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Binge-Watching Netflix? Insights From Data Donations

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Abstract

Netflix is often credited with mainstreaming binge-watching through its release strategy and interface features. However, despite this reputation, data on actual consumption patterns remains scarce, enabling Netflix to shape the narrative about how content is consumed on its platform and what this implies about content quality and viewer attentiveness. This article provides unique empirical insights into Netflix viewing patterns in the Netherlands, based on a pilot study involving data donated by 126 subscribers. It introduces a definition of binge-watching tailored for computational analysis and offers an empirical understanding of its prevalence and manifestations. The findings suggest that binge-watching is a diverse and complex activity. While it is seemingly popular, in that it is practiced by many subscribers, the data suggest it occurs less frequently and is less extreme than would be expected from the hype.

Keywords

binge-watching; data transparency; Netflix; streaming; viewing patterns

1. Introduction

In 2013, streaming service Netflix released all episodes of the first season of its original series *House of Cards* simultaneously, breaking with television's traditional model of scheduled programming. Consequently, the series and follow-up releases were linked to the concept of *binge-watching*, i.e., the consumption of multiple episodes of a TV show in one viewing session. Originally associated with fan cultures, binge-watching gained widespread popularity and entered the mainstream largely due to Netflix's influence (Jenner, 2017). Its significance was further highlighted when binge-watching was selected as the Collins Word of the Year in 2015 ("'Binge-watch'—Collins word of the year 2015," 2015). In its early promotional campaigns, Netflix consistently emphasized binge-watching as a form of viewer control. In 2013, Ted Sarandos, then chief content officer, stated, "Our own original series are created for multi-episodic viewing, lining up the content with new norms of viewer control for the first time" (Netflix, 2013). The company framed its release strategy as "giving people what they want" and celebrated its technological achievement in understanding audience behavior (Jenner, 2020, p. 270). While many other streaming services initially followed suit, they have since abandoned the binge-release strategy due to their inability to sustain long-term engagement. Netflix, however, remains committed to it—at least for the time being. The uncritical adoption of the term binge-watching by researchers has been criticized by Turner (2021), who argues that it hinders our understanding of contemporary consumption practices. In part, this is because no standard of the term exists, and perceptions and operationalizations of binge-watching are too diverse (Mikos & Castro, 2021, p. 112). Our assumptions about binge-watching, Turner argues, could differ significantly when supported by empirical research (Turner, 2021, p. 235). A major obstacle for such research is the lack of access researchers have to consumption data from streaming platforms. Netflix, for instance, maintained a policy of non-transparency regarding viewership data until late 2018, when it began selectively sharing data about its original series (Wayne, 2022). This trend toward increased transparency progressed with the 2021 release of datasets on the top 10 Netflix titles and continued in late 2023 with the launch of the bi-annual *Netflix Engagement Report* ("What we watched," 2023). However, as Lotz (2023) notes, "Netflix is only sharing information it wants to share." Even today, the number of subscribers watching specific content items remains vague. Empirical data are crucial for researchers analyzing streaming services to better understand their role in culture and society.

Several scholars (Lotz, 2021a; McKenzie et al., 2023; Scarlata, 2023) have tried to analyze usage patterns by analyzing top 10 data or datasets released by Netflix. These studies faced many limitations in dealing with many unknowns. A promising new path towards empirically grounded research into binge-watching is so-called "data donations," i.e., the voluntary sharing of user data for research purposes, made possible by the EU's General Data Protection Regulation (GDPR). Based on Netflix digital trace data donated by 126 subscribers in the Netherlands, this article seeks to answer the research question: What are the prevalence and key characteristics of binge-watching behavior among Netflix users in the Netherlands in 2023?

In this article, we first explore the lack of data transparency around streaming services such as Netflix and how this enables them to define their own success without providing space for scrutiny. We then reflect on the various ways that binge-watching has been researched, the problems with the term's fuzziness, and the lack of empirical studies that would help evaluate Netflix's narratives. Subsequently, we elaborate on our data donations methodology, the data donation packages we received, and how we analyzed these data. Here, we provide our operationalization of binge-watching and analyze how users consume content on Netflix, examining not only the prevalence of binge-watching but also how it happens—including which devices are used, at what times, and which shows are watched. In the conclusion, we reflect on the limitations of the study, the implications of our findings for the understanding of contemporary viewing practices, and avenues for further research.

2. Theoretical Framework

2.1. Netflix and the Mainstreaming of Binge-Watching

In 2013, Netflix commissioned Harris Interactive to conduct an online survey of nearly 1,500 TV streamers about how viewers watch its content. The study found that binge-watching is popular, with 61% of respondents reporting that they binge-watch regularly, meaning that they watch 2–6 episodes of the same TV show in one sitting. The survey concluded that binge-watching makes shows more enjoyable and that 51% prefer to binge with at least one other person (Netflix, 2013). Boldened, in part, by this survey, Netflix positioned binge-watching as "the new normal" and claimed to have introduced innovative storytelling practices that lead to more attentive viewing (Tryon, 2015). In its promotional discourses, Netflix has used binge-watching to position itself as improving upon traditional television (Wayne, 2022).

Netflix has encouraged binge-watching not only by releasing entire series at once but also through interface features like "skip intro" and "post play" (Jenner, 2023, p. 135). As Jenner (2023) highlights, these strategies have played a role in integrating binge-watching into mainstream television culture. However, the practice of binge-watching has a much longer history, with scholars linking it to earlier control technologies such as VCRs (Kompare, 2005) and DVDs (Brunsdon, 2010). As van Es (2024) cautions, we should critically assess Netflix's narratives about the status of binge-watching on its platform rather than accepting them at face value and reproducing them in academic publications. A key challenge in doing so lies in gaining access to consumption data.

In audience studies, the concept of binge-watching has been examined through various approaches. From a uses and gratification perspective, research has focused on the motivations and needs driving this behavior (e.g., Pittman & Sheehan, 2015; Steiner & Xu, 2020). Binge-watching has also been analyzed as a broader audience practice, highlighting behaviors like the "distracted" or "casual" binge-watcher (Tryon & Dawson, 2014). Additionally, there is a tradition of examining television use in everyday life and domestic spaces, providing a deeper understanding of how media consumption structures daily routines and home environments (Bury, 2018; Evans, 2011; Mikos & Castro, 2021). Earlier work in the field of fan studies examined how binge-watching of DVD box sets transformed television consumption (e.g., Hills, 2007; Kompare, 2005).

