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Can't Stop Scrolling: Understanding the Online Behavioral Factors and Trends of Short-Video Addiction

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Abstract

The pervasive use of short-video applications has raised concerns about their potential negative effects on users, particularly addiction. Existing research often relies on psychological questionnaires, which lack real-world behavioral data, limiting scalability and analytical depth. To address this, we assess the addiction status of short-video platform users using a standardized psychometric questionnaire, combined with platform behavioral data and interview responses to uncover features associated with addiction. Using feature-based modeling, we scale to a dataset of 10,111 addiction-labeled users and identify key indicators of addiction, including prolonged daily watch time, especially at night, and excessive video consumption, while also revealing that higher watch frequency is not fully correlated with addiction. Additionally, we find that addicted users tend to consume a narrower range of content, suggesting a filter bubble effect. Our large-scale analysis provides valuable insights for platform designers, policymakers, and mental health professionals seeking to promote healthier engagement and mitigate the risks of short-video addiction.

Code & Dataset — https://github.com/tsinghua-fib-lab/short-video-addiction

1 Introduction

Short-video platforms are some of the most successful multimedia applications in recent years. The pervasive integration of short video platforms into our daily lives has led to a surge in concerns regarding the potential for short video addiction, an issue that holds significant ramifications for both individual well-being and the broader social fabric (Peng, Lee, and Liu 2022; Chung 2022; Sulasula 2023). Short videos, characterized by their brevity and ease of consumption, have become an integral part of the modern digital experience, captivating users with engaging content (Zhang et al. 2023; Chen et al. 2022; Zuo et al. 2022). However, this widespread popularity has substantial implications for individual well-being and society, including compromised mental health (Li 2023), decreased productivity (Duke and Montag 2017; Washington 2021), and strained social relationships (Yang, Ti, and Ye 2022). Meanwhile, the risk of addiction to such platforms is of heightening concern (Zhang et al. 2023; Chen et al. 2022). Addiction is the tendency for people to indulge in a certain behavior without being able to control themselves, and to a point that has negative impacts on the person's life despite short-term gratification (Marlatt et al. 1988). Addressing the risks associated with short video addiction is crucial not only for safeguarding individual users, but also for fostering a healthier online environment. Digital addiction has been studied early on in the development of the world wide web (Stănculescu and Griffiths 2022), and short-video addiction is the latest iteration of such a phenomenon (Lu et al. 2022).

Despite the burgeoning interest in digital addiction (Atwan, Salha, and Mahamid 2022; Stănculescu and Griffiths 2022), existing research has predominantly focused on other forms of online addictions (Ali et al. 2022; Duke and Montag 2017; Balakrishnan and Griffiths 2017; Singh and Singh 2019), leaving short-video addiction comparatively understudied (Chao 2023). Furthermore, the lack of real-world labeled datasets specific to short video addiction has hindered the development of predictive models and effective intervention strategies (Peng, Zhang, and Li 2019). This paper seeks to address these shortcomings by shining a spotlight on the underexplored domain of short-video addiction using a combination of offline surveys and interviews as well as online user data. To achieve this, we first conduct an offline psychometric survey to assess the addiction status of a group of users from a leading short video platform. We then integrate real-world behavioral data from the platform, alongside user interviews, to identify addiction-related features. Next, we apply feature-based labeling to scale up our addiction-labeled dataset, allowing for a comprehensive analysis of the characteristics and formation of short video addiction. Through this approach, we aim to catalyze advancements in understanding and mitigating short video addiction, laying the groundwork for more targeted and impactful interventions. We also conduct a downstream investigation to determine the overlap between addicted users and users experiencing the filter bubble effect, a phenomenon characterized by low content diversity (Pariser 2011), relating two potentially harmful outcomes of heavy short-video platform usage.

To summarize, the key contributions of our study can be

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outlined as follows.

- We construct a novel short-video addiction-labeled user dataset by integrating offline psychometric survey responses and interviews with online large-scale behavioral data, scaling up to over 10,000 users, surpassing traditional methods that are predominantly reliant on surveys or interviews.
- We quantitatively uncover crucial insights into user engagement, ranging from content consumption habits to temporal engagement patterns, comparing the differences between non-addicted and addicted users.
- We conduct a downstream analysis on the relationship between user addiction and content diversity, revealing a strong connection between addicted users and the presence of filter bubbles.

2 Related Work

Digital addiction. The rise of digital technologies, such as smartphones, online stores, digital games, and video platforms, has raised concerns about excessive use and the risk of addiction. Digital addiction has been studied in scenarios such as internet gaming (Petry et al. 2015), and it has been found to show similar patterns with substance addiction (e.g., drugs or alcohol), leading to significant impairments in individuals' lives, with behavioral, emotional, and physical consequences (Alavi et al. 2012; Griffiths 2005). The creation of Bergen Facebook addiction scale (BFAS) (Andreassen et al. 2012; Atwan, Salha, and Mahamid 2022) kicked off a trend of many works on social media addiction (Al-Samarraie et al. 2022; Cheng et al. 2021; Stănculescu and Griffiths 2022).

Short-video addiction. Short video platforms, with personalized feeds and engaging content, have given rise to a unique form of addiction driven by instant gratification and concise information (Zhang et al. 2023; Chen et al. 2022), requiring adaptations of scales like BFAS for diagnosis (MPh 2015; Yang, Ti, and Ye 2022), with research using psychometric scales to link this addiction to negative offline effects (Peng, Lee, and Liu 2022; Chung 2022; Sulasula 2023) and impaired cognitive functions like attention and focus (Chen et al. 2022). Meanwhile, Zannettou et al. (2024) associate engagement signals of several TikTok users, and then analyze the user engagement with short-format videos to shed light on the effectiveness of TikTok's recommendation algorithm, using empirical and authentic traces from these real users. Another work on TikTok by Qin, Omar, and Musetti (2022) explores the factors contributing to TikTok addiction among adolescents, particularly focusing on the roles of information quality and system quality. In contrast, our work aims to uncover the online behavioral factors of addiction, using large-scale user data from the platform to derive correlations, determine risk factors for various user groups, and make associations between addiction and content diversity. Therefore, despite the above research efforts, there is a lack of insights about the connection between short video platform usage and offline addiction status. This study aims to bridge this gap by exploring short-video addiction behavioral trends using online user activity rather than exclusively relying on offline, questionnaire-based methods (Jeong, Jung, and Lee 2020) or cognitive behavioral monitoring (Chen et al. 2022).

Filter bubble. The filter bubble is another notable outcome of heavy social media usage, where users are exposed to a narrow range of content (von der Weth et al. 2020; Pariser 2011). Short video platforms are no different, with highly personalized recommendations that have been shown to lead to the filter bubble phenomenon (Li et al. 2022, 2023). In turn, several works have explored methods to increase diversity of recommendations and combat filter bubble formation. For instance, Zheng et al. (2021) and Yang et al. (2023) applied graph neural networks to enhance diversity using structural features and neighbor sampling, while Gao et al. (2023) proposed a tunable recommender system to prevent overexposure. The filter bubble effect on social media has also had implications that go beyond user experience, such as its influence on elections (Vasconcelos et al. 2021; Santos, Lelkes, and Levin 2021), community interactions (Hosseinmardi et al. 2021), and misinformation (Sidorenko Bautista, Alonso-López, and Giacomelli 2021). Doomscrolling, a behavior linked to filter bubbles, refers to the compulsive consumption of negative or distressing content (Ytre-Arne and Moe 2021). Studies have highlighted the psychological toll of doomscrolling, associating it with increased anxiety, distress, and reduced well-being (Ytre-Arne and Moe 2021; Mannell and Meese 2022; Satici et al. 2023). While doomscrolling is typically associated with consuming negative content, it shares similar dynamics with addiction, as it often involves compulsive, repetitive behavior driven by algorithmic recommendations. Our work explores the relationship between low diversity as a result of the filter bubble and short video addiction as products of short-video recommendation.

