. This organization is also shaped by the tension between global connectivity and territorial differentiation. As Lobato observes, "the clash between the internet's capacity for global distribution and the territorial nature of media trade, taste, and regulation" constitutes a significant tension within digital media distribution (Lobato, 2019).

Rankings are a core component of this platform architecture. Rieder, Matamoros-Fernández, and Coromina (2018: 52) describe ranking cultures as "unfolding processes of hierarchization and modulation of visibility" involving users, content creators, and platform interventions. Ranked outputs therefore emerge from interactions among algorithms, data sources, institutional objectives, platform arrangements, and user practices. Although numerical order may appear straightforward, the underlying processes are multifaceted and socially consequential (Beer, 2017). Rankings enable comparison, establish thresholds, and direct attention toward a limited set of visible items. They can also have recursive effects: appearing in a ranking can itself become newsworthy or promotional material, potentially generating further exposure and contributing to continued visibility.

Ranking systems, then, do not simply decode a pre-existing hierarchy of cultural value. By defining categories, thresholds, positions, and eligible objects, they help produce the hierarchy they display. As Striphas (2015: 395) observes, contemporary cultural activity increasingly involves delegating "the sorting, classifying and hierarchizing of people, places, objects and ideas" to computational processes. Algorithmic culture therefore extends beyond automating previously manual operations; it redistributes classificatory authority across computational systems, commercial institutions, data infrastructures, and human practices. The result is not the disappearance of cultural authority but its reconfiguration through platform procedures and data infrastructures.

In this study, platform visibility is defined narrowly as an item's observable presence, persistence, and relative position within Netflix's publicly disclosed weekly ranking environment. It is therefore an operational property of the published Top 10 rather than a direct measure of audience size, viewing intensity, exposure across the interface, or preference. This definition does not assume that rankings are determined solely by algorithmic recommendation or that all ranked titles receive equal promotion. Instead, the observed ranking is treated as the output of an assemblage that may include release timing, catalog availability, marketing, social discourse, interface design, recommendation, and audience viewing. Because the country-level Top 10 reveals only the final ordered list, these mechanisms cannot be isolated. The analysis can measure the recurring public ranking artefact, but it cannot reconstruct the complete process that generated it.

This analytical approach is consistent with scholarship on algorithmic culture. Hallinan and Striphas (2016) argue that Netflix's recommender system contributed to a cultural model in which computational processes shape taste formation. Their analysis presents the Netflix Prize not merely as an engineering competition but also as an attempt to "reinterpret what culture is—how it is evaluated, by whom, and to what ends" (Hallinan & Striphas, 2016: 119). Algorithmic recommendation can therefore be understood as a form of cultural decision-making rather than simply a technical mechanism for matching users with content.

Gomez-Uribe and Hunt (2015) discuss the business value of personalized recommendation from an engineering perspective, whereas Frey (2021) situates recommendation within broader histories of film selection and cultural authority. More recent analyses emphasize that the Netflix Recommender System is a sociotechnical arrangement rather than an isolated mathematical instrument. For instance, Gaw (2022: 706) defines algorithmic logics as "the assumptions, processes, and mechanisms that govern the construction of taste" within the Netflix platform. She identifies datafication, reconfiguration, interpellation, and reproduction as interconnected logics through which Netflix organizes cultural taste while presenting its operations through the language of objectivity, personalization, and user agency. Pajkovic (2022) similarly approaches the Netflix Recommender System from a relational perspective. His reverse-engineering analysis examines the system's commercial and circular operational principles while revealing the "complex and networked nature of taste-making" (Pajkovic, 2022: 214). Recommendation systems can thus influence the distribution and consumption of film and television not by independently determining audience choices, but by operating within networks that include users, algorithms, interfaces, data structures, corporate objectives, catalogue arrangements, and broader cultural contexts.

Taken together, these studies suggest that visibility on streaming platforms is shaped by both personalized and non-personalized mechanisms. Although the country-level Top 10 is non-personalized, it operates within a highly personalized service and forms part of a broader ecology of discoverability. The list should therefore be examined as a distinct but interconnected component of Netflix's wider system for ranking, recommending, promoting, and circulating audiovisual content.

