"Are You Still Watching?": Exploring Unintended User Behaviors and Dark Patterns on Video Streaming Platforms

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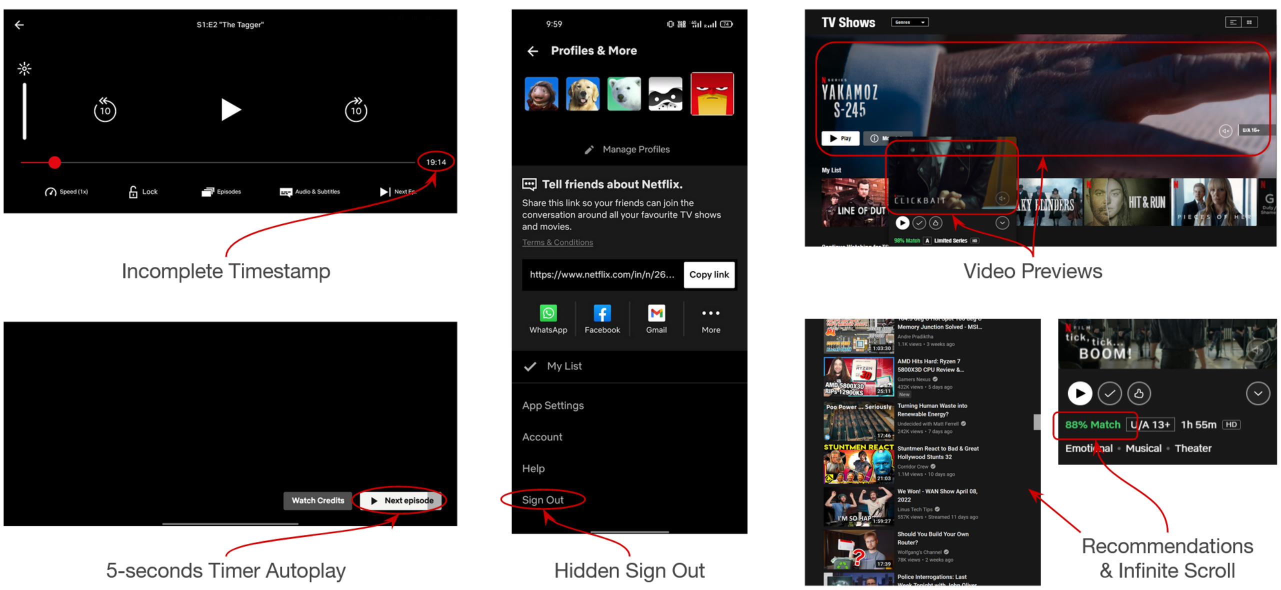

Figure 1: Instances of problematic UI features found on video streaming platforms, including autoplay timers with no exit options, infinitely scrolling recommendations, instant-start video previews, incomplete timestamps, and hidden sign out. Based on an analysis of UI artifacts found on 4 popular platforms (Netflix, YouTube, Disney+ Hotstar and Amazon Prime Video) that stream videos to mobile/tablet devices, laptops, and televisions, we identify dark patterns related to video streaming— "feature fog", "extreme countdown", "switchoff delay", "attention quicksand", and "bias grind"— and examine how these UI patterns can negatively affect users' wellbeing.

* Jaivrat Saroha and Kyzyl Monteiro made an equal contribution to the research presented in this paper.

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ABSTRACT

Dark patterns in UI promote addictive behaviors. We explore how the effects of dark patterns in video streaming applications can be exacerbated by a range of temporal and contextual factors. Previous work has shown that excessive watching is potentially detrimental to physical and mental health. We conduct a diary study with 22 viewers over 228 sessions to gain insight into users' states of mind and to identify users' emotions while interacting with 4 popular streaming platforms. We analyze users during both the selection phase and the completion phase, finding meaningful correlations between user mood and contextual behaviors that highlight how particular individual characteristics and viewing situations can lead to negative behaviors. We discuss the implications of our findings, highlighting important UI design considerations to enhance digital wellbeing. Furthermore, we collect artifacts of problematic UIs, and present a novel taxonomy of dark patterns found in popular video streaming platforms from a user-centric perspective.