3 Research Overview

3.1 Study Framework

This section outlines the framework of our study, which integrates multiple data sources to investigate short-video addiction, construct a large-scale addiction-labeled dataset, and uncover key behavioral patterns and characteristics of short-video addicted users.

As depicted in Figure 1, our study begins with assessing user addiction through a standard psychometric scale (Andreassen et al. 2012), complemented by follow-up interviews for qualitative insights. This information is then integrated with over 1.3 billion online user logs and profile data to develop a comprehensive addiction-labeled dataset. Users are categorized into addicted and non-addicted groups, with the addicted group further refined into severely addicted and mildly addicted, resulting in three distinct categories. By identifying key addiction-associated features and applying feature-based classification methods, the dataset is scaled to include 10,111 labeled users. Extensive analyses are then conducted, including feature-based, temporal, and filter bubble analyses, alongside detailed investigations into addiction severity using fine-grained criteria.

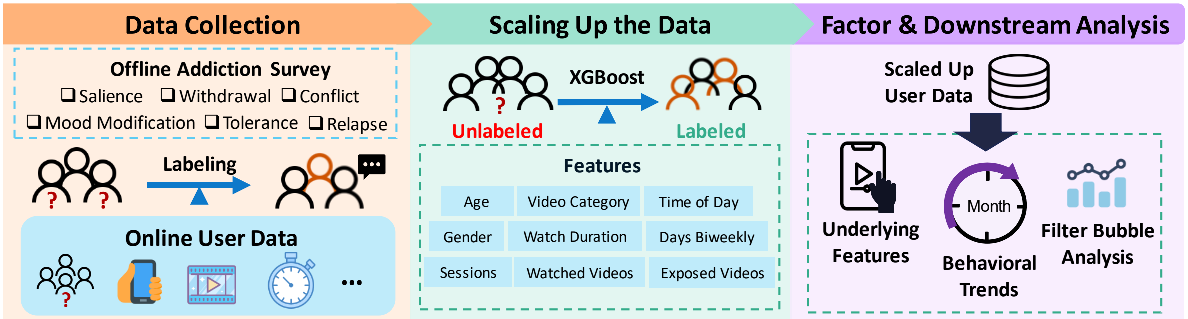


Figure 1: An overview of our short-video addiction evaluation framework, which integrates an offline survey with online user data and user interviews to construct an addiction-labeled dataset, followed by scaling up via feature-based labeling and extensive analysis to uncover distinctive behavioral patterns and filter bubble implications for addicted users.

3.2 Data Collection

Our analysis leverages data sourced from one of China's leading and largest short-video platforms, similar to TikTok, and notable for featuring a single-column interface consisting of an endless feed of personalized videos powered by a robust recommendation system (Aggarwal 2016). The platform boasts nearly 700 million active monthly users and more than 40 million uploaded videos per day. The platform users are primarily 35 years old or younger, slightly more male than female, and are mostly from low-tier cities in China (third-tier or lower). The data used in this work was collected in collaboration with the company, maintaining full anonymization and user privacy.

Survey. We conduct psychometric surveys specifically designed to assess addiction to short videos among users of the platform under study. Adult participants are recruited through online channels, including research recruitment websites and WeChat posts, while teenage participants, above the age of 15, are recruited in person outside high schools when parents are present for pick-up. All participants, or in the case of teenagers, their parents, provide consent for the use of their survey responses and online platform data, which are anonymized using assigned user IDs. Each participant receives an approximately $7 dollars incentive upon completion.

To ensure data quality, we exclude individuals who failed to answer the reverse-check question correctly, provided invalid IDs, or displayed inconsistencies between their reported offline responses and observed online behaviors (e.g., self-reported substantial time spent on the platform but no activity logged in the month prior to survey completion). In total, 239 survey respondents are included in the study, recruited on September 11–12, 2023, and between May 27 and July 11, 2024. Among these participants, 137 are assessed as addicted to the short-video platform under study using the addiction assessment scale discussed below, with 90 classified as severely addicted and 47 as mildly addicted, and the remaining 102 categorized as non-addicted.

Our survey design is rooted in well-established psychosocial theories (Andreassen et al. 2012), and tailored specifically to evaluate short-video addiction among online users. We adapted the six-item BFAS, a renowned tool based on Griffiths' components model of addiction (Griffiths 2005), to categorize users into "addicted" and "non-addicted" groups. Further details on the survey design and scale components can be found in the Appendix. The questions in our adapted scale are outlined in Table 1. Following the polythetic cutoff criteria established by Andreassen et al. (2012), participants scoring 3 or above on at least four of the six items are classified as addicted, while others are non-addicted. To further explore the spectrum of addiction, and in line with findings from Ali et al. (2022) and Primi et al. (2021) that higher scores correspond to greater levels of addiction, we categorize participants scoring 3 or above on at least five or more items and above the average addiction score in our sample as severely addicted. The remaining addicted participants are characterized as mildly addicted.

Item	Question	Rating
1	Spent a lot of time thinking about or planning use of the platform?	1-5
2	Felt an urge to use the platform more and more?	1-5
3	Used the platform to forget about personal problems?	1-5
4	Tried to cut down on the use of the platform without success?	1-5
5	Become restless or troubled if prohibited from using the platform?	1-5
6	Used the platform so much that it negatively impacted your job/studies?	1-5

Note: In the survey, the term "the platform" was replaced with the actual name of the platform to ensure clarity.

Table 1: Short-video addiction psychometric assessment.

Online User Data. In addition to survey data, we collaborate with the short-video platform and obtain a comprehensive dataset with over 1.3 billion user-video interactions spanning two periods: November 15, 2022, to September 10, 2023, and April 26 to July 11, 2024. The first period includes 10 months of logs for 10,111 users. Among these, 10,086 users were randomly selected from the platform's full user base on November 15, 2022, ensuring that logs were available for these users throughout the 10-month period and capturing a diverse sample of the platform's user population. The remaining users are surveyed participants with addiction labels, whose survey responses were collected on September 11–12, 2023. Logs from July 1 and July 5–14, 2023 are unavailable due to issues with the platform's backend system. The second period consists of one month of logs starting one day before survey participation for an additional 214 surveyed users, whose addiction labels were assessed between May and July 2024. The online dataset includes user profiles, detailed behavioral records (e.g., watch durations, engagement behaviors), and metadata for all interacted videos (e.g., video duration and category).

Integrating both survey and online user datasets, the composition of users in our study is as follows: The 239 surveyed users self-reported an age range of 16 to 61 ($M = 33.7$, $SD = 8.4$) and a gender distribution of 106 males and 133 females. Their platform-recorded profiles, derived from system algorithms and user-provided data, show an age range of 11 to 78 ($M = 33.9$, $SD = 15$) and a gender distribution of 109 males and 130 females. For the 10,086 randomly selected users, platform-recorded profiles indicate an age range of 5 to 79 ($M = 35.5$, $SD = 17.8$), with 5,746 males and 4,365 females. The addiction status of these randomly selected users will be determined in subsequent analyses.

Follow-up Interview. To investigate the underlying mechanisms of short-video addiction and gain deeper insights into this phenomenon, we conduct interviews with users classified as addicted in the survey. All adult participants from the addicted group are invited to participate in one-on-one follow-up interviews to share their experiences with the platform under study. Ultimately, 11 participants consented to participant in an online semi-structured interview lasting 30–45 minutes. The interviewees, aged 18 to 67 ($M = 34$, $SD = 16$), included 8 males and 3 females. Each participant received an incentive of approximately \$9.50. The interviews cover the usage of the platform under study, including frequency, context, purposes, and engagement behaviors like searching for content or browsing randomly. We also explore participants' perceptions of addiction and ask them to compare their experience of our focused platform with other platforms, like TikTok and long-video platforms, discussing potential factors that contribute to addictive behaviors. These interviews complement the quantitative data and offer rich insights into the perspectives and behaviors of addicted users.