2.2. Streaming Metrics and the Construction of Popularity

Audience measurement has always depended on institutional decisions about which metrics, timeframes, and populations matter. Digital platforms intensify these issues by collecting extensive behavioral data while selectively disclosing only some indicators. Napoli (2011) describes the audience as an evolving institutional construct, while Webster (2014) argues that media structures distribute attention rather than simply reflecting unmediated preferences. In streaming markets, proprietary data enable

platforms to construct narratives of popularity while limiting opportunities for external verification. The resulting asymmetry is both methodological and industrial: platforms possess granular behavioral information, whereas researchers, producers, journalists, and regulators generally encounter selected indicators designed for public circulation. The disclosed metric is therefore not equivalent to the full audience process from which it was derived.

Netflix's public metrics have changed substantially over time. The company initially emphasized household starts, later reported hours viewed, and subsequently introduced a global 'views' metric calculated by dividing viewing time by runtime. Country-level Top 10 files, however, retain only weekly ranks and cumulative weeks in the Top 10. Wayne (2022) argues that Netflix's audience data should be interpreted not only as measurement but also as industrial discourse, while Lotz (2021b) emphasizes the cultural power implicated in streaming-era definitions of popularity and visibility. Public rankings communicate scale and success, normalize particular definitions of popularity, and circulate through negotiations with producers, advertisers, journalists, regulators, and audiences. Their publication therefore performs a dual function: it offers a limited empirical description of content performance while simultaneously producing a communicative object that can travel through entertainment journalism, promotional campaigns, industry reporting, and social media. Popularity is not merely revealed in this process; it is rendered into a platform-defined and publicly recognizable form.

Scarlata (2023: 7) likewise emphasizes "both the data being produced by the top 10 ranking and the broader industrial function of the list." The Top 10 represents only the most visible segment of a much larger catalogue; it is governed by platform-defined rules and cannot independently reveal exposure, promotion, or total demand. Even so, systematic analysis can identify patterns within the disclosed system. Wayne and Ribke (2024: 1348), for example, argue that Netflix's Global Top 10 system "misrepresents both the production and consumption of its most popular geographically diverse global content." Idiz, Noordegraaf, and Vliegenthart (2025: 98) similarly maintain that "a critical and systematic analysis of Netflix's Top 10 can yield insights into viewing trends." These studies show that platform data can be analytically useful when claims remain proportional to what the data actually disclose. This position also accords with work on discoverability, which conceptualizes platform power in terms of coordinating users, content creators, and software to make content more or less visible and engaging (McKelvey & Hunt, 2019).

Accordingly, this study avoids treating the rankings as measures of national audience share, popularity volume, or viewer preference. A rank of 1 means only that Netflix placed an item first within a given country-category-week under its own measurement rules; it does not disclose the magnitude of the gap between ranks 1 and 2, the number of accounts involved, or the demographic composition of viewers. The analysis instead focuses on positional persistence: how long items remain within the visible Top 10 threshold and how rapidly the ten available positions are replaced. The study therefore examines the temporal behavior of the published ranking system rather than attempting to reconstruct the complete viewing behavior of Netflix subscribers in Türkiye. This narrower formulation preserves the analytical value of the dataset without treating ordinal positions as audience totals.

2.3. Film and Television as Distinct Temporal Regimes

Streaming services present films and television programs within a unified interface, yet the two formats retain different temporal affordances. Feature films typically enter the platform as completed, self-contained works. Their visibility may peak around release, acquisition, promotion, or external events, while sustained weekly presence depends on continued discovery or renewed attention. Television content, by contrast, is frequently organized around episodes, seasons, serial narratives, recurring franchises, and viewing completed across multiple sessions. Although streaming has transformed scheduling, release patterns, and binge viewing, it has not eliminated serial formats' capacity to sustain attention over time (Jenner, 2018; Lotz, 2022).