CCS CONCEPTS

• **Human-centered computing** → *User studies*; *Interaction design theory, concepts and paradigms*; • **Social and professional topics** → *Codes of ethics.*

KEYWORDS

User Interface Design, Video Streaming Platforms, Binge-Watching, Dark Patterns, Digital Wellbeing

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1 INTRODUCTION

The use of digital platforms for engaging in various online activities is often contaminated by the presence of manipulative and deceptive design practices. These "dark patterns" push people to, for example, spend money on products they didn't intend to buy, to install apps they don't need, or to give away their personal data [39]. Naming these deceptive practices can help users to become more aware of design traps. For instance, users have become more savvy in avoiding "clickbait," a term initially coined by Jay Geiger and later used by Harry Brignull that refers to a range of strategies to hijack a user's attention and entice them to visit particular websites [6]. In this paper, we examine the design of popular video streaming platforms and analyze their UIs in terms of digital wellbeing parameters, including autonomy and user control, identifying dark patterns specific to video streaming.

People view increasing amounts of content via video streaming platforms. Recently, for example, Netflix's *Squid Games* recorded an online viewing total of 1.65 billion hours within 28 days of its release [46]. Moreover, usage of video streaming platforms is addictive [21, 32]. In his book 'Hooked,' Nir Eyal explains that, similar to drug addiction, emotional triggers for habit creation on online platforms often consist of temporarily suppressing negative feelings [18]. These triggers can include feelings of loneliness, boredom, or a need for social recognition. This leads to a vicious cycle of constantly diverted attention towards streaming platforms organized to fulfill temporary needs and desires [62]. Recurrent engagement in digital activities over these video streaming platforms have the potential to form new compulsive behaviors that are detrimental to the overall wellbeing of the user.

Studies have highlighted the adverse effects of excessive video watching, which include increased anxiety, sleep deprivation, and physical fatigue [17, 27, 53]. Video watching may also further induce depression-related symptoms in extended viewing sessions [59].[1] These negative effects highlight the importance of studying binge-watching habits. In this paper, we explore the role of common video streaming UI features, such as Autoplay and Recommendations, in forming unintended viewing behaviors. Additionally, we identify a range of UI patterns on video streaming platforms that disregard user well-being.

We conducted a preliminary exploratory survey on video watching with 180 university students aged 18-25. The analysis revealed that beyond "ease of content access," the primary major factor behind extended viewing behaviors on streaming platforms, the next two major factors are "mindless viewing habits" and "use of UI features" (such as Autoplay and Recommendations). We then conducted open-ended semi-structured interviews on a representative sample of 12 out of these 180 participants to gain initial insights into their general viewing habits. The interviews indicated that while video streaming platform UI features are seen as convenient for a shorter viewing duration, they habitually promote compulsive watching for a longer viewing duration. We further discovered that these platforms reduce user autonomy and self-control while video watching, and that this negatively impacts a user's sense of digital wellbeing.

These preliminary observations informed the design for our main study. To understand the role of UI features in manipulating contextual behaviors in short and long duration of viewing, we designed a diary study to record the states of mind and emotions of 22 users at both the interaction selection phase and the video completion phase, i.e., first at the start of the session and then again at end of the session. Further, we also recorded the level of autonomy and ease of use for each UI feature in short duration viewing versus long duration viewing. Based on our findings from this main study, we collect and analyze UI artifacts of Netflix, YouTube, Amazon Prime Video and Disney+ Hotstar that represent dark patterns of video streaming platforms. We then present a novel taxonomy of dark patterns found in popular video streaming platforms— "feature fog," "extreme countdown," "switchoff delay," "attention quicksand," and "bias grind"— from a user-centric perspective. Finally, we conduct interviews with 15 new participants regarding these dark patterns, highlighting their impact on digital wellbeing as seen from user's perspective.