4 User Addiction Classification

4.1 Feature Identification

Acknowledging that addiction forms and evolves over time (Chen, Li, and Duan 2023; Zhang, Wu, and Liu 2019), we link the 239 surveyed users' addiction status with their online user logs from the most recent month up to the survey collection date. From this integrated addiction-labeled dataset, we determine key online features distinguishing addicted and non-addicted users (see Appendix for more details on the analysis conducted to identify these features).

Several addiction-associated features are identified, including both demographic and behavioral factors. Demographic factors, such as age and gender, are obtained from the short-video platform. Behavioral features include daily watch time, time-based watch time, daily watch sessions, days watched biweekly, unique video category count, daily exposed videos, and daily watched videos. Daily watch time is the time spent actively watching videos (viewed for more than 0 seconds). Time-based watch time is categorized into specific periods: midnight (0am–6am), morning (6am–12pm), noon (12pm–2pm), afternoon (2pm–6pm), and evening (6pm–0am). Daily watch session is the number of continuous video-watching sessions a user engages in per day. A session is defined as a series of videos watched consecutively, with less than 10 minutes of inactivity between videos. Days watched biweekly refers to the number of days within a two-week period during which a user actively engages with video content. Unique video category count represents the number of unique video categories that a user explores. In this case, video categories refer to the most fine-grained classifications, such as a specific soccer team rather than broader themes like sports in general. Daily exposed videos refers to the number of unique videos presented to the user per day, including those that are scrolled past without active engagement, and those that are actively watched. This metric captures the reach and visibility of videos for the user. Daily watched videos represents the number of unique videos actively watched by the user per day.

Our identified addiction-associated characteristics are supported by researchers in other fields of study. For instance, demographic factors such as age and gender have been closely linked to short-video addiction (Lu et al. 2022; Zhang, Wu, and Liu 2019). Moreover, the inclusion of specific time-based and engagement metrics, such as detailed watch times and session data, draws upon the psychological concept of flow experience: a state of immersion where individuals lose a sense of time and space due to deep focus on an activity (Miranda et al. 2023; Ye et al. 2022). These metrics allow us to move beyond simplistic measures like usage frequency or duration, capturing the immersive nature of user engagement that often characterizes addictive behaviors. In fact, insights from interviews further support this, with two participants highlighting "forgetting time" as a key factor in their usage, echoing prior research on time distortion in digital addiction (Miranda et al. 2023). Additionally, studies have highlighted night and midnight watching as a key behavioral pattern associated with addictive tendencies (Yang et al. 2021; Abdel-Salam et al. 2019), reinforcing the significance of temporal engagement in identifying addiction. Importantly, our study recognizes that heavy usage of a short-video app, which is often measured by other researchers to infer addiction, does not necessarily equate to diagnosed addiction. Addiction is related to the activity negatively impacting people's productivity and life (Washington 2021). Thus, we identify features that are more strongly associated with addiction than others, rather than simply focusing on features related to heavy use.

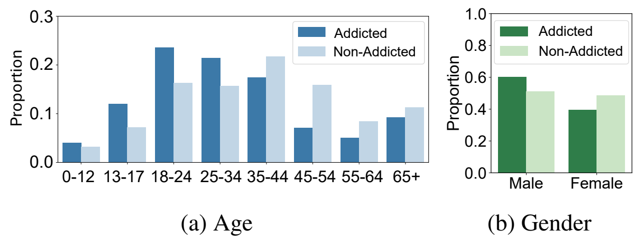


Figure 2: Demographic distributions for addicted and non-addicted users based on online profiles.

4.2 Feature-based Labeling

To expand our labeled dataset for more comprehensive analysis, we employ XGBoost, a scalable machine learning algorithm based on gradient boosting decision trees, known for its ability to handle large datasets and deliver high predictive performance (Chen and Guestrin 2016). XGBoost is particularly suited for this task due to its ability to capture complex feature interactions and its built-in mechanisms for handling imbalanced data. Using addiction-related features from users' recent behavioral data and their addiction labels, the model predicts addiction statuses, enabling monthly labeling for comprehensive analysis.

Specifically, we employ stratified 5-fold cross-validation, a technique that divides the dataset into five subsets while preserving the class distribution in each fold, to evaluate the performance of XGBoost models. Models are trained using the same feature set, with a weighting parameter applied to address class imbalance. We train two XGBoost models: the first model classifies users as addicted or non-addicted, and the second model differentiates addicted users as severely or mildly addicted. The performance metrics for these models are detailed in Table 2.

The trained models are then applied to classify all unlabeled data, including additional months of surveyed users and all months of randomly selected, unlabeled users. This process resulted in a fully labeled, temporally structured dataset with 10,111 users. This comprehensive dataset enables in-depth analysis and provides valuable insights into user behavior trends over time.

5 Factor Analysis

5.1 Feature-based Analysis

We first investigate the patterns distinguishing addicted and non-addicted individuals using the most recent month of data from the expanded labeled dataset, which consists of 6190 addicted users and 3921 non-addicted users. Specifically, we visualize the distribution of key demographic and behavioral features, to determine the pattern differences between the addicted and non-addicted groups. We also apply Welch's t-test to determine the statistical significance of the observed differences, accounting for the unequal variances within the groups. For demographic features, in Figure 2a, addicted individuals are most prevalent among teenagers and young adults (ages 13–24), with the highest proportion observed in the 18–24 age group. This prevalence slightly

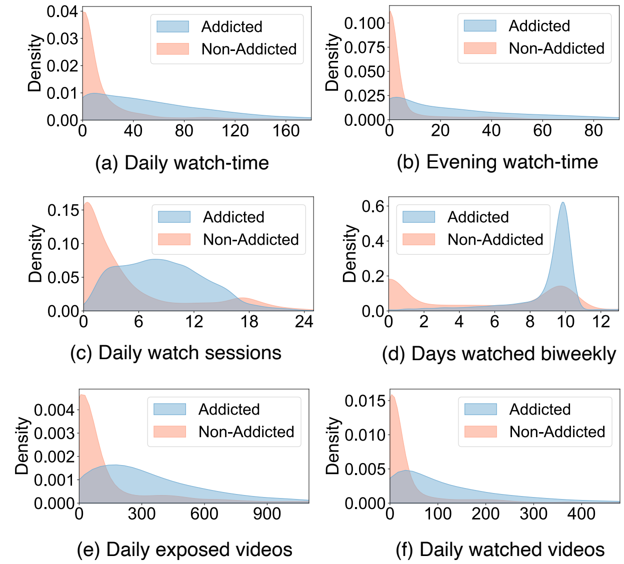


Figure 3: Feature distribution comparisons between addicted and non-addicted users.

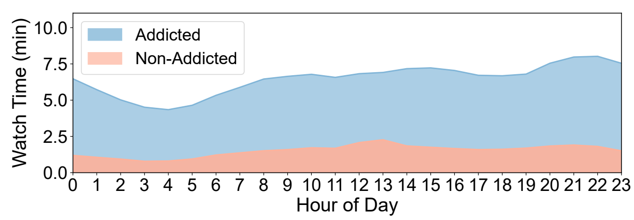


Figure 4: Hourly watch-time patterns compared between addicted and non-addicted users.

decreases yet remains substantial in the 25–34 age range. In contrast, addiction rates are significantly lower among middle-aged users (ages 35–64) and remain slightly lower among elderly users (ages 65+). There is a significant difference in the age distribution between the addiction groups ($t(8220) = -15.67$, $p < 0.001$). This finding aligns with prior research indicating that adolescents and young adults are more susceptible to short-video addiction due to their developmental stage and higher engagement with short-video platforms (Lu et al. 2022; Zhang, Wu, and Liu 2019). Gender distribution also differs significantly between the groups, with addiction being more prevalent among males, while non-addicted users show a relatively balanced distribution ($t(8214) = -8.91$, $p < 0.001$), as depicted in Figure 2b.