The distinction between film and television needs to be understood within the broader transformation of internet-distributed media. Lotz (2017) argues that subscription portals reorganize television distribution by replacing scheduled channel flows with searchable and on-demand libraries. In this respect, television's temporal organization shifts from broadcaster-controlled scheduling toward combinations of platform release strategies and viewer-controlled consumption. Jenner (2016) describes Netflix's relationship with binge-watching as part of a broader redefinition of contemporary television, while Mikos (2016) argues that video-on-demand services enable flexible viewing practices that extend beyond conventional schedules. Tryon (2015) further demonstrates that Netflix incorporated binge viewing into its industrial and promotional identity, presenting uninterrupted serial consumption as a distinctive feature of on-demand television.

These developments do not make television temporally uniform. Full-season releases may concentrate viewing within a relatively short period, whereas weekly releases can distribute attention across several weeks. Older titles may also return to visibility after a new season, adaptation, promotional campaign,

or renewed public discussion. Nevertheless, television's episodic and seasonal organization creates multiple potential points of entry and re-entry. Films, by contrast, generally lack an equivalent internal serial structure, even when they belong to franchises or gain visibility in response to external events.

This distinction suggests higher churn for films and greater persistence for television content, but it should not be treated as deterministic. Some films achieve long catalogue runs, while some television titles disappear after a single week. Moreover, Netflix's reporting structure itself shapes the comparison: films are generally reported as individual titles, whereas television content is typically reported by season. The empirical comparison is therefore partly between content forms and partly between the classificatory units through which Netflix reports them. A film usually enters the dataset as a single bounded title, while a television franchise may appear across multiple separately ranked seasons. This structure can extend the observable life cycle of television content without reflecting uninterrupted attention to the same season, and it may mechanically contribute to aggregate differences in persistence.

Persistence also has a hierarchical dimension. Items occupying stronger positions are more likely to remain in the ranking in subsequent weeks because a high current position indicates stronger relative performance within that measurement period. However, this association may differ by content format. If television engagement unfolds across more viewing sessions, or if serial attention accumulates, an equivalent current position may correspond to a higher probability of continued presence for TV than for film. The analysis tests this conditional association without claiming that rank causes retention. Rank is treated as a positional predictor within Netflix's disclosed system, while retention may reflect the combined influence of audience activity, promotion, seriality, catalogue placement, recommendation, reporting structure, and events outside the platform.

3. Method

3.1. Research Design and Data Source

The study uses a longitudinal secondary-data design. The primary source was Netflix's official All Weeks – Countries Top 10 dataset, downloaded from the Netflix Top 10 data portal on 28 June 2026 (Netflix, 2026). The dataset contains weekly country rankings from 4 July 2021 through 21 June 2026. Records were filtered to country = Turkey and country_iso2 = TR. The final corpus comprised 5,200 item-week observations across 260 consecutive weeks, with ten film records and ten TV records for each week.

The source file includes variables such as country, week, category, weekly rank, show title, season title, and cumulative weeks in the Top 10. Country-level records do not include views, hours viewed, or runtime; the analysis therefore relies exclusively on ordinal ranking data. All transformations were conducted on a local copy of the official spreadsheet, and the analyses were performed in Python. The observation period is complete through 21 June 2026; consequently, results for calendar year 2026 represent partial-year evidence.

3.2. Operationalization of Visibility and Measures

Table 1. Operational Definitions

Variable	Definition	Range / Coding
Weekly turnover	Number of items in the current week's Top 10 that were absent from the preceding week in the same category	0–10
Item appearances	Number of distinct weeks in which an item appears in the category Top 10	1–260
Next-week retention	1 if an item reappears in the same category in the immediately following week; 0 otherwise	0 / 1
Rank strength	11 minus weekly rank; higher values correspond to stronger (closer-to-rank-1) positions	1–10
Rank-weighted visibility	Sum of rank strength across all item appearances; an analytic index of repeated positional visibility, not audience size	Positive integer
Time	Number of weeks since 4 July 2021	0–259

Source: Author's operationalization based on Netflix country-level Top 10 records.

For empirical purposes, visibility is operationalized only through information observable in the country-level Top 10: whether an item is present, the position it occupies, how long it remains within the ten-position threshold, and whether it returns the following week. Weekly turnover captures replacement within that threshold; item appearances capture persistence; rank strength reverses the ordinal rank so that higher values represent stronger positions; and rank-weighted visibility summarizes repeated positional presence across weeks. These measures describe the temporal and positional structure of Netflix's published ranking output. They do not measure audience size, viewing intensity, interface

impressions, recommendation exposure, or national preference.