In summary, our paper consists of three main efforts: (1) We conducted a preliminary survey with 180 participants and follow-up interviews with 12 of those participants (Section 3); (2) We conducted an online diary study with 22 participants (Section 4); (3) we developed a taxonomy of video streaming dark patterns and interviewed 15 participants to reflect on these dark patterns (Section 5). We discuss our findings and their implications for UX design in Section 6. The main contributions of this paper are:

- We identify temporal changes in user state of mind at the video selection phase and subsequent feelings at video completion phase, as observed in video watching experiences. The user experiences are recorded over a 20 day long diary logging study for popular UI features like Autoplay and Recommendations on 4 popular video streaming platforms.

[1] https://www.nbcnews.com/better/health/what-happens-your-brain-when-you-binge-watch-tv-series-ncna816991

- We provide qualitative findings for a comparison of UI features based on their ease of use and autonomy affordability parameters, and thereafter identify two significant contextual behaviors, work behavior and viewing hours, that are indicated in exacerbating binge-watching habits.
- We present a novel taxonomy of dark patterns as seen on video streaming platforms from a user-centric digital wellbeing perspective.

2 RELATED WORK

2.1 Negative effects of binge-watching

Intrigued by the growing involvement of users in binge-watching and its rising social relevance, researchers have collected various metrics for analyzing video watching as a digital activity. These include wellbeing parameters, such as engagement metrics [8, 16, 20, 21, 40, 42], metrics that incorporate design for positive emotions, such as satisfaction and happiness [7, 12, 14, 28, 38, 43, 54], and metrics that indicate detrimental effects on physical and mental health, such as heightened anxiety levels, fatigue, sleep deprivation, and feelings of isolation and guilt [17, 27, 45, 53, 59].

Due to alarming health concerns, researchers have shifted focus to analyze the parameters of user context that result in unhealthy video watching habits. These parameters include physical context (time of day, duration, location, screen preference) and psychological context (moods, feelings) [13, 41, 42, 60]. Researchers have also examined how the proliferation of online video streaming platforms influences important social and emotional aspects of a user. These incorporate a wide range of relevant factors, including the cultivation of empathy, anticipated regret, fear of missing out, automaticity, wellness, perceptions of goal conflict, and academic performance [27, 49, 56].

We use the physical, psychological, social and emotional aspects introduced in previous work as contextual behaviors influencing user UI interaction on video streaming platforms. We term contextual behaviors with respect to popular video streaming platform UI features like Autoplay and Recommendations as "individual characteristics" and "viewing preferences." We study how these factors interact with each other in video watching and thereby result in unintended compulsive viewing behaviors. We study these unintended viewing behaviors by finding out what the user's overall state of mind is while interacting with the video streaming platform UI features while also investigating their resultant feelings at the video completion phase. We are also interested in analyzing difference in autonomy and ease of use of each of the UIs at both the start and end of a video watching session. Since video watching can have these aforementioned negative consequences, it is important to talk about the wellbeing of users engaged in digital activities and how certain deceptive design patterns can disrupt the digital wellbeing of users.

2.2 Dark patterns

Many researchers have investigated how companies abuse users' limited cognitive abilities and biases [15, 19, 25]. Studies show that users make different decisions when provided with the same information based on how it is framed [5, 36, 51, 52]. These studies highlight how users give higher weight to readily accessible information [50] and become susceptible to impulsive decision making the longer they have to wait before they get a reward [1]. Users have certain vulnerabilities while involved in various digital activities and do not always act in their best interests [10]. This highlights the importance of ethics in designing online experiences [9, 22, 23]; though attention grabbing may be a necessary aspect of a user interface, it should not impact the end-user's wellbeing while doing so. Recently, many researchers have investigated how to design user interfaces to support a general sense of satisfaction and other positive emotions [2, 7, 12, 14, 28, 38, 43, 54]. Specifically for video watching, Swart et al. [47] present the design and evaluation of an ad detection toolkit on YouTube, thereby instantiating discussions on ethics of UI design and how to overcome malicious designer intents. Peters et al. [40] describe four spheres of experience that are relevant to design technology for ensuring user wellbeing in various digital experiences. In addition to focusing on the interface, they examine the tasks that are enabled, the user's behavior patterns, and the user's "overall life." Following Peters et al., we are interested in the UI design decisions necessary for video watching as seen from the perspective of a user's overall life.