Behaviorally, addicted individuals tend to watch videos for longer periods per day compared to non-addicted individuals as shown in Figure 3a ($t(10111) = 48.67$, $p < 0.001$, aligning with prior literature (Liu, Lee, and Liu 2023; Abdel-Salam et al. 2019). Figures 3b and 4 reveal that addicted users consistently spend more time watching videos throughout the day compared to non-addicted users, with a notable increase during late-night hours. This pattern aligns with our interview findings, where 82% of addicted partic-

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Addicted / Non (Best)	0.809	0.846	0.815	0.830	0.822
Addicted / Non (Avg.)	0.666 ± 0.079	0.712 ± 0.070	0.701 ± 0.091	0.705 ± 0.076	0.729 ± 0.055
Severe / Mild (Best)	0.750	0.762	0.889	0.821	0.733
Severe / Mild (Avg.)	0.590 ± 0.093	0.699 ± 0.033	0.656 ± 0.170	0.666 ± 0.107	0.632 ± 0.052

Table 2: Performance Metrics of XGBoost Models.

ipants reported primarily watching videos in the evening or at night. For instance, two interviewees mentioned, "I usually watch after work", while four others specifically stated, "I watch at night, from 7 to 8 pm." These findings align with previous research states that increased watch time and nighttime viewing as hallmark behavioral pattern associated with addiction, often linked to disrupted sleep and reduced productivity (Chen, Li, and Duan 2023; Yang et al. 2021; Abdel-Salam et al. 2019).

Interestingly, as illustrated in Figure 3c, non-addicted users generally engage in fewer daily viewing sessions than addicted users but occasionally surpass them at higher session counts (around 18–20 sessions), while addicted users maintain overall higher session frequencies ($t(6800) = 58$, $p < 0.001$). Figure 3d highlights further differences in biweekly engagement. Addicted users predominantly watch videos on approximately 10 days within a two-week span. On the other hand, non-addicted users display a bimodal pattern, with a higher density at fewer days (around 0–2 days) and a secondary peak around 10 days. Most non-addicted users engage on fewer than three days biweekly, but some demonstrate behavior comparable to addicted users at higher engagement frequencies ($t(5097) = 53.86$, $p < 0.001$). These patterns suggest that daily watch sessions or biweekly watch days alone may not be sufficient to fully distinguish the two groups, as some non-addicted users exhibit engagement patterns resembling those of addicted users at higher session frequencies and increased biweekly activity. Figure 3e and 3f, the daily exposed videos, i.e., videos presented to users regardless of whether they actively watch them, and the daily actively watched videos all show that addicted individuals engage significant more than the non-addicted individuals ($p < 0.001$ for both exposed and watched videos). In general, these results show the distinct engagement patterns characterizing addicted and non-addicted users.

5.2 Temporal Analysis

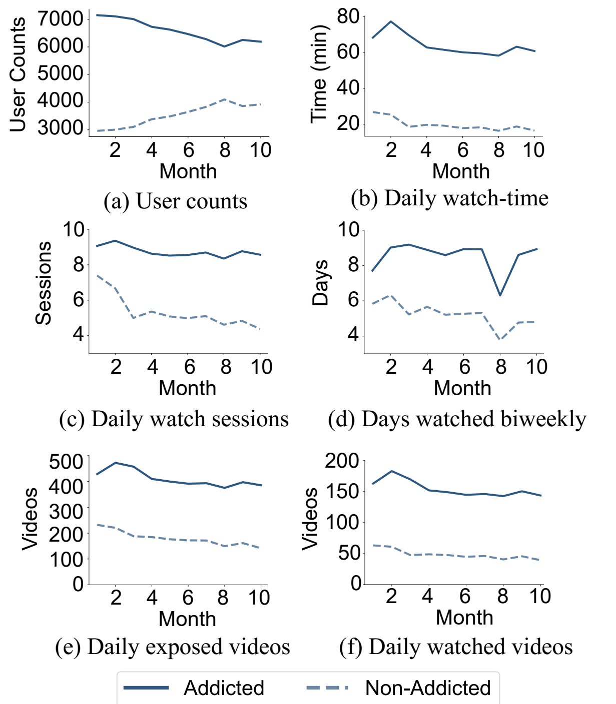
We depict the temporal dynamics of user addiction status through a longitudinal graph over a 10-month period. Figure 5a illustrates a gradual decline in the count of addicted users over time, contrasted with a corresponding rise in the non-addicted user base. These progressive changes confirm that our feature-based classification is not solely based on demographic attributes but also takes into account the interactive factors. In addition, the development pattern is characterized by a discernible direction, indicative of non-randomness. As shown in Figures 5b-f and Figure F in Appendix, addicted users consistently demonstrate significantly higher engagement across all identified features compared to non-addicted users throughout the 10-month period. This pattern reinforces the robustness of the behavioral distinctions identified between the two groups. It is worth noting that online user logs for July 1 and July 5–14, 2023, are missing (primarily affecting the 8th month and slightly the 9th month), resulting in slight fluctuations in user counts and biweekly engagement days but without impacting the overall trends or behavioral differences between the groups.

To better understand the temporal dynamics of user behaviors, we analyzed transitions in addiction states between consecutive months. For each month and its subsequent month, users were categorized into one of four transition states based on whether their addiction status (addicted or non-addicted) remained the same or changed. Figure 6 and Figure G in the Appendix reveal clear behavioral distinctions across these transition states. Users transitioning from addiction to non-addiction demonstrate substantial reductions in daily watch time, engagement during specific time periods of the day, watch sessions, days watched biweekly, and video exposure, reflecting disengagement from intensive platform use. Conversely, users transitioning from non-addiction to addiction display significant increases across these metrics, indicating heightened platform engagement. Users maintaining their addiction or non-addiction status show less pronounced changes, with addicted users experiencing slight declines across metrics except for biweekly engagement days, which see a small increase, while non-addicted users maintain consistently low engagement levels.

These findings align with earlier feature-based analyses, further validating the relevance of these metrics in understanding addiction dynamics. By examining transitions over time, our findings reveal that the identified features, such as heightened watch time, particularly during evening and midnight hours, increased days of usage, higher session frequency, and greater video consumption and exposure, intensify as addiction develops. Conversely, these features diminish as users transition from addicted to non-addicted states. This dynamic progression highlights the value of these features in identifying and addressing transitions between the two states, guiding targeted interventions to promote healthier and more balanced platform usage.

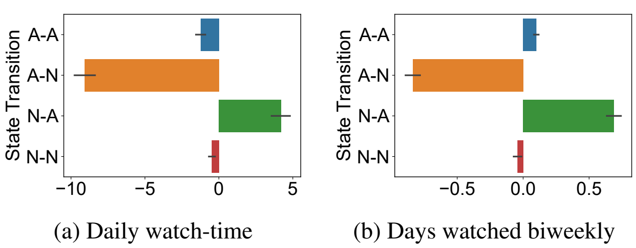
5.3 Case Study

To gain deeper insights into the habits and behaviors of addicted users, we conduct one-on-one interviews with eleven adult users diagnosed as addicted based on their survey responses. All participants reported using the platform un-



(a) User counts (b) Daily watch-time (c) Daily watch sessions (d) Days watched biweekly (e) Daily exposed videos (f) Daily watched videos

Figure 5: Temporal feature distribution comparisons between addicted and non-addicted users.