Turner (2021, p. 231) has rightfully criticized the widespread use of the term binge-watching, arguing that it has been applied to characterize so many different viewing practices. Noting the dominance of a textualist tendency in existing research, he calls for more empirical research. More specifically, he remarks:

> The most curious aspect of television studies' examination of binge-viewing is how little research has involved observing actual audience behavior and how much of the discussion of binge-viewing has been prosecuted instead through the analysis of a select group of television texts, most commonly *Breaking Bad* and *House of Cards*. (Turner, 2021, p. 233)

Most studies that have focused on audiences, he argues, rely on surveys, interviews, or focus groups instead of direct observation. Significantly, self-reported data have been shown to be affected by recall bias or social desirability bias, leading to potential inaccuracies (Wu-Ouyang & Chan, 2023). As such, trace data from Netflix may, despite its own biases and limitations, offer a valuable contribution to the understanding of audience consumption.

In television studies, the concept of binge-watching has been defined in various ways, and it lacks a universally accepted definition (Mikos & Castro, 2021, p. 112). Most definitions, however, share a common focus on viewers watching multiple episodes of the same series rather than episodes from different series or films

(Jenner, 2023, p. 132). Pierce-Grove (2021, p. 98) highlights that discussions about binge-watching often emphasize the number of episodes consumed rather than the total time spent viewing. She explains that episodes act as natural decision points, where viewers decide to keep watching or stop.

2.2. Lack of Data Transparency

Data on audience consumption are scarce. Netflix maintained an anti-transparency data policy until late 2018 when it began selectively releasing data for its original series (Wayne, 2022). A significant policy shift occurred in 2021 with the release of three datasets showcasing the top 10 titles, though these did not include viewing hours. This trend towards greater transparency continued in late 2023 with the introduction of the first bi-annual *Netflix Engagement Report*, detailing six months of content viewing hours, release dates, and content availability. The second report, following criticisms of the first, was said to offer several improvements. Here, they separated films and series and added runtime as well as views (calculated as total hours viewed divided by runtime). These data disclosures can be discussed as a shift to what we propose to call a phatic data policy, in that the release of these datasets is designed to be a performance of transparency with the aim of building a relationship of trust rather than providing meaningful insight into consumption on the platform. Researchers still lack the data needed to evaluate the cultural and societal significance of Netflix and its content. Consequently, they often turn to the limited data that have been strategically shared, the use of proxies such as the top 10 feature, or small-scale qualitative research methods that rely on self-reported information.

2.3. Studies With Real-Life Interaction Data

Given the lack of transparency, both present and past, it is unsurprising that studies on video-on-demand (VoD) services and binge-watching using actual interaction data are extremely rare, with only a handful of such studies available. Trouleau et al. (2016), for instance, analyzed a sampled set of 3,488 anonymized users from a US-based pay-per-content VoD service over a 16-month period from 2014 to 2016. Their study found that while binge-watching accounts for 22.2% of all viewing sessions, it is not a consistent behavior. In fact, 64% of users in their dataset binge-watch at least once, and 11% engage in hyper-binge at least once. These results are almost a decade old, and consumption patterns have likely changed since then. Additionally, viewing habits in a specific cultural setting and on a pay-per-content model likely differ from those of a subscription-based service like Netflix and data collected from the Netherlands.

A more exploratory study by Castro et al. (2021) examined 40 Netflix viewing sessions from 11 millennials in their homes over a 10-day period. The researchers combined data from a browser extension that tracked interactions with the Netflix interface with information from questionnaires. Their study found that binge-watching sessions were more frequent on weekdays than weekends, and that the most popular times to binge-watch were during the evening and night. The average binge-watching session among their participants lasted 2 hours, 10 minutes, and 40 seconds.

Similar to Castro et al., Shao (2024) used the Netflix Viewing Stats browser extension to capture profile-specific activities across various devices and conducted interviews. The study involved a small sample of 31 participants in the US who submitted their viewing data over a one-week period in 2020. Although their primary research focus was not on binge-watching, the findings indicated that repeat viewing (or binge-watching) was common, with Netflix usage in general peaking at prime-time hours (8 PM–11 PM). A big caveat, however, is that the data collection period coincided with the Covid-19 pandemic. This period is known to have significantly increased streaming video consumption, likely skewing the results.

Overall, these empirical studies show that binge-watching is a popular practice, but they also emphasize the variability in binge-watching behavior. However, questions remain regarding the generalizability of these findings. The latter two studies, in particular, underscore the difficulties in acquiring reliable viewing data, often leading to small sample sizes, limited demographic representation, and limited time frames being covered by the dataset.

3. Methods: Data Donations

In this pilot study on Netflix binge-watching, we make use of the data donations framework as laid out by Boeschoten et al. (2022). Under the GDPR, citizens have the right to access and receive a copy of their personal data from data processors such as Netflix. The data donations framework enables users to share their profile data from different online platforms and digital services with researchers in a privacy savvy way.

For practical reasons, the present study focuses on the Netherlands. In September 2013, Netflix entered the Dutch media landscape, and since then, competition has expanded significantly. Nonetheless, Netflix dominates the subscription video-on-demand (SVoD) market and is accessible in nearly half of all households in the Netherlands (49%), significantly surpassing its closest competitor, RTL Videoland, which has a market share of 20% ("Netflix dominates Dutch streaming market," 2023). However, many streaming platforms are experiencing financial difficulties, and there is a slowdown in the previously rapid market growth (Commissariaat voor de Media, 2023). This explains the recent crackdown on Netflix password sharing, which was implemented to discourage users from sharing accounts and to encourage them to get their own subscriptions.

For our study, Netflix subscribers in the Netherlands were asked to share their data as Data Download Packages (DDPs) to research consumption behavior. In collaboration with the panel recruitment company Ipsos I&O, 401 respondents were invited to complete a survey on their Netflix usage and then asked to share their Netflix data via a secure sharing portal, Port (Boeschoten et al., 2023). This platform, integrated into participants' web browsers, extracts only the data relevant to the study from their DDPs. Participants could review and delete any data they did not wish to share before donating. Only data from the main account holders, who gave consent, were collected, and respondents identified their personal profiles to ensure only their data were included.