The term "dark pattern" was originally described succinctly by UX designer Harry Brignull as "a user interface carefully crafted to trick users into doing things they might not otherwise do" [6]. In addition to highlighting immediate manipulations that lead to problematic outcomes, we find it useful to extend this definition to include interactions that can produce detrimental consequences to a user's wellbeing over a longer period of time. That is, we classify the design of any interface elements that disregard the end user wellbeing as a dark pattern. Conti and Sobiesk [11], Lewis [34], Greenberg et al. [26], and Gray et al. [24] also investigate dark patterns, finding a range of problematic UI designs across contemporary websites and applications. For example, Zagal et al. [63] describe the dark patterns that are specific to gaming and Mathur et al. [37] delineate dark patterns related to shopping. In this paper, we classify dark patterns for the digital activity of video watching through studying user behaviors on 4 video streaming platforms, adding new categories of classification to the literature of dark patterns. While the perspectives used for listing dark patterns can have various stakeholders, including designers and policy makers, and different use cases, including commercial deployability and governmental regulations, our research is focused on raising awareness in the community regarding dark patterns as perceived from the end-user perspectives.

3 PRELIMINARY SURVEY

We conducted an exploratory questionnaire on 180 university students aged 18-25, recruited through email. The questionnaire contained multiple choice objective questions related to video watching. We came up with a list of factors that cause general addiction (fear of missing out, loneliness, while relaxing, habit formation) [31, 32] and augmented it with factors that are specific to binge-watching from existing literature [13], including "ease of access of digital media" and "power of compelling content". We asked the participants to self-report on these objective questions using a 5-point Likert scale in order to gather information on their feelings as influenced by these factors while they binge-watch.

To understand how these UI elements lead to unintended viewing habits, we also conducted open-ended semi-structured interviews with 12 of the survey respondents. In order to get more in-depth feedback from both self-reported bingers and regular viewers for our interviews, we randomly selected 3 participants from each of the following categories of self-reported daily viewing hours: 0-3 hrs, 3-5 hrs, 5-7 hrs, and 7+ hrs. Initially, we asked icebreaker questions about user's daily video watching habits, general experiences, and opinions about the online video streaming services they have used. The questions encouraged users to introspect about the way they watch, focusing on how and why they used certain features and ignored others. We showed different application screens and played videos on four major platforms— Netflix, Amazon Prime Video, Disney+ Hotstar, and YouTube, which were revealed as the most popular to our participants through the preceding survey— to induce users to recall prior personal experiences on streaming platforms. Most participants chose more than one platform when indicating their preferences, identifying the four most widely used platforms in India. Further, we quizzed users on which UI features they believed had positive and negative effects on their viewing behavior. The interviews were conducted online on Google Meets and each interview lasted on average for 22 minutes.

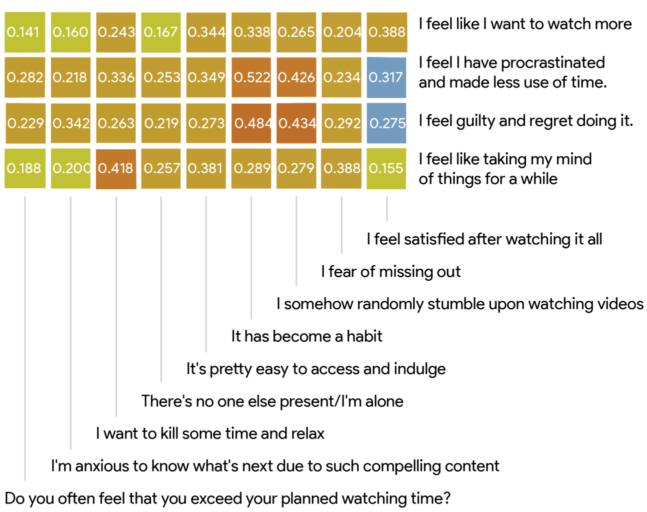

Figure 2: This chart presents the Pearson correlation results of our preliminary study, showing the statistical correlation between factors responsible for binge-watching and the participants' associated feelings with these factors. Here, redder/warmer colors indicate higher correlation, while bluer/cooler are inversely correlated. Our survey found that a majority of users developed binge-watching habits and have felt regret when engaging in binge-watching behaviors.