3.3. Analytical Procedure

The analysis proceeded in five stages. First, descriptive statistics were calculated separately for films and TV, including the number of unique items, mean and median appearances, the proportion of one-week items, mean weekly turnover, and next-week retention. Second, we compared weekly turnover across categories using a paired-samples t-test because each film observation corresponded to a TV observation for the same week-to-week transition. We also reported a Wilcoxon signed-rank test as a distribution-robust comparison. The standardized mean difference was calculated as paired Cohen's d.

Third, Spearman's rank correlation assessed the association between an item's first observed rank and its total number of appearances. Because lower numerical ranks represent stronger positions, a negative correlation indicates that stronger debuts are associated with longer total presence. Fourth, a binary logistic regression estimated next-week retention as a function of format (TV = 1), rank strength, linear time in weeks, and the interaction between TV and rank strength. Cluster-robust standard errors were calculated by item to account for repeated item-week observations. Predicted probabilities were calculated at the mean time point to facilitate interpretation of the interaction. Fifth, separate linear regressions of weekly turnover on time assessed whether category churn changed monotonically over the observation period. We graphed twelve-week rolling averages for descriptive visualization, while significance tests used the unsmoothed weekly values. All tests were two-sided with alpha = .05. Exact p-values are reported where informative; values below .001 are reported as $p < .001$.

3.4. Ethics and Research Integrity

Because the study analyzes aggregate, publicly available, non-personal secondary data released by Netflix, ethics committee approval was not required. The dataset contains no human-participant interventions, surveys, interviews, user comments, account identifiers, private information, or individual-level viewing histories. No data were collected from social-media profiles or online communities. The analysis code retained only the variables necessary to reproduce the reported statistics. Interpretation is explicitly limited to Netflix's published ranking environment.

4. Findings

4.1. Dataset Profile and Descriptive Patterns

The dataset consisted of 5,200 item-week records: 2,600 film observations and 2,600 TV observations. Across the full period, 1,105 unique films and 719 unique television seasons or items appeared in the lists. The lower number of unique TV items is consistent with greater reuse of ranking positions over time. On average, a film item appeared for 2.35 weeks (median = 2), whereas a TV item appeared for 3.62 weeks (median = 3). One-week appearances were also more common among films (34.2%) than among TV items (27.0%). The category difference was more pronounced at the weekly level. Film lists introduced an average of 4.66 new titles between consecutive weeks, compared with 3.20 new TV titles. Thus, nearly half of the film Top 10 was replaced each week, compared with approximately one-third of the TV list. Correspondingly, the probability that an item reappeared in the following week was 53.4% for films and 68.0% for TV.

Table 2. Descriptive Statistics by Category

Statistic	Films	TV
Ranked item-week records	2,600	2,600
Unique items	1,105	719
Mean item appearances (weeks)	2.35	3.62
Median item appearances (weeks)	2	3
One-week items	34.2%	27.0%
Mean weekly turnover	4.66	3.20
SD of weekly turnover	1.32	1.15
Median weekly turnover	5	3
Next-week retention	53.4%	68.0%

Source: Netflix All Weeks – Countries dataset; author's calculations.

4.2. Weekly Churn and Category Differences

A total of 259 week-to-week transitions were available for paired comparison. Film turnover exceeded TV turnover by an average of 1.46 positions per week. The paired-samples t-test indicated a statistically significant difference, $t(258) = 12.63$, $p < .001$, with a substantial standardized effect size ($d = .78$). The Wilcoxon signed-rank test produced the same inferential conclusion ($W = 3{,}064$, $p < .001$), indicating that the result was not dependent on the normality assumption. Figure 1 presents twelve-week rolling averages to show the temporal pattern while

reducing the influence of single-week fluctuations. Film turnover exceeded TV turnover across nearly the entire observation period. Although both series fluctuated, the category difference persisted rather than being confined to a brief release cycle or a single year.