The 401 respondents were recruited via panel sampling to include different demographic backgrounds. The average range for all respondents was 49 years, with a range from 18 to 65. They also evenly split into male and female respondents (52% vs 48%, respectively). Of all respondents, only 126 (31.4%) successfully donated their data. The average age of respondents who donated their data is 41.9 years, with a range from 18 to 71. The majority identifies as male (61.1%), with noticeably fewer female respondents in the sample (38.9%). Most respondents share their Netflix account within the same household (70.6%) but fewer do so with others outside of their household (31%). Compared to all survey respondents, the subsample of users who donated their data is, on average, younger and more skewed towards male respondents.

To address the research questions, the different computational analyses of content consumption primarily relied on viewing activity data. Furthermore, the analysis only focused on TV shows. Inspired in part by Turner (2021, pp. 236–237), the main goals were to explore:

- How many users engaged in binge-watching, and what percentage of the total viewing sessions did binge-watching account for?
- At what times of the day and week is binge-watching most prevalent among Netflix users, and what devices are most frequently used for binge-watching?
- Which Netflix series had the highest number of unique binge-watchers, and to what extent do users overlap with the series they binge?
- What clusters of binge-watchers can be identified based on patterns of day–time combination, show length (short vs. long), preferred device type, number of sessions, and average session length?

All analyses were executed in Python 3.

Relying on interaction data to explore binge-watching is not without limitations and uncertainties. Netflix's approach to predicting user behaviors and preferences relies heavily on this data without considering the underlying motivation behind users' actions. This practice has been described by Rouvroy (2013, p. 143) as "data behaviorism." Likewise, while we can identify patterns, we cannot explain them. That would require additional, more qualitative methods. Put differently, interaction data reduce the complexities of human behavior and often lacks contextual meaning (boyd & Crawford, 2012, p. 670). For example, account sharing on Netflix blurs lines between what different users are doing on the platform. Additionally, for some users, Netflix is seen as "a kind of electronic companion or video wallpaper" (Tryon & Dawson, 2014, p. 227). This challenges the assumption that every interaction equates genuine interest and highlights the inherent uncertainty as to whether viewers are actively watching. Moreover, as van Dijck (2014, p. 199) notes, platforms are not neutral intermediaries; rather, they are influenced by technological and commercial biases. These biases influence what data are collected; prioritizing information relevant to their business objectives. Nevertheless, analyzing interaction data can provide useful insights into general consumption patterns and trends, helping to interrogate Netflix myths.

3.1. Defining Binge-Watching

Based on a transdisciplinary review, Merikivi et al. (2020, p. 702) propose a convergent definition of binge-watching as the "consumption of more than one episode of the same serialized video content in a single sitting at one's own time and pace." While the definition has been criticized for the low number of episodes (Mikos & Castro, 2021, p. 112), it is useful for our purposes because it provides the following clarifications. Binge-watching concerns: serialized video content (TV series) and watching the same series consecutively in one session.

Serialized content describes TV shows that consist of several episodes and, possibly, seasons. To watch a series or "show" consecutively within a session means that several episodes are watched in a row. Nonetheless, the definition still raises some methodological challenges. For starters: How do you count the consumption, or rather "views," of an episode? If we turn to Netflix, they had originally defined a view as completing at least 70% of an episode or movie. However, in 2019, they redefined a view as watching two minutes of the content item, which, to them, sufficiently indicated the intent of viewing. This definition was also short-lived, highlighting the subjective and constructed nature of what constitutes a "view." Presently, Netflix measures views by dividing the total hours watched by the total runtime of a show or movie. This approach is frustrating for our understanding of the popularity of content because it obscures the actual number of unique viewers, as repeated viewings are also included in the calculation.

An equally important aspect of defining binge-watching is the question of what counts as a single session. Castro et al. (2021, p. 9) consider a viewing session as "any viewing activity that is bounded by 15 min of non-viewing before and after," arguing that a longer break would break immersion. However, we found this "rule" too strict (e.g., watching six episodes of a series at night and having a 45-minute break between episodes three and four would have been treated as two separate sessions). After inspection of examples for different thresholds, we observed that lower thresholds seemed more prone to splitting what actually appeared to be single sessions. Eventually, we found that a 60-minute interval best matched the intuitive understanding of a session, as most inspected examples looked like completed, separate sessions in comparison to one another; this threshold also aligned with the duration set in a previous study (Trouleau et al., 2016). Furthermore, while Merikivi et al. (2020) suggest considering individual viewing patterns as a basis to more accurately operationalize binge-watching based on users' personal pace, our more uniform approach is sufficient for the general exploration of content consumption.

To identify sessions we first, for each user ID, checked the time difference between consecutive activities (interacting with a title on Netflix). If the gap between activities exceeded 60 minutes, the session was marked as "completed," and a new session began. Titles watched consecutively with breaks of less than 60 minutes were grouped into the same session. This approach ensures that all viewing activities within a 60-minute window are considered part of the same session. Additionally, at least one title needed to be fully watched for the session to be valid. Finally, we assigned session IDs to these groups of titles.

To identify binge sessions, however, further criteria needed to be included. We decided to operationalize a binge session as follows:

- A session must have at least three watched items, with at least two of them marked as fully watched (at least 70% viewed of the total runtime).
- In addition, a session must consist mostly of episodes from the same show, meaning that more than 50% of the items in the session come from a single show.

Sessions meeting the above criteria are labeled as "Binge" in the original dataset, while all other sessions are marked as "Non-Binge."

In this article, we focus on viewing data for TV shows in the year 2023. By default, Netflix viewing data have interaction data for watched titles per user, including a user ID, start time, number of hours watched, title name, and device used. We enriched the data by labeling each title for its content type (TV Show, Movie, Documentary, Other), the show title where applicable (since the default data list individual episodes), the release year, total runtime, percentage watched, and an indication whether a title was fully watched or not (based on a 70% threshold).

The final dataset included 51,635 individual interactions with TV shows on Netflix in 2023 for 126 users. These were grouped into 10,519 sessions, of which 3,389 sessions (32.2%) met our criteria to count as a binge session. The following analyses focus only on the binge sessions.

4. Analysis

4.1. How Popular Is Binge-Watching?

We have found various metrics that support the claim that binge-watching, under our lenient definition, is fairly popular (in terms of how many people do it) and common (in how frequently it occurs). Our dataset for 2023 includes a total of 15,958 hours spent watching TV shows on Netflix, with 8,537 hours (53.5%) being part of binge-watching sessions. In that year, 116 users (92%) had at least one binge-watching session. After removing 10 extreme outliers from the analysis, the average number of binge sessions per user was 21.5. The most common number of sessions (mode) was 2, while the median number of sessions was 18.5.