The survey and follow-up interviews helped in establishing an initial empirical understanding of UI influence on user viewing habits. We used the Pearson correlation method in our statistical analysis. Figure 2 summarizes the results of the study. While compelling content was found to be the most significant factor, ease of access (SD 0.735, $p<0.0001$) and habit formation (0.420, $p<0.0001$) were two other significant contributors that promoted binge-watching. 75% of users felt that ease of access to video content and viewing habits promoted by Autoplay and Recommendations led to excessive viewing. Further, 90% of users also confessed that they often exceeded their planned watching times. We found that people who did so experienced negative emotions, felt higher levels of regret, procrastinated, and were dissatisfied immediately following the excessive viewing session.

All participants in the preliminary survey mentioned that although the UI features are easy to use, they are also responsible for promoting compulsive viewing in certain situations. Based on the results of our preliminary survey, we made the following hypotheses:

H1 - *We hypothesize that users tend to have a compulsive state of mind in longer usage of a video streaming platform and regret over-watching.*
H2 - *We also hypothesize that the commonly used features like Autoplay and Recommendations increase compulsiveness in their long term usage.*
H3 - *We further hypothesize that UI dark patterns are responsible for the reduction in user autonomy and self-control on video streaming platforms.*

4 ONLINE DIARY STUDY

In our preliminary survey, habit formation was found to be one of the prominent variables responsible for causing over-watching sessions. We therefore contextualize the "habit loop" of trigger, routine, investment and reward [18] for video watching as experienced by users in terms of their moods and feelings. The habit loop for video watching can be summarized as consisting of the following four stages: 1) External *triggers* presented via UI elements and internal psychological states, such as loneliness, boredom, "FOMO," etc.; 2) The resulting *action* of diverting a user's attention; 3) The *reward* of temporary enjoyment and satisfaction; and 4) The continued *investment* into the content of the story, such as wanting to find out what happens in the next episode after the previous episode ends on a cliffhanger.

We use this conceptualization to design an online diary study with concluding follow-up interviews to investigate hypotheses **H1** and **H2**. We encouraged participants to watch videos naturally and fill in the diary prompts with responses to help us gain an understanding of their thought process while they select an interaction, and subsequently to understand their emotional tendencies after concluding a video. That is, the diary activity occurs at two temporal stages, one at the start and one at the end of a session.

4.1 Recruitment & Protocol

We recruited participants via emails circulated throughout Indraprastha Institute of Information Technology Delhi (IIIT-Delhi). To ensure a mix of "bingers" and regular viewers, we selected 6 students from each category of self-reported average viewing hours per day: 0-3 hrs, 3-5 hrs, 5-7 hrs, and 7+ hrs. This was done to include an equal number of people in a mix of homogeneously time-varied video watching categories, which allowed us to gain a more comprehensive view that includes the extreme cases of participants' video watching behaviors. All 24 participants (13 females and 11 males, all within 18-25 years of age) were required to sign a consent form for sharing their viewing data preferences and assured of data confidentiality prior to beginning the study.

Binge-watching is defined as watching at least 2–3 episodes in a row [29]. Hence, participants were encouraged to fill in the diaries if they watched at least 2 videos within a session. To avoid influencing natural viewing behavior, we gave them a 20-day period to record at least 7 viewing sessions. To encourage them to complete the study, we provided weekly prompts to users via emails containing information about the status of their current progress in terms of the number of video session watched versus sessions remaining, and further reminding them to fill out entries when viewing a video session. All participants responses were recorded on Typeform. Each participant was incentivized with INR 100 for completing the study. We conducted follow-up interviews with each participant to gain additional insights on the trends observed after analyzing the data.