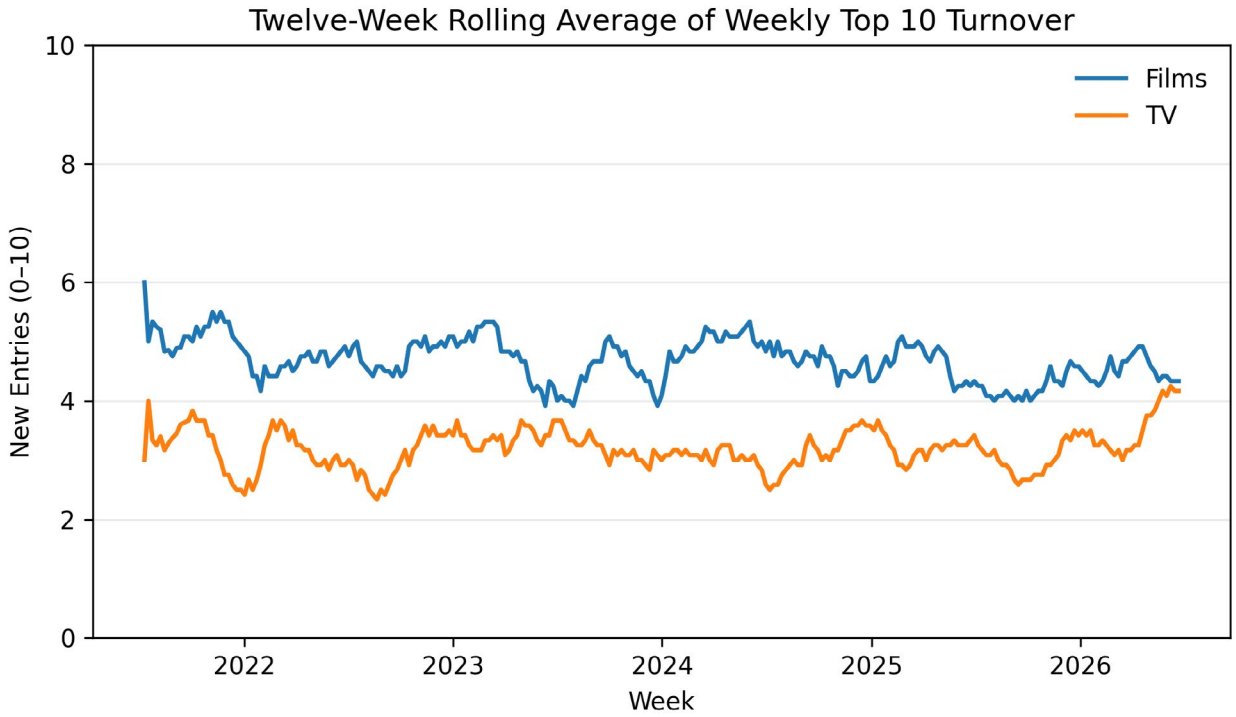


Figure 1. Twelve-Week Rolling Average of Weekly Top 10 Turnover
Source: Netflix All Weeks – Countries dataset; author's calculations. Rolling averages are descriptive; inferential tests use weekly values.

Table 3. Paired Comparison of Weekly Turnover

Series	Mean	SD	N
Films	4.660	1.318	259
TV	3.205	1.152	259
Paired difference	1.456	1.856	259

Note: Paired $t(258) = 12.63$, $p < .001$, Cohen's $d = .78$; Wilcoxon $W = 3{,}064$, $p < .001$.
Source: Author's calculations.

4.3. Rank and Next-Week Retention

An item's first observed position was strongly associated with its total number of appearances. Spearman's rho was -0.560 for films ($p < .001$) and -0.614 for TV ($p < .001$). Because rank 1 is the strongest position and larger rank numbers indicate weaker positions, the negative signs mean that stronger initial placements were associated with more weeks in the Top 10. Reporting the coefficients with explicit minus signs also avoids confusing the inverse numerical coding of rank with the substantive direction of the association. This relationship is descriptive rather than causal; both initial rank and persistence may reflect underlying audience activity, promotional effort, interface exposure, or other unobserved factors.