Excluding eight outliers (based on interquartile range), the average length of a session is roughly 2.28 hours, with the median session duration close to 2.14 hours. The mode session length is 2.06 hours, suggesting a frequent pattern of sessions lasting just over 2 hours. The shortest session is 0.47 hours (around 28 minutes). This concerned a user who watched two full episodes of *Gudetama: An Eggcellent Adventure*, a Japanese series with a runtime of 10 minutes per episode. This finding immediately raises questions about how we have chosen to define binge-watching, as it likely wouldn't be intuitively categorized as bingeing by most people. Still, these are rare exceptions, and most users watch content that is considerably longer. The longest binge session in our corpus is just under 5 hours.

On average, we found that users watched approximately 3.1 full episodes per binge-watching session, with adjustments made for outliers. The median is 3 episodes, indicating that half of the session consists of 3 or more episodes. The most common number of episodes watched (the mode) is 2, while the standard deviation is 1.25, reflecting moderate variation in the number of episodes watched. The number of episodes watched per session ranges from a minimum of 2 to a maximum of 7, suggesting that most binge-watching sessions consist of a relatively small number of episodes. These results highlight a tendency for users to watch between 2 and 3 episodes during a typical binge session.

Since there is no universally accepted definition of binge-watching, and we opted for a more lenient one, we felt it important to consider the impact of adjusting our definition and explore how it might affect the understanding of binge-watching. Table 1 shows that, with higher thresholds for watched content items, the overall proportion of binge sessions declines. The (near) identical percentages for total sessions and weekly average sessions indicate a consistent distribution. Overall, we see that while more "extreme" binge-watching occurs, it only seems to account for a small fraction of all sessions. Overall, however, bingeing remains fairly popular and common. This aligns with previous empirical research using log data (Shao, 2024; Trouleau et al., 2016). It is also important to note that the percentage of users engaging in binge-watching, regardless of which threshold is used, is significantly higher than the 2016 findings from Trouleau et al. for pay-per-content services (Trouleau et al., 2016). It is also much higher than reported in the 2013 Netflix-commissioned study (which relied on self-reported data, potentially leading to underreporting, but also used a two-episode threshold; Netflix, 2013).

Table 1. Comparing definitions: changing the threshold (adjusted for outliers).

	2 watched	3 watched	4 watched	5 watched	6 watched
# users	116 (92%)	108 (86%)	88 (70%)	69 (55%)	53 (42%)
% total sessions	32.2	14.8	8	4.7	2.8
% weekly average sessions	32.1	14.8	8	4.7	2.8

4.2. When Do Users Binge?

Figure 1 shows the number of binge sessions over the course of 2023, highlighting weekends (orange) and selected holidays in the Dutch calendar (red: Easter, Liberation Day, King's Day, Ascension Day, Christmas, New Year's Day, Pentecost). Here, peaks for binge-watching sessions appear throughout the year, but notable spikes coincide with weekends and holidays. A more in-depth analysis shows that the average number of binge sessions mostly happened on weekends. On average, there were 8.99 sessions on working days compared to 11.47 sessions on weekends. A two-sample t-test was conducted to compare the average number of sessions on working days and weekends. There was a significant difference in the number of sessions between working days (M = 8.99, SD = 3.11) and weekends (M = 11.47, SD = 3.71), $t(363) = -6.50$, $p < .001$. Binge sessions are seemingly not exclusive to weekends and holidays.

Another important factor influencing binge-watching appears to be the time of day. Figure 2 shows the frequency of sessions per hour of the day (i.e., how many were started at that hour). Most binge-watching sessions occur in the evening, accounting for 41% of the total, while 36.5% take place in the afternoon. Morning sessions are less common, making up 16.9% of the total, and nighttime sessions are the least frequent at 5.4%. For this analysis, the sessions were further categorized into four time periods: Morning (6 AM–12 PM), Afternoon (12 PM–6 PM), Evening (6 PM–12 AM), and Night (12 AM–6 AM). A one-way ANOVA revealed a significant effect of time of day on the number of binge-watching sessions, $F(3, 1143) = 155.75$, $p < .001$, with evening (M = 3.92, SD = 1.85) showing the highest number of sessions, followed by afternoon (M = 3.53, SD = 1.91), morning (M = 2.01, SD = 1.14), and night (M = 1.19, SD = 0.51).

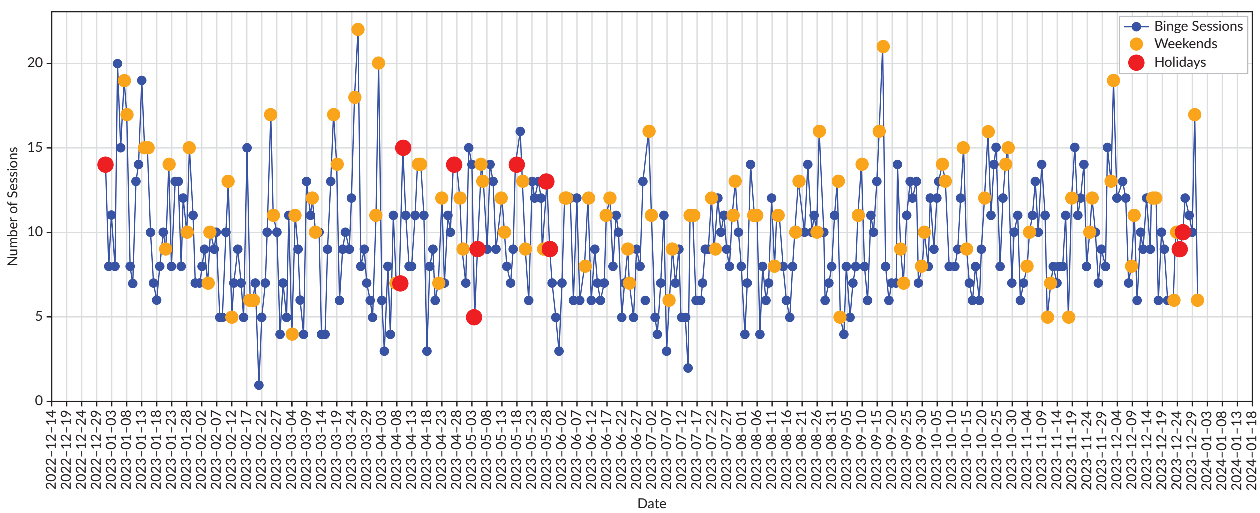

Figure 1. Binge sessions over time.