4.2 Method

Regretful and mindless behaviors are often assumed to be a result of various content related factors like video and audio quality, liking or disliking characters in a story, the quality of script, etc., each of which is subjective for each individual participant. However, according to our survey, we found regretful behaviors to be caused by unconscious and unplanned viewing of undesirable content, or due to over-watching. For this reason, we explicitly designed our prompts to investigate user moods as a result of over-watching and undesirable content. This gave us the following four options for each prompt of user feeling: "satisfaction due to desirable content and duration," satisfaction due to desirable content but regret due to over-watching," "satisfaction due to duration but regret due to undesirable content," and "regret due to undesirable content and over-watching."

Dual Process Theory acts as our framework to investigate thinking patterns and user perceptions in video watching as it is intended to reveal both conscious (controlled, mindful) and unconscious (automatic, mindless) thinking patterns [30], as manifested in user viewing behaviors when interacting with UI features to navigate to the next video in a session. This is done by providing options that display an equal number of mindful/conscious states of mind, mindless/unconscious states of mind, and an option in between them for each UI interaction. In general, participants were encouraged to use additional comments for any diary prompt using the "others (please specify)" option, wherever necessary.

To capture user affect, we provide 12 categories of distinct positive and negative emotions in equal numbers that are relevant to video watching as options, following the approach used in the PANAS scale [57]. We also include one neutral emotion so as to span all emotional valences. Motivated by the SAM pictorial scale [58], we represented each emotion with a different cartoon graphic so that users could quickly make decisions regarding their perceived emotions. All options in the diary study are randomly organized and presented. All options are formulated as a result of individual user characteristics and viewing preferences with respect to video streaming platform UI features (Autoplay, Recommendations, Search, Save/Watch Later). Details of the diary study prompts and user response options are provided in Section 1 of the supplementary material document.

Our online diary contains prompts for participants to reflect on their use of UI features, the context (place, time, social setting), feelings (satisfaction, regret, or somewhere in between) and their state of mind (mindful, mindless, or somewhere in between). The diary prompts are used to record user state of mind of participants at the video selection (interaction) stage and user feelings subsequently at the video completion stage. Further, the prompts also include rating each UI feature on the basis of its ease of use and autonomy affordability on a scale of 0 to 10 at both of these stages.

Our follow-up interviews are designed to reveal reasons behind the trends observed in the user responses over the data logged in the diary study. For this reason, we generated hypothetical video watching situations related to user context, viewing preferences, and individual characteristics, that would remind users of their past experiences at the two video watching phases (selection and completion), at different temporal stages (start and finish) of viewing. This helped them reflect on reasons behind their UI-related feature interactions and watching behaviors in general. This also gave us an opportunity to engage users in a discussion regarding the implications of problematic UI design features as seen from a digital wellbeing and user-centric design perspective.

Mean of observed viewing time	F	M	Total
30 min - 1 hr 15 min	3	3	6
1 hr 15 min - 2 hr	4	2	6
2 hr - 3 hr 15 min	3	3	6
3 hr 15 min +	2	2	4

Table 1: Participant distribution for online diary study based on their observed average daily viewing hours

4.3 Analysis

All participants were anonymized before starting the analysis. Our study's attrition rate was 8.33% (2 dropouts), excluding cases where the participants logged less than 7 sessions. Since the observed average daily viewing hours of participants in the study differed from users' self-reported daily viewing hours, we homogenized the participant categories after all data logging was complete based on their observed mean viewing hours (see Table 1). 22 users registered 228 sessions (163 laptop/PC, 51 mobile/tablet, 14 television sessions) across 20 days, with one participant logging 9 entries and the remaining logging at 10 or more entries. 15 participants finished logging within 10 days, and the remaining took the entire 20 days to complete the logging.

We observed that participants overwhelmingly viewed entertainment-related content (95.6%). Participants were required to rate each interaction on a 10 point scale on two aspects: "ease of use" and "autonomy afforded." A higher ease of use rating means that the functionality of the interaction makes the video watching session more convenient. A higher autonomy scale means that the user has more freedom to make an autonomous decision. Conversely, lower the rating on autonomy scale indicates more compulsiveness.