(a) Daily watch-time (b) Days watched biweekly

Figure 6: Behavioral changes during transitions between addiction and non-addiction states. "A" denotes addicted, "N" denotes non-addicted, "A-N" represents users transitioning from addicted to non-addicted, and "N-A" represents users transitioning from non-addicted to addicted. "A-A" and "N-N" indicate users maintaining their state.

der study more than three days a week, and many access it daily. However, these adults often resisted the addiction label, frequently emphasizing their self-control and insisting that daily use does not equate to addiction, despite the standard psychometric assessment tool and their reported life impacts indicating clear signs of addiction. For instance, one interviewee stated, "I'm not particularly addicted. I just browse for a while when I'm bored every day." Some participants attributed addiction to a lack of self-control, with two respondents asserting, "I'm not addicted. I can control myself." Many associated addiction with adolescence rather than adulthood. One participant responded, "I'm definitely not addicted. I have self-control. I'm an adult, not a child." Another mentioned, "I'm not addicted because I'm not young anymore. I'm not from that generation, so I don't get addicted." This belief, linking addiction to adolescence and a perceived lack of self-control, complicates efforts to address the issue, highlighting the need for objective, quantitative methods to assess addiction unobtrusively.

To explore the unique appeal of short-video platforms, we examine participants' perspectives on both short and long video formats. Participants consistently expressed a strong preference for short videos, citing their brevity, engaging nature, and suitability for fast-paced modern lifestyles. One participant remarked, "Long videos take too much time, and I often can't finish them. Videos lasting one or two minutes are just right." Another shared, "I prefer short videos because they offer more variety. For longer content, like movies, I usually watch highlights or reels." These observations highlight the distinct advantages of short-video platforms, particularly their ability to provide quick, engaging content that seamlessly fits into busy schedules.

The appeal of short videos is further amplified by personalized content, which keep users engaged with tailored recommendations. While these features cater to users' needs for both relaxation and entertainment, they can also encourage extended and repetitive use. Endless scrolling provides a continuous stream of content, making it easy to lose track of time. When asked about the features that might drive addiction, one participant responded, "It's the relaxing content. Before you know it, time has just passed." Participants valued the platforms' ability to deliver a blend of entertaining, educational, and news content on topics such as fitness, parenting, and current events. However, the same features that make short videos convenient, brevity, personalization, and accessibility, may inadvertently induce compulsive consumption and over-reliance on these platforms.

6 Filter Bubble Analysis

In this section, we attempt to establish the connection between two of the social impacts of short-video recommendation: addiction and the filter bubble effect. The filter bubble is a phenomenon characterized by low diversity of content, and arises out of the extreme personalization facilitated by recommendation algorithms on social media platforms (Pariser 2011). Due to the single-column feed on short video platforms, the emphasis of the recommendation algorithm is higher, and therefore the filter bubble on such platforms is of special interest to researchers (Piao et al. 2023; Sukiennik et al. 2025). A user being in a filter bubble can lead to boredom and dissatisfaction with the platform (Li et al. 2023), but more importantly, could also limit the information and exposure they are getting about the world, posing implications on the societal level (Lazovich 2023). While some prior works have examined the relationship between heavy usage and diversity (Fu et al. 2024), the relationship and causality between these two phenomena are not entirely understood. Understanding their relationship can provide insights into creation of robust intervention mechanisms that could potentially alleviate issues at once. Therefore, in addition to understanding the specific user behaviors and demographics that pose implications towards addiction, we also undertake analysis to determine the relationship between the filter bubble and addiction.

As we can see in the prior section, addiction among short-video users is prevalent. Because of the special connection between filter bubble and addiction as two potentially harmful outcomes of short video platform usage, we aim to quantify the nature of the relationship between these the phenomena. Intuitively, we believe that addicted users may be more likely to fall into filter bubbles than non-addicted users, because heavy usage of a platform tends to lead to a decrease in diversity of content (Li et al. 2022). To conduct this analysis, we gather the category information of all videos watched by users in the scaled up data over the ten-month period. Due to the diverse nature of short-video content, a single category is usually not enough to fully classify a given video. Therefore, we leverage two additional categories, forming a three-level hierarchical category structure for each video, allowing us to assess the users' filter bubble status at different layers of "depth". The deeper the category level, the more fine-grained the category is; therefore being in a filter bubble at a deep level has different implications than a shallow level. For example, in an extreme case, if an individual follows sports among other categories at the top level, the lower levels would include specific sports, i.e. basketball or football, followed by specific teams and players at the lowest level. Among the three category levels, where each video possesses one category at each level, there are: 43 first-level categories, 123 second-level categories, and 796 third-level categories. The categories take a tree structure, with level one being the root.

In order to quantify such filter bubble status, we calculate relative coverage based on categories seen vs. categories existing per level, as follows:

$$\mathcal{C}_{l,t} = \frac{n_{\text{seen},l,t}}{n_{\text{total},l}}, \quad (1)$$

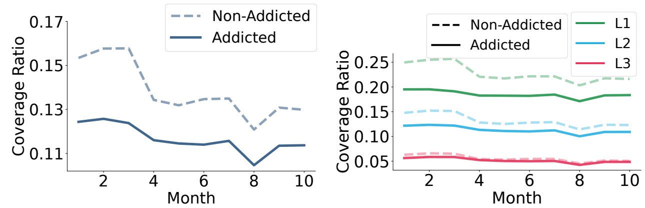
where $C_{l,t}$ denotes coverage at category level l and month t and n represents the number of categories, either seen or existing at that level.

Then, we follow Sukiennik, Gao, and Li (2024) in using a criterion to quantify whether a user u is either "in" or "out" of the filter bubble for each level and each month:

$$\mathcal{B}_{u,t} = \begin{cases} \text{"in"}, & \text{if } C_{u,t} < Q(C_{\cdot,t}) \\ \text{"out"}, & \text{otherwise} \end{cases}, \quad (2)$$

where $Q(C_{\cdot,t})$ represents the chosen quantile of the distribution of $C_{\cdot,t}$ at time t. As Q is set to the 50% quantile, this simply represents the median number of categories seen across all users at a given month.

Because each group of users (i.e. addicted vs. non-addicted) is a different size, groups with more users have a chance of seeing more categories overall. To avoid bias towards higher groups having higher coverage, we leverage a bootstrapped sampling method to ensure that only same-sized samples are being compared. For each month, we take the number of users in the smallest group and then sample the other groups with that number of users, and repeat for 1000 iterations, finally taking the mean over all of them. In



(a) Overall Coverage (b) Coverage per Level

Figure 7: Comparison of overall coverage and category-level coverage over time between addicted and non-addicted users.

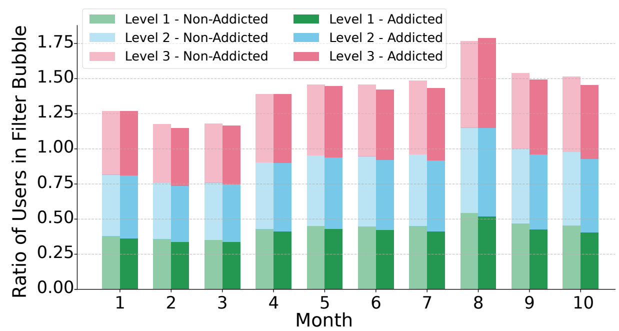


Figure 8: Filter bubble status over time for addicted and non-addicted users

this way, we can obtain coverage results that can be compared across groups.

In Figure 7a, we display the coverage ratio of all addicted users vs. that of the non-addicted users. We can see that the intuition is correct, with the addicted users having much lower coverage, with coverage also decreasing over time, whereas non-addicted users have much higher coverage, decreasing in a similar trend.

Then, in Figure 7b, we break down the coverage ratio for addicted and non-addicted users into their respective category levels for each month. We first note that the deeper the category level, the lower the coverage ratio overall, which points to the importance of measuring the filter bubble effect at different category levels. Moreover, we find that for levels 1 and 2, the coverage ratio of addicted users is substantially lower than that of non-addicted users, whereas at level three they are very similar. This means that item diversity does not have substantial implications for addiction at the lowest category level, whereas it does for the top two levels.