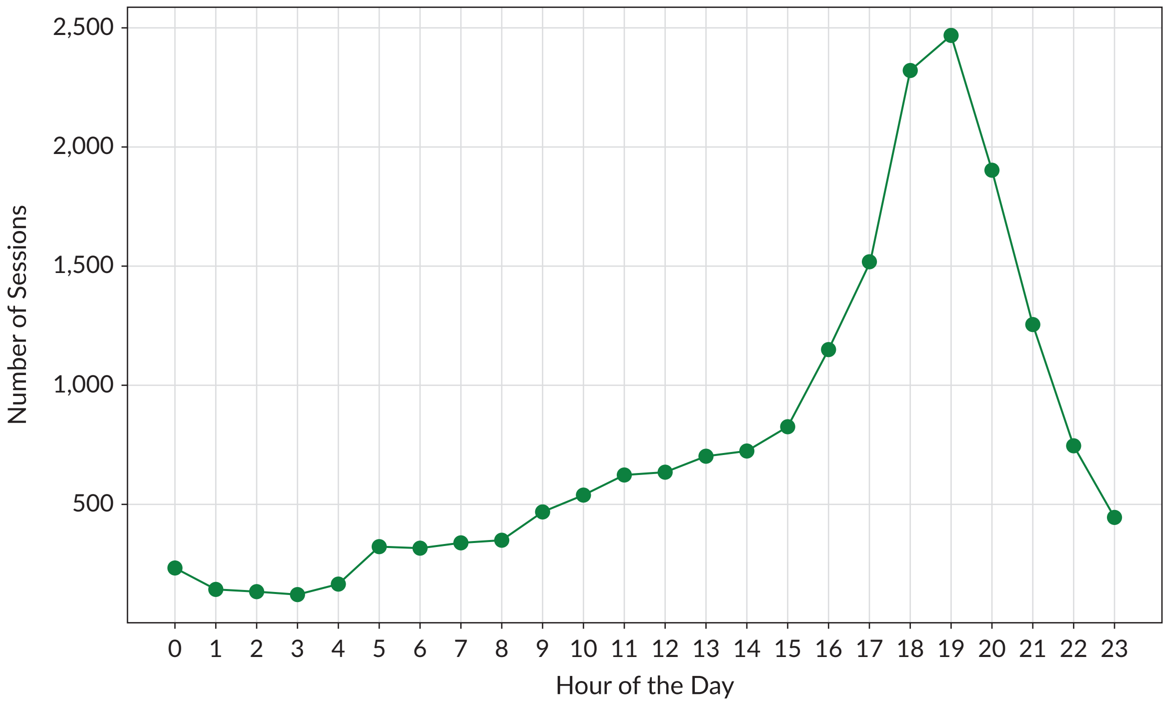

Figure 2. Number of sessions over the day.

Zooming in on common day and time combinations for binge-watching sessions (Figure 3) reveals a preference for evenings, particularly on weekdays. Notably, 19.5% of all binge sessions occur on weekend evenings (Friday, Saturday, and Sunday). Interestingly, Sunday afternoons emerge as the most popular time for binge-watching. Trouleau et al. (2016) discovered that viewing behavior on VoD services varies based on factors like the day of the week and time of day—patterns that similarly apply to binge-watching habits.

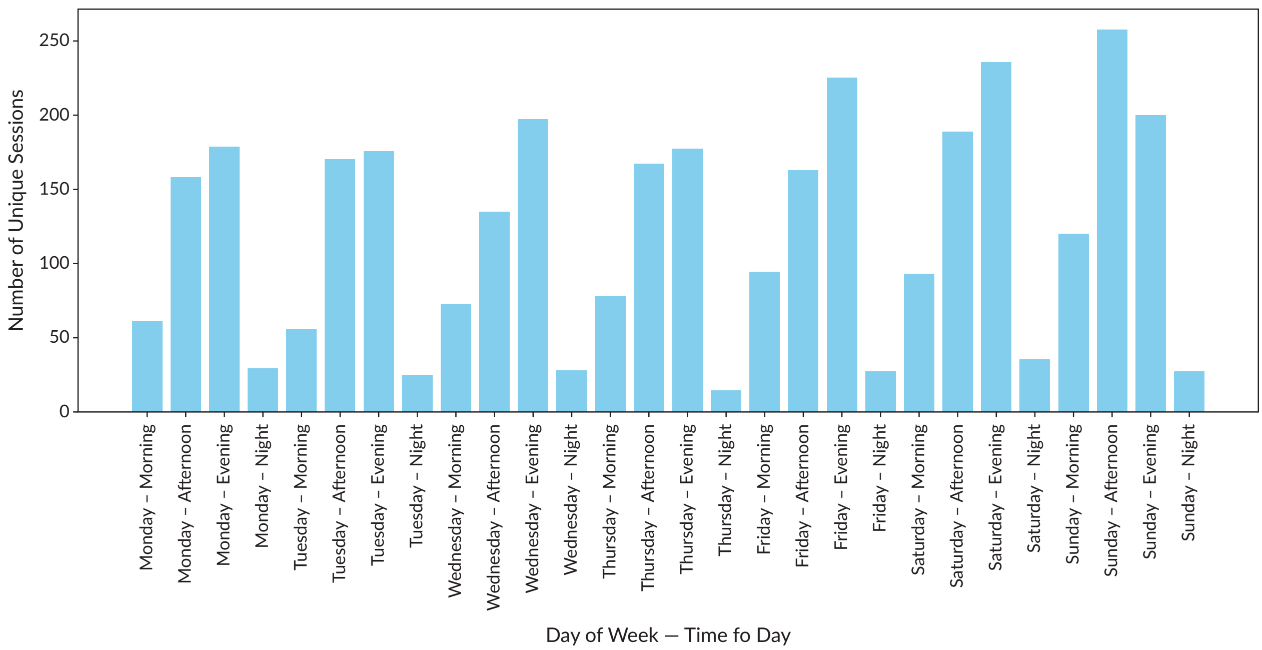

Figure 3. Popular time periods for binge sessions during the week.

4.3. On What Devices Do Users Binge?

When looking at the devices used for binge-watching sessions (see Table 2), users mostly watch multiple episodes in succession on TVs, with fewer viewings on mobile devices and tablets, and PCs/laptops.