For the entire analysis, *Autoplay* refers to the automatic playing of the next video in the episode list or an auto-generated queue of video streaming platforms upon completion of a video, or when reaching the final part (e.g., credits) of a video. *Search* refers to the UI functionality of manually typing text to search for relevant videos over the content data collection of the streaming platform. *Save/Watch Later* refers to the UI functionality of saving a video for viewing later by adding it to a "playlist" or "collection". *Recommendations* refers to the list of videos presented to viewers on the streaming platform as suggested videos (including synonyms like "More like this", "You may like", "xx% match"), represented as thumbnails with a descriptive text title. Since Netflix includes subcategories within Recommendations, we include UI features on YouTube like "Trending/Explore," "In-Video Pop-Up," and "Subscription" interactions to represent the overall Recommendations category. This creates a more level playing field for comparing UI features across different platforms.

After combining them together, we present analysis of four features: *Autoplay*, *Recommendations*, *Search*, and *Save/Watch Later*. Participants chose Autoplay an overall 150 out of 456 video session phases (32.89%). The mean ease of use and autonomy ratings of Autoplay were 8.59 and 4.85, with a standard deviation of 1.56 and 2.53, respectively. Participants chose Recommendations an overall 143 out of 456 video session phases (31.35%). The mean ease of use and autonomy ratings of Recommendations were 7.71 and 5.44, with a standard deviation of 1.86 and 2.79, respectively. Participants took to Search an overall 51 out of 456 video session phases (11.18%). The mean ease of use of search was 7.83 (s.d.=1.47). Only seven video session phases had participants who chose Save/Watch Later interaction.

We classify contextual behaviors in two categories, namely, users' "individual characteristics," such as observed viewing hours, self-reported planner, and affect tolerance, and "viewing preferences" such as platform, extended viewing, and work behavior. To better understand the two features used most often, Autoplay and Recommendations, we analyzed the effect of our variables— feelings, state of mind, ease of use, compulsiveness, individual characteristics, viewing preferences— due to the use of Autoplay and Recommendations on our dependent variable (start of session, end of session). To analyze the discrete variables (feelings, state of mind, individual characteristics, and viewing preferences), we ran two independent logistic regressions, one each for Autoplay and Recommendations. We use odds ratio (OR) for interpreting the relationship between each of these discrete variables.

4.4 Results of Online Diary Analysis

We initially compare the overall results of Search and Save/Watch Later features with Autoplay and Recommendations. We then present the "ease of use" and "autonomy" results of Autoplay and Recommendations. We finally present the results displaying the effect of Autoplay and Recommendations on user state of mind and feelings.

4.4.1 ***Search and Save/Watch Later versus Autoplay and Recommendations***. Search had 78.43% of its total video session phases, where participants clicked on what they wanted to watch rather than watching suggested content. This was higher than Autoplay and Recommendations, where only 50% and 52.45% of their respective total video session phases had participants who clicked on the interaction suggestions that they actually liked. Further, 98.04% of video session phases with Search interactions had participants satisfied in that they watched the desired content after completing the video.

The mean ease of use of search (7.83) was almost comparable with Recommendation (7.71), but relatively less than Autoplay (8.59). However, as we moved to the end of a session, the Ease of Use of Search moved to 8.03, higher than that of Recommendations (7.52), but still lower than Autoplay (8.40). Also, the mean autonomy rating of Search was 6.68, which was higher than Autoplay (4.85) and Recommendations (5.44). This suggested that although Search is rated as a better autonomy-enabling interaction than Recommendations, when we move towards the end of a session, people nonetheless use Recommendations (84 video sessions) more than Search (30 video sessions).

Save/Watch Later had 71.43% of its total video session phases where participants clicked on what they wanted to watch and did not watch mindlessly. Further, 100% of video session phases had participants satisfied with what they watched after completing the video. The autonomy rating of Save/Watch Later when we move to the last two videos was highest at 6.66, which meant this feature induced the least compulsiveness out of all the features when moving towards the end of a video session phase.