We next employ Equation 2 to determine the evolution in filter bubble formation over the time-period in question, plotting the ratio of users in and out of the filter bubble for each category level and month in Figure 8, and for the addicted and non-addicted user groups. For space considerations, the ratio for all the category levels are stacked on top of each other for each given user group. A cursory glance at the figure reveals that the ratio of users in the filter bubble is similar between the addicted and non-addicted users over time. However, upon closer inspection, we notice that among non-addicted users there is a higher incidence of filter bubble at category level 1. This contradicts with the implications in Figure 7b, which due to the raw coverage ratio, leads us to believe that there would be a lower incidence of filter bubble among the top two category levels. This finding is supported by Fu et al. (2024), who discover that users with heavy usage do not necessarily have the most diverse content preferences. On the other hand, more addicted users fall into filter bubbles in levels two and three. The ratio of users in the filter bubble at levels two and three is the lowest for both addicted and non-addicted groups. We also note that there is a slight upward trend in filter bubble incidence for both groups over the ten-month time period, which is consistent with the implications from decreasing coverage ratios in Figure 7b[1].

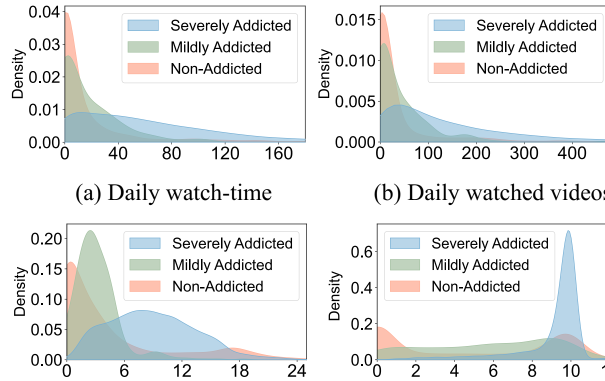
The potential reasons for the findings above are as follows: Low coverage at certain category levels does not necessarily lead to higher filter bubble incidence because the hierarchical structure of categories limits users' exposure to only a small fraction of the lowest-level categories. Meanwhile, addicted users experience higher filter bubble incidence overall because prolonged platform use allows the recommender system to better personalize content, reducing diversity and reinforcing the filter bubble effect. Additionally, the higher likelihood of addicted users being in deeper filter bubbles suggests that addiction is influenced not only by time spent and personalization but also by other factors, as discussed in Section 5. This nuanced relationship between filter bubbles and addiction highlights the need for further exploration in future research.

7 Fine-grained Addiction Criteria

Building on the distinction between addicted and non-addicted users, prior studies recommend a gradient scoring system to further classify addicted individuals into mild and severe categories (Ali et al. 2022; Primi et al. 2021). In this section, we delve into these finer distinctions, analyzing behavioral patterns across addiction severity levels to deepen our understanding of addiction severity and the variations between addicted and non-addicted individuals.

To explore the distinctions among the three levels of addiction, we conduct analyses using the most recent month of data, consisting of 5,791 severely addicted, 399 mildly addicted, and 3,921 non-addicted users. The age and gender patterns for severely and mildly addicted users share similarities but distinctly different from non-addicted users (see Figure D in the Appendix). Severely and mildly addicted users are predominantly found among teenagers and young adults (under 25), with their prevalence declining as age goes beyond 35. Mildly addicted users are slightly younger on average compared to severely addicted users, while non-addicted users are more commonly observed in middle to older age groups. In addition, a greater proportion of males are in the severely and mildly addicted groups compared to females, while non-addicted group has a nearly equal gender distribution. This shows that males might be more prone to develop addictive behaviors, particularly at higher severity levels.

[1] Fine-grained addiction criteria filter bubble results are provided in Appendix D.



(a) Daily watch-time (b) Daily watched videos

(c) Daily watch sessions (d) Days watched biweekly

Figure 9: Feature distribution comparisons across three levels of addiction.

For behavioral engagement, activity levels gradually intensifies from non-addicted to mildly addicted to severely addicted users across key features such as daily, time-specific (e.g., evening), and hourly watch time as well as exposed and watched videos, as shown in Figures 9a-b, 10, and Figure E in the Appendix. Severely addicted users demonstrate the highest levels of engagement, with a peak during the evening hours, while mildly addicted users display intermediate engagement patterns, bridging the behaviors of non-addicted and severely addicted users.

Moreover, for visit frequency metrics, i.e., daily watch sessions and days watched biweekly in Figures 9c-d, engagement generally increases from non-addicted to severely addicted users. However, some non-addicted users occasionally display behaviors similar to severely addicted users, consistent with our earlier findings in Section 5.1, where we compare addicted and non-addicted users. While our previous temporal analysis in Section 5.2 highlights clear distinctions between the overall averages of discussed features, these findings suggest that users with different addiction levels have distinct behavioral patterns in certain features, e.g., watch time and video watched, yet overlapped in others. Metrics like watch sessions and days may be insufficient alone to fully differentiate addiction levels, highlighting the need for multiple behavioral metrics.

Additionally, our downstream analysis on the filter bubble phenomenon across three levels of addiction, detailed in the Appendix, further validates the distinctions observed in the behavioral patterns of addicted and non-addicted users. Overall, the findings demonstrate a gradual progression from non-addicted to more severe addiction patterns, aligning with those observed between addicted and non-addicted users, and underscore the utility of fine-grained criteria in distinguishing addiction levels.

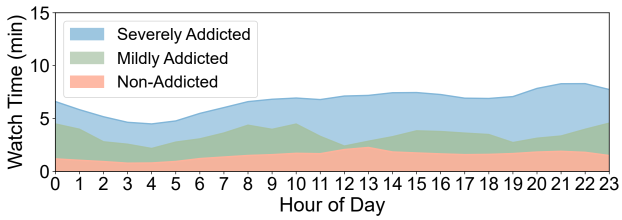


Figure 10: Hourly watch-time patterns compared across three levels of addiction.

8 Discussion and Conclusions

This study addresses short-video addiction, a timely and prevalent digital phenomenon, through a dual offline-online approach. Leveraging a widely recognized psychometric scale, qualitative interview insights, and extensive in-app user data, we develop behavior-based addiction classification models, generating a dataset of 10,111 addiction-severity labeled users and identifying nuanced online behavioral patterns indicative of short-video addiction.

The findings from Section 5 indicate several key behavioral features that are associated with addiction, such as prolonged daily watch time, heightened late-night engagement, and the volume of videos consumed. Furthermore, analysis on user demographics reveals varying addiction risks based on age and gender, with teenagers, young adults, and males showing a higher risk of addiction. We also find that some intuitive metrics like session frequency and biweekly usage days alone are not sufficient to fully distinguish addicted users from non-addicted ones. In light of these findings, we propose several recommendations. Specifically, younger users require targeted interventions, such as digital literacy programs, to prevent an early onset of short-video addiction. For users whose addiction disrupts their sleep, we suggest usage reminders or limits during late hours. For researchers, the non-intuitive findings suggest that addiction should be assessed through more nuanced behavioral patterns rather than solely relying on heavy usage.

The filter bubble analysis results reveal important and nuanced insights into the relationship between addiction and the filter bubble phenomenon. Specifically, addicted users are exposed to a less diverse array of content than non-addicted users based on category coverage. Furthermore, a breakdown of the users in filter bubbles based on category depth shows that non-addicted users have narrower exposure at the broadest category (level 1) whereas addicted users tend to have deeper-level filter bubbles (levels 2 and 3). These findings suggest that addiction may limit the diversity of content exposure, reinforcing a narrower range of topics or interests.