The clustered logistic regression included 5,180 item-week observations. Rank strength was the strongest predictor in the model. For films, each one-unit increase in rank strength was associated with a 58.4% increase in the odds of next-week retention (odds ratio = 1.584, 95% CI [1.528, 1.644], $p < .001$). The interaction between TV and rank strength was also positive (odds ratio = 1.141, 95% CI [1.076, 1.209], $p < .001$), indicating a steeper association between strong current position and continued presence for TV. The linear time coefficient was not significant. The main effect of TV was marginal when rank strength was set to zero, which lies outside the observed 1–10 range; substantive interpretation should therefore rely on predicted probabilities rather than on that isolated main effect.

At the mean time point, a film ranked first had an estimated 90.6% probability of remaining in the Top 10 the following week, compared with 60.4% at rank 5 and 13.2% at rank 10. The corresponding probabilities for TV were 98.0%, 81.8%, and 18.9%. Figure 2 shows that the gap between categories is especially pronounced in the middle and upper ranks. Within the fitted model, strong placement combined with TV category membership was associated with the highest predicted probability of continued weekly visibility.

Table 4. Clustered Logistic Regression Predicting Next-Week Retention

Predictor	b	Clustered SE	Odds Ratio	95% CI	p
Constant	−2.377	0.130	0.093	0.072–0.120	< .001
TV	0.290	0.159	1.337	0.978–1.827	.069
Rank strength	0.460	0.019	1.584	1.528–1.644	< .001
Linear time	0.0003	0.0005	1.000	0.999–1.001	.583
TV × Rank strength	0.132	0.030	1.141	1.076–1.209	< .001

Note: N = 5,180 item-week observations; cluster = item; McFadden pseudo R^2 = .276. Rank strength = 11 − rank.
Source: Author's calculations.

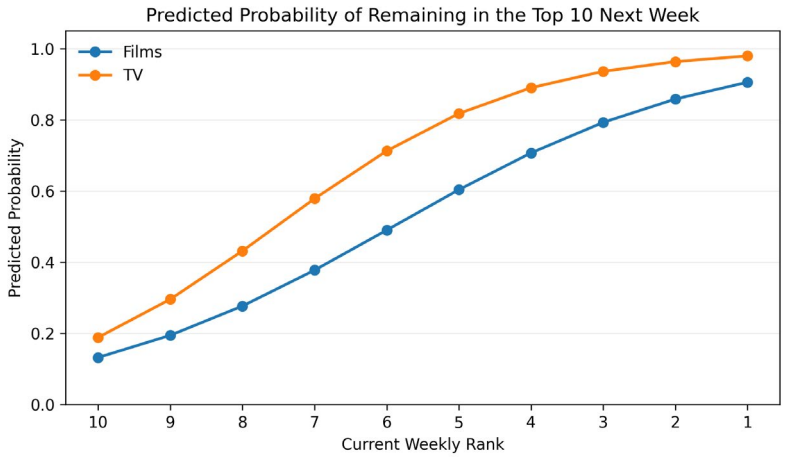


Figure 2. Predicted Probability of Remaining in the Top 10 Next Week
Source: Author's estimates from the clustered logistic regression at the mean time point.

4.4. Concentrated Visibility and Long-Running Items

The rank-weighted visibility score identifies items that combined strong chart positions with repeated appearances. In the film category, KPop Demon Hunters was the clearest outlier, accumulating 150 points over 29 weeks and an uninterrupted run of 23 weeks. Red Notice followed with 80 points across 13 weeks. In the TV category, Gupi: Season 1 accumulated 216 points across 34 consecutive weeks, while Squid Game: Season 1 and Kral Kaybederse: Season 1 recorded 186 and 176 points, respectively.

These cases illustrate why duration and position should be considered together. A title can obtain a high score by maintaining a very strong position for a shorter period or by sustaining moderately strong positions over a longer period. The score is intentionally simple and transparent, but it remains an index of positional visibility rather than audience magnitude. It cannot distinguish whether continuity reflects new viewers, repeat viewing, season completion, interface exposure, external publicity, catalogue conditions, or other mechanisms.