Table 2. Devices used for watching TV on Netflix in 2023 from subscribers in the Netherlands.

	Binge	Non-binge
TVs (incl. streaming boxes and game consoles)	72.6%	64.4%
Mobile phones/tablets	14.2%	25.3%
PCs/laptops	13.1%	10.2%

These percentages per device for binge closely mirror official data released by Netflix in 2018 concerning all viewing on the platform (see Kafka, 2018). Most viewing occurs on TVs. Table 2 shows that these percentages are noticeably different when looking at the devices used for watching TV series on Netflix during non-binge sessions. In particular, we find an uptick in mobile phones and tablets in non-binge sessions. A possible factor explaining these differences might be variations in content type (e.g., complex vs. snackable) or viewing situation (e.g., individual vs. collective).

Digging deeper into this matter, we looked at the distribution of long versus short TV shows across device types. TV shows were broadly categorized into short (less than 30 minutes runtime) and long (more than 30 minutes runtime). There are 720 unique show titles in the dataset, of which 576 (80%) count as long shows and 144 (20%) as short shows.

Almost 80% of viewings on TVs concern long shows, compared to 75% for PCs/laptops, and 59% for mobile devices. Shorter shows are more commonly consumed on mobile phones and tablets. The observed differences between device types vis-a-vis show length are statistically significant ($\chi^2[2, N = 18{,}424] = 555.63$, $p < .001$). This has been further supported by analyzing the device types and the average runtime of watched shows. A Kruskal-Wallis test revealed a significant difference in show runtimes across device types, $\chi^2(2) = 354.40$, $p < .001$, with shorter runtimes on mobile devices ($M = 37.6$, $SD = 14.1$, $N = 2{,}623$) compared to longer runtimes on PCs/laptops ($M = 42.56$, $SD = 15.44$, $N = 2{,}424$) and TV ($M = 42.77$, $SD = 13.91$, $N = 13{,}377$), findings supported by an ANOVA, $F(2, 18221) = 146.25$, $p < .001$. Shorter shows are more likely to be watched on mobile devices and longer ones are more common on TV and PCs/laptops. The choice of screen type for binge-watching may thus be influenced by differences in viewing habits, such as whether the viewing is done individually or in a group.

4.4. What Do Users Binge-Watch Most?

Figure 4 displays a classic long-tail distribution ($N = 720$) of binge-watched shows. The steep rise indicates that a small number of shows attract a significantly larger audience, while the majority have only a small number of viewers. Out of the 116 unique users that binge, 81.9% binged the top 15 shows, 78.5% the top 10 shows, and 63% the top 5 shows. A small number of TV shows seem to attract the most attention, i.e., have a large audience share. This raises questions about the role of niche content on the platform and the cultural power of specific content items. Bars in red mark Netflix Originals in the top 20 shows based on unique viewers.

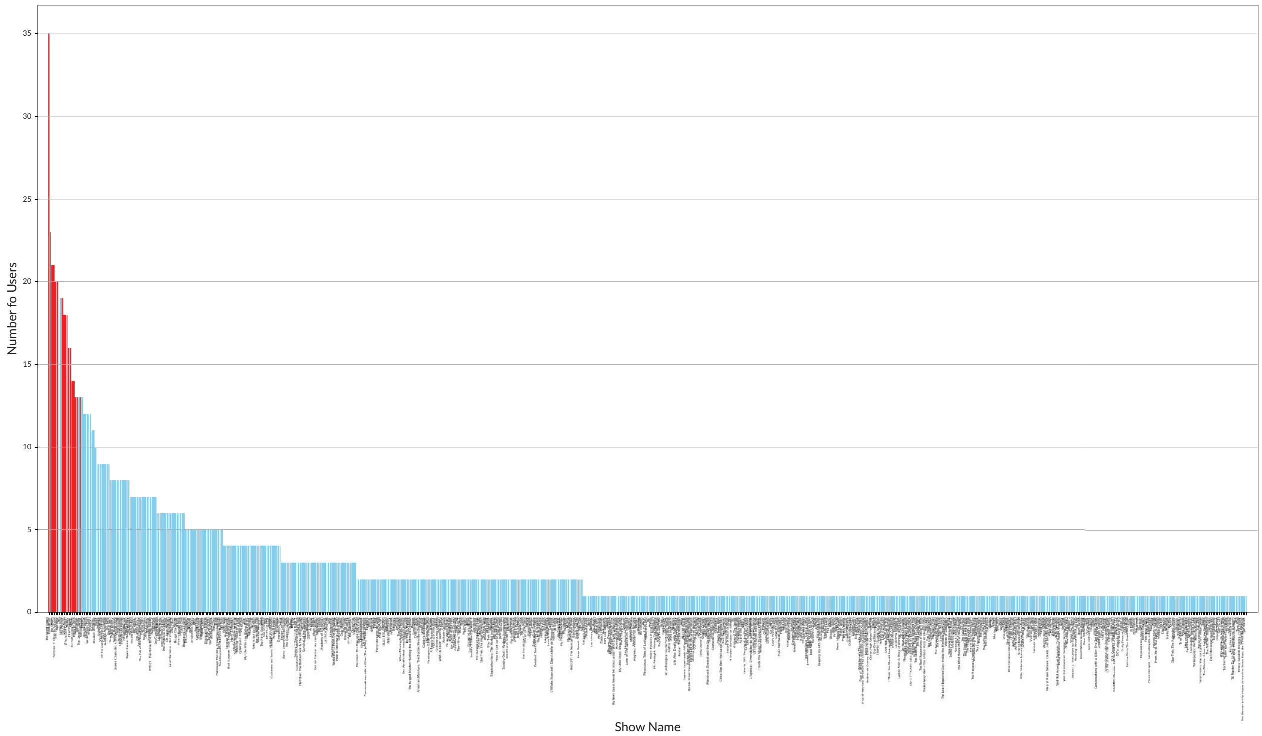

Figure 4. Unique users per TV show title.

Table 3 confirms that the top 10 most binge-watched TV shows, based on unique users, are primarily Netflix Originals, identifiable by the red “N” in their title artwork. (Even though *Knokke Off* isn’t an Original in the Netherlands, it is a Dutch-Flemish co-production between Dingie, VRT, and Netflix). The dominance of Netflix Originals and co-productions raises the question: Are these series truly as bingeable as Sarandos suggests, or are they simply more visible and easier to discover due to Netflix’s interface layout and recommendation system? Have they also benefited from the batch release strategy? Or is it a combination of all these factors?