In sum, this study provides crucial understanding into the behavioral and demographic dimensions of short-video addiction. By integrating psychometric assessments with online in-app behaviors, we demonstrate how demographic factors and engagement patterns collectively influence addiction, and the relationship between addiction and the filter bubble. These findings offer a foundation for targeted interventions and more informed strategies to address the growing challenge of short-video addiction. These contributions also hold practical implications for professionals in clinical settings. By leveraging our work, practitioners could gain a better understanding of their patients' addiction status and identify behaviors that may contribute to addiction. With this knowledge, clinical practitioners may be better positioned to recommend behavioral modifications that could help mitigate addiction. Furthermore, these interventions could be implemented at the platform level to proactively prevent the onset of addiction.

We acknowledge several limitations of our study. While our survey-labeled dataset provides a strong foundation for analyzing short-video addiction, a larger sample size could further enhance the analysis, particularly when examining users with varied addiction intensities. Additionally, our temporal dataset spans a single period and may be influenced by platform-specific artifacts or external factors. Future studies could expand upon this work by incorporating longer-term datasets and adding more demographic features and behavior indicators to derive deeper insights into addiction behavior patterns. Researchers can also investigate the correlations between short video addiction and other harmful trends such as doomscrolling. In conclusion, our study contributes to the understanding of short-video addiction, offering a crucial foundation for developing targeted interventions aimed at mitigating its negative effects.

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Ethics Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes

(b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
(c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
(d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? NA
(e) Did you describe the limitations of your work? Yes
(f) Did you discuss any potential negative societal impacts of your work? NA
(g) Did you discuss any potential misuse of your work? NA
(h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes
(i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes

2. Additionally, if your study involves hypotheses testing...
(a) Did you clearly state the assumptions underlying all theoretical results? NA
(b) Have you provided justifications for all theoretical results? NA
(c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? NA
(d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? NA
(e) Did you address potential biases or limitations in your theoretical framework? NA
(f) Have you related your theoretical results to the existing literature in social science? NA
(g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? NA

3. Additionally, if you are including theoretical proofs...
(a) Did you state the full set of assumptions of all theoretical results? NA
(b) Did you include complete proofs of all theoretical results? NA

4. Additionally, if you ran machine learning experiments...
(a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? Yes
(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? Yes
(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? Yes
(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? NA
(e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? NA
(f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? NA

5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
(a) If your work uses existing assets, did you cite the creators? NA
(b) Did you mention the license of the assets? NA
(c) Did you include any new assets in the supplemental material or as a URL? Yes
(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? Yes
(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes
(f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? NA
(g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? NA

6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
(a) Did you include the full text of instructions given to participants and screenshots? Yes
(b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? Yes
(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? Yes
(d) Did you discuss how data is stored, shared, and deidentified? Yes

Ethics Statement

We follow strict ethical guidelines to protect participants' rights and privacy, with approval from the local university's Institutional Review Board (IRB), application number THU-03-2024-0024. All materials, including consent forms and questionnaires, were reviewed and approved by the IRB. Participants, including parents of minor participants, are provided with a research description, instructions, and a consent form. Participants are fully informed about the study's purpose, data usage, and their rights, including the ability to withdraw at any time without consequence. Consent is obtained from all participants, with parental consent required for minors. Only individuals aged 15 or older are eligible to participate in the survey, and only adults are invited for interviews. For interview participants, additional consent is obtained to ensure their understanding of the voluntary nature and objectives of the interviews. Interviewers conduct mid-session check-ins to address any potential psychological discomfort and remind participants of their voluntary participation. All data, including survey responses, interviews, and online behavioral data, are anonymized using reassigned user IDs and securely stored on the platform under study, ensuring strict confidentiality throughout the study.

APPENDIX

A Addiction Assessment Scale

Our short-video addiction scale employs Griffiths' widely recognized components model of addiction, which integrates psychosocial principles to define six key dimensions of internet addiction (Griffiths 2005):

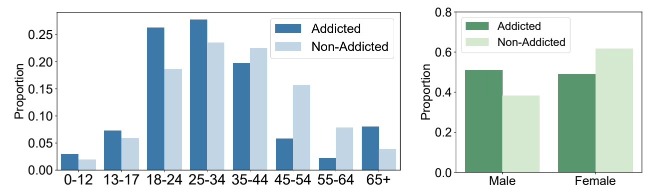
- **Salience:** A particular activity becomes the most important thing in an individual's life, dominating their thoughts, feelings, and behaviors.
- **Mood modification:** Engagement in the activity leads to a significant change in mood.
- **Tolerance:** An increasing need to engage in the activity more frequently or intensely to achieve the same effects.
- **Withdrawal symptoms:** Discontinuation of the activity leads to discomfort, including physical and emotional symptoms.
- **Conflict:** The activity gives rise to conflicts in life, such as relationships, work, and education.
- **Relapse:** A tendency to repeatedly return to the previous patterns of behavior despite attempts to reduce or abstain.

In addition, our adapted BFAS scale has been widely recognized for measuring social media addiction (Andreassen et al. 2016) and also utilized in the context of video addiction (Balakrishnan and Griffiths 2017). In this case, we modify the scale for our target demographic by replacing "Facebook" with the name of the short-video platform used in the study. To enhance the survey's precision and integrity, we include a reverse question, i.e., "Felt indifferent to not using [platform name]?" This question contrasts with one of the original scale items, "Become restless or troubled if you have been prohibited from using [platform name]?", and is designed to verify response consistency. The survey utilizes a 5-point rating scale, ranging from 1 ("never") to 5 ("very often").

B Analysis for Feature Identification

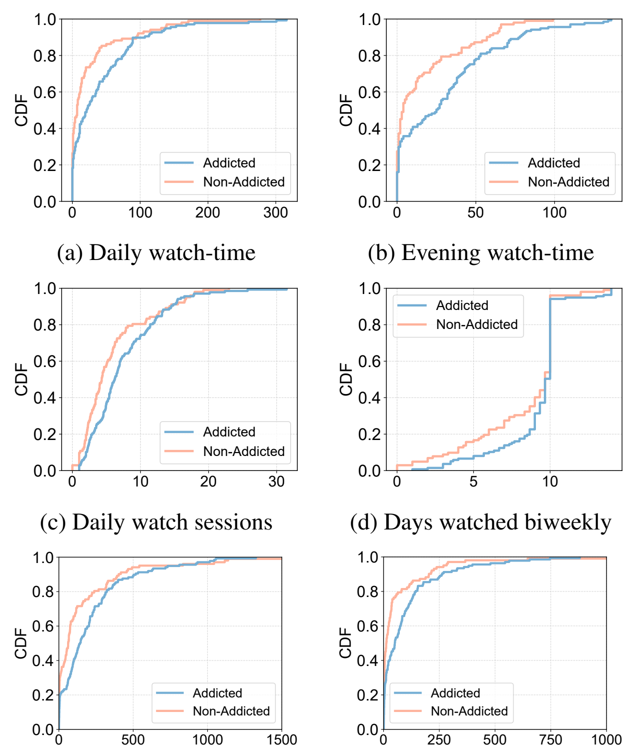
As shown in Figure A, notable differences in age and gender distributions are observed between addicted and non-addicted users. Specifically, addicted users are more likely to be younger individuals (below the age of 35) or older adults (65+). Additionally, the proportion of addicted males is higher than non-addicted males, while the proportion of addicted females is lower compared to non-addicted females. More addicted males than non-addicted males and fewer addicted females comparing to non-addicted females. The CDF graphs in Figures B and C highlight significant behavioral differences between addicted and non-addicted users across several dimensions. Addicted users exhibit substantially higher daily watch time (Figure Ba), participate in more daily watch sessions (Figure Bc), and engage on more days biweekly (Figure Bd). Furthermore, they are exposed to and actively watch more videos daily compared to non-addicted users (Figures Be and Bf, respectively).