4.5. Temporal Stability

Although week-to-week variation was evident, turnover showed no statistically significant linear trend over the full observation period. For films, the estimated slope was -0.0019 positions per week (p = .076); for TV, it was 0.0010 (p = .282). There is therefore insufficient evidence that the ranking environment became systematically more or less volatile between July 2021 and June 2026. The persistent difference between categories is more notable than any linear temporal trend: film rankings consistently showed higher turnover than TV rankings, despite fluctuations tied to particular release cycles.

5. Discussion

The first major finding is that film and TV rankings operate with different temporal rhythms. Films showed substantially higher turnover: on average, 4.66 of the ten positions changed each week, and more than one-third of film titles appeared only once. Rather than treating this pattern simply as a difference in content popularity, it is more productively interpreted through platform visibility and ranking cultures. The Top 10 functions as a limited visibility threshold in which entry by one title necessarily coincides with displacement pressure on others. In

this sense, the film list organizes attention through relatively rapid cycles of appearance and replacement. The exceptional persistence of titles such as K-pop Demon Hunters and Red Notice does not negate this pattern; instead, it demonstrates that durable visibility is possible within an otherwise high-churn ranking environment.

Table 5. Highest Rank-Weighted Visibility Scores by Category

Category	Item	Score	Weeks	Mean Rank	Longest Streak
Films	KPop Demon Hunters	150	29	5.83	23
	Red Notice	80	13	4.85	13
	Untouchables	70	9	3.22	9
	Chasing the Wind	65	12	5.58	10
	Brother in Love 2	63	10	4.70	9
TV	Gupi: Season 1	216	34	4.65	34
	Squid Game: Season 1	186	27	4.11	16
	Kral Kaybederse: Season 1	176	28	4.71	18
	Wednesday: Season 1	169	27	4.74	13
	Another Self: Season 1	144	21	4.14	14

Note: Score = Σ(11 − weekly rank). Ties are ordered by total weeks; only the five highest items per category are shown.
Source: Netflix All Weeks – Countries dataset; author's calculations.

This temporal perspective extends the analysis of discoverability beyond a single chart snapshot. As Rieder, Matamoros-Fernández, and Coromina (2018) suggest, rankings modulate visibility by continuously ordering a limited set of items, while McKelvey and Hunt's (2019) concept of discoverability emphasizes the platform's role in coordinating content, interfaces, and users. Repeated Top 10 lists therefore produce a temporal organization of attention: some titles receive brief bursts of public prominence, whereas others occupy the visible threshold for longer periods. For films, the ranking sequence is characterized more strongly by replacement and short-duration visibility. A single Top 10 appearance should consequently not be treated as evidence of lasting popularity; duration, recurrence, and position provide a more defensible description of what the ranking data actually show. The data cannot determine whether release strategy, audience behavior, marketing, interface design, or some combination of these factors produced this pattern.

TV content followed a more persistent pattern. TV items remained in the ranking longer and were more likely to reappear the following week, particularly when they already held strong positions. This is compatible with the temporal affordances of serial viewing, in which episodes and seasons can distribute engagement across multiple sessions and sustain discussion over time. However, the difference should not be attributed to serial audience behavior alone. Netflix's reporting structure is itself consequential: a television season aggregates multiple episodes under one ranked entry, whereas a film is generally reported as a single bounded title. Season labels, episode counts, release schedules, franchise recognition, recommendation, and promotional practices may therefore contribute to the greater persistence observed for TV. The interaction between category and rank strength should be read within this measurement context. At rank 5, for example, the fitted probability of next-week retention was more than twenty percentage points higher for TV than for film, but this gap describes the behavior of Netflix's ranking categories rather than an isolated causal effect of seriality.

These findings also clarify the distinction between platform visibility and audience demand. Country Top 10 lists indicate which titles crossed Netflix's public visibility threshold, their relative positions, and how long they remained there, but they do not reveal how many people watched, how long they watched, who watched, or the magnitude of the difference between adjacent ranks. A movement from rank 2 to rank 5 can result from changes in the focal title, changes in competing titles, or both. Likewise, disappearance from the Top 10 does not imply that viewing ceased; it indicates only that the title no longer occupied one of the ten reported positions. In Wayne's (2022) terms, the ranking is both data and industrial discourse: Netflix defines the measurement rules, categories, and public presentation through which 'popularity' becomes visible. The present results therefore support a cautious use of ranking claims in research, journalism, and promotion. Two items may both be described as Top 10 titles while exhibiting radically different trajectories of persistence and positional strength. The study also illustrates an approach to platform research that