Table 3. Top 10 TV shows based on unique users and average episodes per session.

Show	Netflix Original TV shows	Number of users	Average episodes completed per session	Runtime (min)
The Night Agent	Yes	35	3.6	45
Knokke Off	No	23	4.3	35
Lupin	Yes	21	4.1	46
The Crown	Yes	21	3.5	56
Formula 1: Drive to Survive	Yes	20	3.7	38
Manifest	Yes	20	4.8	42
Sex Education	Yes	20	4.7	52
Liebes Kind	Yes	19	3.4	48
You	Yes	19	3.8	47
The Witcher	Yes	18	4.2	58

Interestingly, *Manifest* and *Sex Education* have a notably higher average number of episodes completed per session, while *Liebes Kind* and *The Crown* have lower averages. Since *Sex Education* and *The Crown* have similar runtimes, this suggests that episode runtime is not the main factor influencing how many episodes are watched in one sitting. Further investigation, particularly through qualitative methods, could help clarify this behavior.

Returning to the question of device type, Figure 5 suggests the devices used for watching the top 10 TV shows based on unique users. Here, we find noticeable differences, such as *The Witcher* and *The Crown* being mostly streamed on PCs/laptops, while *Liebeskind* and *Sex Education* are mostly watched on mobile devices; users watching *The Night Agent* and *Manifest* do so primarily via TVs. Again, various factors may explain these differences (e.g., individual versus collective viewing of these series), necessitating further research.

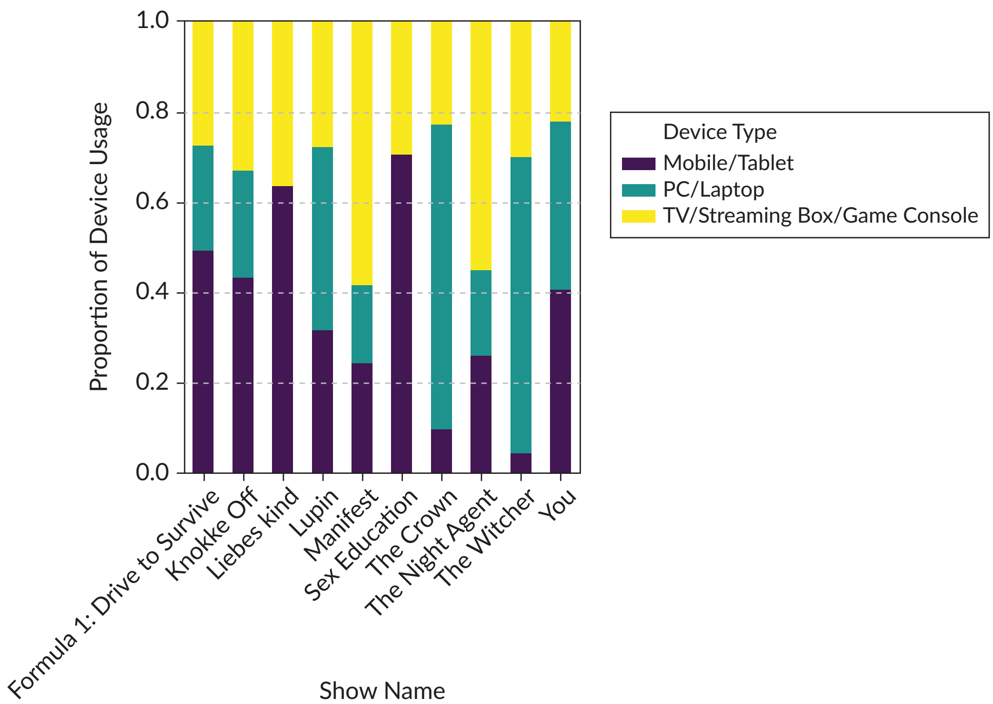

Figure 5. Top 10 TV shows and devices.

4.5. What Different Types of Binge-Watchers Can Be Identified?

We also explored whether there are different types of binge-watching users using a cluster analysis considering the following features: day–time combination, show length (short vs. long), preferred device type, number of sessions, and average session length. We herein expand Trouleau et al.'s (2016) approach, which identified user groups based on watched episodes per session. Corresponding to their research, it becomes apparent that binge-watching is not a consistent behavior.

The optimal number of groups (or clusters) was determined using Silhouette scores, which evaluate how well items fit within their assigned groups compared to others. Using this method, k-means clustering was applied to divide binge-watch users into two groups. These groups differ primarily in terms of session count and session length (Figures 6 and 7). The remaining categorical features do not show statistically significant differences between the clusters, suggesting they play a less important role in defining the groups.

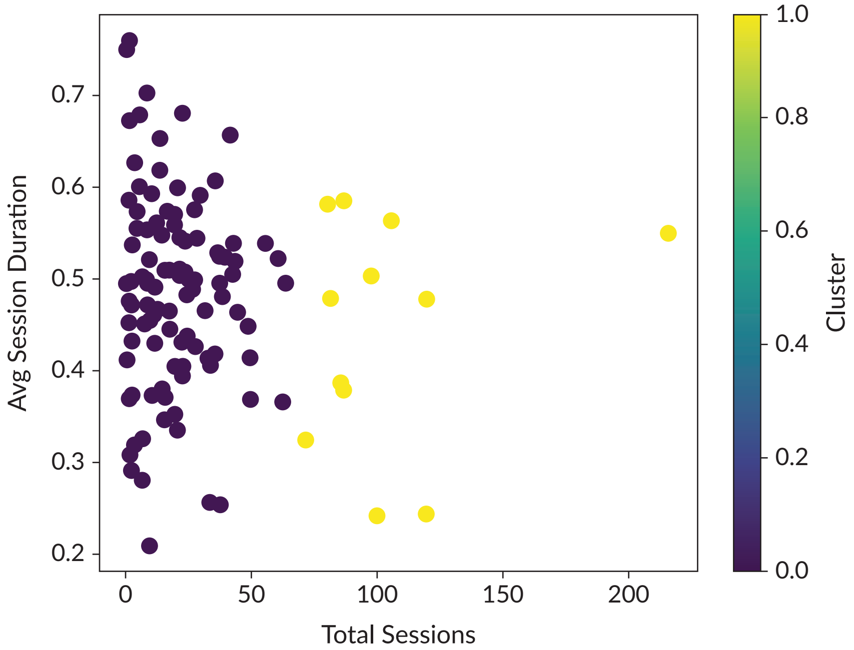

Figure 6. User clusters.