Time-specific watch-time trends, such as in Figure Bb and hourly watch-time patterns, as shown in Figure C, further emphasize these distinctions. Addicted users consistently exhibit higher engagement throughout the day, with a pronounced increase during evening and late-night hours compared to their non-addicted counterparts. In fact, this feature investigation was inspired by qualitative insights from user interviews, which revealed that addicted participants often reported late-night viewing as a common habit. These findings align with our results, further highlighting the importance of this feature in distinguishing addicted users from non-addicted ones. These findings highlight behavioral features such as daily and hourly watch time, session counts, biweekly engagement, and video consumption as key indicators of short-video addiction. These features provide a strong foundation for identifying and understanding addictive behaviors on short-video platforms.



(a) Age distribution (b) Gender distribution

Figure A: Demographic distributions for addicted and non-addicted survey users based on online profiles.



(a) Daily watch-time (b) Evening watch-time

(c) Daily watch sessions (d) Days watched biweekly

(e) Daily exposed videos (f) Daily watched videos

Figure B: Comparing behavioral features between addicted and non-addicted users for survey participants.

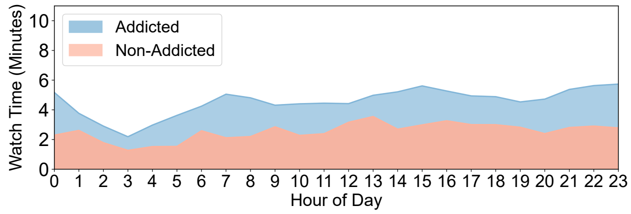
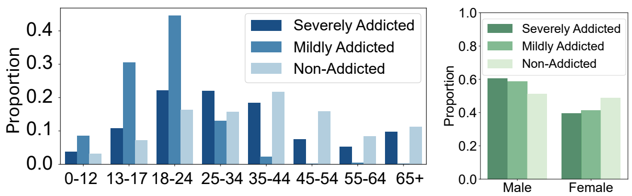


Figure C: Comparing hourly watch-time between addicted and non-addicted users for survey participants.



(a) Age (b) Gender

Figure D: Demographic distribution comparisons across three levels of addiction.

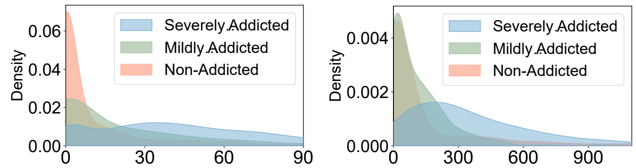
C Supplementary Analysis for Temporal Feature Analysis

The temporal analysis of daily watch-time over 10 months shows consistent differences between addicted and non-addicted users across all periods of the day (morning, noon, afternoon, evening, and midnight), as illustrated in Figures Fa-e. Addicted users consistently exhibit higher watch times than non-addicted users in every time period, with the largest engagement observed in the evening (Figure 5c). These differences remain stable throughout the 10-month period.

Additionally, the transitional analysis of behavioral features, such as daily watch sessions, evening watch-time, daily exposed videos, and daily watched videos, is presented in Figure G. These features exhibit consistent patterns with the findings reported in the main paper, emphasizing that transitions from addiction to non-addiction, and vice versa, differ significantly from each other and from conditions where users maintain a stable addiction or non-addiction status.

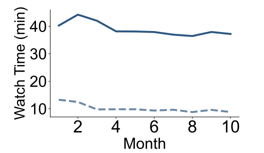
D Feature and Filter Bubble Analysis Using the Fine-grained Criteria

Feature-based Analysis. In our feature-based analysis of the three levels of addiction, as discussed in Section 7 of the main paper, we conduct various demographic and behavioral comparisons among severely addicted, mildly addicted, and non-addicted users, as shown in main paper's Figures 9 and 10, as well as Figure D and E in the Appendix. Consistent with the main findings in Section 7, a clear declining progression trend emerges, with engagement metrics, i.e., evening watch-time and daily exposed videos, decreasing from severely addicted to non-addicted users, further reinforcing the distinctions across addiction levels (see

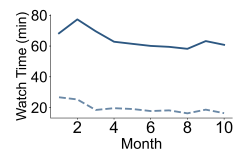


(a) Evening watch-time (b) Daily exposed videos

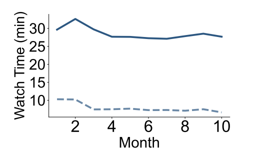
Figure E: Additional Feature distribution comparisons across three levels of addiction.



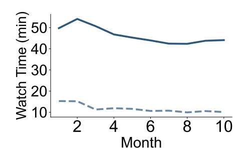
(a) Daily morning watch-time



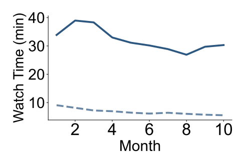
(b) Daily noon watch-time



(c) Daily afternoon watch-time



(d) Daily evening watch-time

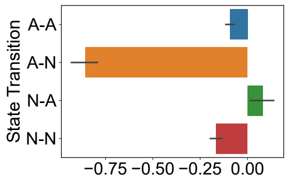


(e) Daily midnight watch-time

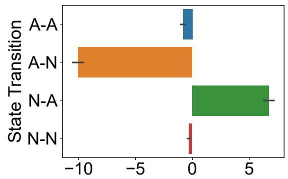
Figure F: Temporal distribution of daily watch-time across different time periods for addicted and non-addicted users.

Figure E).

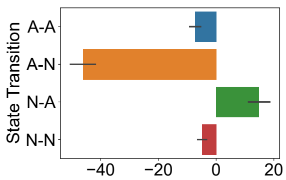
Filter Bubble Analysis. We also conduct the analysis on content diversity and the filter bubble in relation to user addiction. Similar to section 6, we first plot the overall coverage and the coverage per category level over time in Figures Ha and b, but now using the fine-grained addiction criteria, which splits addicted users into two groups: mildly addicted, and severely addicted. The trend of figure Ha shows that different degrees of addiction indeed have a distinct impact of coverage, with the coverage of mildly addicted users in between that of non-addicted and severely addicted users. The pattern of decrease in coverage with increasing addiction level is seen in Figure Hb for category levels one and two, but it is inconsistent for level three categories. In this case, addicted users have coverage similar to that of non-addicted users, whereas the coverage of severely addicted users is slightly lower. From this we can infer that the correlation between addiction and diversity does not apply to categories at the third level. The reason for this could be that, because average coverage is already very low at all levels, there is another factor that is affecting diversity at this level



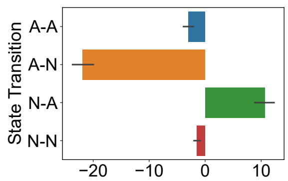
(a) Daily watch sessions



(b) Evening watch-time



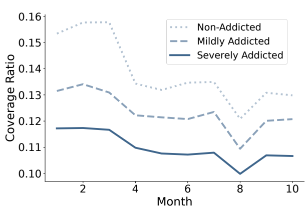
(c) Daily exposed videos



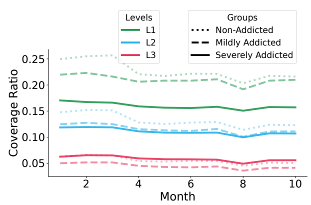
(d) Daily watched videos

Figure G: Changes in daily watch sessions, evening watch-time, daily exposed videos, and daily watched videos, during transitions between addiction and non-addiction states. ”A” denotes addicted, ”N” denotes non-addicted, ”A-N” represents users transitioning from addicted to non-addicted, and ”N-A” represents users transitioning from non-addicted to addicted. ”A-A” and ”N-N” indicate users maintaining their addiction or non-addiction status, respectively.

for all users, regardless of addiction status.



(a) Overall Coverage



(b) Coverage per Level

Figure H: Coverage over Time Using Fine-grained Criteria