relies on official aggregate data rather than individual-level traces. Studies based on profiles, comments, or scraped user data can raise ethical and legal questions even when material is publicly accessible. Official ranking files permit analysis of platform-level temporal patterns without accessing personal data. Nevertheless, the absence of personal data does not remove researchers' obligations to document sources, specify transformations, avoid overinterpretation, and distinguish public platform outputs from private audience behavior.

5.1. Limitations and Future Research

Several limitations constrain this study's conclusions. First, ordinal ranks conceal the magnitude of differences between positions, preventing estimation of how many views separate two ranks or comparison of absolute audience size across weeks. Second, Netflix controls the ranking rules and underlying data, which cannot be independently audited. Third, the models exclude potentially relevant variables such as release dates, genre, origin, language, runtime, marketing intensity, recommendation exposure, catalog availability, and external events. These omitted factors may influence both current rank and persistence.

Fourth, the film-TV comparison partly reflects Netflix's internal reporting units rather than content form alone. Television seasons aggregate multiple episodes under a single ranked entry, whereas films generally enter as individual titles. This asymmetry may create a structural opportunity for longer observed persistence in the TV category and should temper any interpretation that attributes the entire category gap to audience behavior or seriality. Fifth, the analysis is limited to one national market and cannot establish whether the observed category difference generalizes to other countries. Sixth, 2026 data are available only through 21 June. Finally, rank-weighted visibility is an analytic index developed for this study; it is neither an official Netflix metric nor a validated measure of audience value.

Future research could extend the design to multiple countries, test whether the film-TV persistence gap varies across markets, and integrate rankings with verified release and catalog metadata. Event-history or multilevel models could estimate duration while accounting for repeated seasons, franchises, and market-level variation. Further work could examine re-entry after absence, the effect of new-season releases on older seasons, or the relationship between global and national trajectories. Such research would be especially valuable if it could separate the temporal effects of content form from those of Netflix's reporting units. Across these extensions, rankings should continue to be treated as partial platform disclosures rather than comprehensive representations of cultural demand.

6. Conclusion

Analysis of Netflix Türkiye's Top 10 rankings across 260 consecutive weeks reveals two distinct temporal patterns of platform-produced visibility. Film rankings changed more rapidly and experienced greater weekly replacement, whereas TV rankings showed greater persistence. On average, 4.66 film positions changed between consecutive weeks, compared with 3.20 TV positions. TV items also appeared for more weeks and had a higher probability of retention on the next week. Current rank strength was strongly associated with continuity, and this association was steeper for TV. Neither category, however, exhibited a statistically significant linear trend in turnover over the observation period.

These findings clarify what can—and cannot—be inferred from platform rankings. Netflix's country-level Top 10 does not directly measure national taste, audience size, or viewing intensity; it constitutes a recurring, platform-defined threshold of relative visibility. Examining ranking sequences rather than isolated weekly snapshots makes it possible to distinguish fleeting from durable visibility and to analyze the temporal organization of attention. At the same time, the greater persistence of TV must be interpreted partly in light of Netflix's reporting structure, which aggregates multiple episodes within season-level entries. The study's broader methodological principle is one of interpretive proportionality: ordinal platform data can support robust claims about position, persistence, retention, and churn, but not about unobserved audience magnitude, individual preference, or causal mechanisms.

Ethics Committee Approval

Not required. The study uses aggregate, publicly available, non-personal secondary ranking data and involves no human participants or identifiable private information.

Informed Consent

Not applicable.

Conflict of Interest

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Data Availability

The raw dataset is publicly available through Netflix's Top 10 data portal. The filtered Türkiye dataset and analysis code are available from the corresponding author on reasonable request.

Artificial Intelligence Use Declaration

During manuscript preparation, OpenAI's ChatGPT was used to assist with language editing, structural organization, and code debugging. The author independently checked the source data, statistical outputs, references, interpretations, and final text and assumes full responsibility for the manuscript.

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