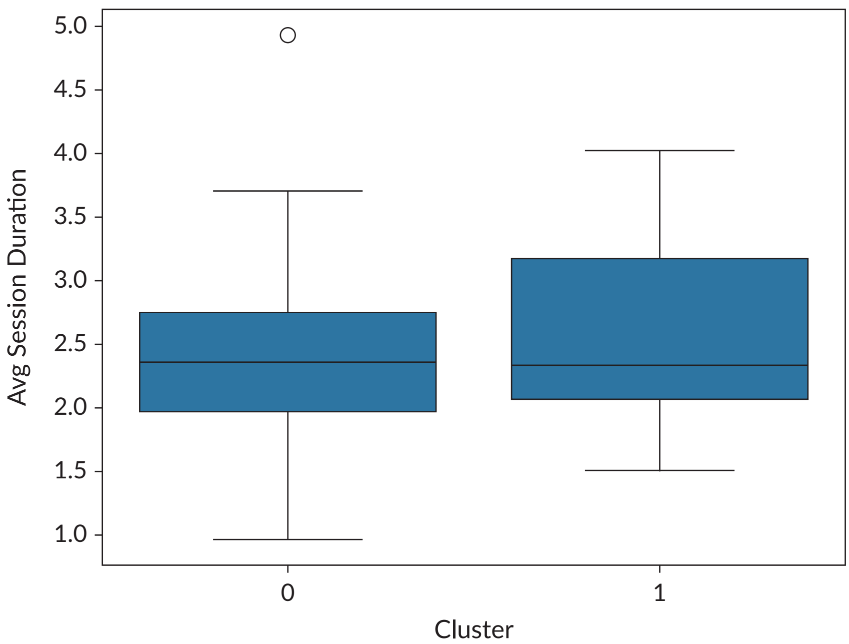

Figure 7. Average session duration per cluster.

The two clusters can be described as "Sporadics" (purple) and "Regulars" (yellow). The Sporadics group consists of users with fewer total sessions, typically under 50, and session durations averaging between 1 to 4 hours, with a mean of 2.39 hours. There is no significant correlation between the number of sessions and session duration in this group, suggesting that these users engage in a wide variety of session lengths, possibly reflecting diverse binge-watching habits, such as opportunistic viewing of specific shows. In contrast, Regulars have significantly more sessions, usually ranging from 70 to 200, with average session durations between 1.5 to 4 hours and a mean of 2.64 hours. In this cluster, users with a higher number of sessions tend to have slightly longer average session durations (suggested by a moderate positive correlation of 0.39).

In our cluster analysis, only two data points emerged as relevant for clustering users: session duration and number of sessions. Based on these, users were split into two large groups with variation within each. This is only one example analysis based on one operationalization of binge-watching. Importantly, content features such as genre or show origin could not be included. Further research is recommended here.

Both clusters have similar ranges of session durations, but Regulars tend to have a slightly higher median and a broader range. While Sporadics have more extreme outliers, their session durations are generally shorter compared to Regulars. This suggests that Regulars typically engage in longer sessions on average, though there is still considerable overlap between the clusters in terms of session duration.

5. Conclusion and Discussion

With this pilot study, we have provided unique empirical insight into viewer consumption on Netflix using data donations, and we hope to have paved the way for the utilization of this method for future research into VoD services. Oscillating between theory and our data, we settled on a definition of binge-watching suitable for analyzing interaction data with computational methods. This exercise demonstrates the complex interpretative work that goes into developing methodologies to calculate binge-watching.

Overall, this study suggests that binge-watching is a popular and common practice on Netflix. However, we should not lose sight of the fact that the majority of viewing sessions are not binge-watching sessions. In fact, most users typically watch a single episode at a time. Additionally, we found that binge-watching is influenced by both time and day, occurring mostly on weekends and during the evenings, with Sunday afternoons being the most popular time for this activity.

Somewhat surprisingly, despite the rise of tablets and smartphones, most binge sessions happen via TVs, including streaming boxes and game consoles. We also observed a long-tail distribution favoring Netflix Originals. Finally, we note that binge-watching takes on many forms, as our data identified two distinct types of binge-watchers: Sporadics and Regulars. In general, we would conclude that binge-watching is a diverse, complex, and multifaceted activity, which explains why there is no single, consistent definition.

While this research provides much-needed trace data to support theoretical work on binge-watching, it raises discussions and reflections on its limitations. First, our data come from voluntary donations and do not offer a representative sample of Netflix subscribers in the Netherlands, making these findings exploratory and potentially skewed. They do, nonetheless, offer more detailed insights into Netflix viewing habits than previous studies have achieved and function as a proof of concept.

Second, Netflix is unique in its strategy, as noted by Lotz (2021b) in calling it a "zebra amongst horses." The question then becomes: How does this compare to other VoD services? Additionally, how does it compare to traditional television? While the binge-watching model remains prevalent in the release strategy on Netflix, it has gradually been losing momentum as it has been using a staggered release method for some of its content. It has also started an ad-supported tier in certain territories and is increasingly experimenting with live-streaming. Both strategies are likely to influence content production, circulation, and consumption. Therefore, it is important to consider, analyze, and reflect on how these practices have evolved over time.

Third, interaction data serve as a proxy for direct observation, but this comes with limitations. Many qualitative and contextual aspects of viewing practices are not captured in digital trace data. For example, we do not know how content was presented to participants by the recommender system or in the interface and if it was *seen* by participants. Furthermore, the quantitative data cannot explain why or how people choose to watch streaming content. This is exactly the type of research that Turner (2021) has also called for. A lot of complexity and context is lost, which could be restored by supplementing data donations with other methods such as participant observations and interviews.

Finally, the definition of binge-watching could be refined by first establishing each user's "normal viewing behavior" and then identifying significant deviations, similar to Trouleau et al. (2016). This approach would provide a more flexible and individualized understanding of unusual viewing patterns. Aside from this, future research opportunities include comparing different streaming services, analyzing multiple territories, but also interrogating Netflix myths like content popularity and locality, and exploring the diversity of viewing habits.

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Conflict of Interests

The authors declare no conflict of interests.

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