We found that although Autoplay and Recommendations help in ease of use, Search and Save/Watch Later are better features in terms of promoting autonomy.

4.4.2 ***Contextual Behaviors: Viewing hours and Work Behavior***. Here we present viewing trends based on significant contextual behaviors, as observed from the regression analysis. Among all the 'individual characteristics' and 'pattern preference' variables, we observed significant viewing trends due to Viewing Hours and Work Behavior.

Viewing Hours – We observed similar trends for Autoplay and Recommendations for the mean observed viewing time (Figure 4(c)). The odds of participants being in the viewing hour category of 1.25 hrs - 2 hrs is less than the odds of participants being in the category 2 hrs - 3.25 hrs, which is further less than the odds of participants being in the category 3.25 hrs or above, as we move from the start of a viewing session to the end, when either of Autoplay or Recommendation is used. The interviews revealed the reason behind this might be the tendency of users to become tired as the they continually watch more. The participants with higher mean observed viewing hours tended to become more tired compared to others. Hence, their selection becomes more mindless, enforcing an extended viewing behavior. For Autoplay, the odds of a participant being in the viewing category of 0.5 hrs - 1.25 hrs is highest, which seems counterintuitive. However, as observed from the concluding interviews, the reason behind this could be that as most participants were university students having lectures and work assignments, they tended to view short season episodes, like Friends, or view short study related videos on YouTube for learning coding skills. P11 said, "At times, I just watch a 10 or 20 minute video, like Friends or Seinfeld while having lunch. It acts as a quick burst of entertainment dose in between the studies without any time waste." P13 said, "I would watch 5 minute coding tutorials here and there just to know how to implement a particular library, lets say on Python. That's the fastest way for me to learn implementing a coding skill."

Work Behavior – We observed opposite trends in work behavior of users while using Autoplay and Recommendations. As we move from the start of a viewing session to the end, the odds of people who use Autoplay while video watching before starting their work *decreases* with respect to people who video watch after completing their work (see Table 1 in the supplementary materials document for values of odds ratio). This is in contrast to Recommendations where the odds increase as we move from start to end. According to the interviews, this might be because people usually use Recommendations to select a new video for viewing. This is in contrast to Autoplay, which makes people watch episodes on a loop, especially in a series. P5 said, "I usually don't start a series before I complete my study targets for the day. It's difficult to concentrate on my studies if I start a series, which makes me less productive. It's just this urge to complete the story before I start anything else."

4.4.3 ***Ease of Use and Autonomy - Autoplay versus Recommendation***. We observed that although users found UI features to be helpful, they also thought them to be compulsive at times in our initial survey analysis. To confirm and quantify this, the following section presents the results on the ease of use and autonomy parameters for Autoplay and Recommendations. On most platforms, the first recommended video is used for Autoplay. Hence, throughout our analysis we consider all the Recommendation videos to be other than the Autoplay videos, i.e., they are mutually exclusive.

Figure 3(b) shows that as we move from the start of a viewing session to the end, the ease of use of both Autoplay and Recommendations decreases marginally. However, Figure 3(c) shows that with time, power of inducing compulsiveness increases more for Recommendations than Autoplay. This is surprising because our intuition is that Autoplay usually goes unnoticed when it offers new episodes in a season for viewing to the user. On the other hand, as one keeps using Recommendations in a video session for selecting new videos, they might become aware that their content biases are reinforced by the Recommendation algorithm. P2 from the interview said, "Once a Hell's Kitchen video was just popped up on my recommended page and I went - Ah, its the algorithm again. I don't want to watch this all the time, stupid algorithm..." We hypothesize that this might be because we used self-rated user responses. This makes the perceived compulsiveness of Recommendation as higher than Autoplay, whereas the actual trend might in fact be the opposite.

To understand the effects of Autoplay and Recommendations and understand their correlation with user moods and feelings, we present our results from regression analysis of Autoplay and Recommendations, coupled with reasons and explanations for certain trends from the follow-up interviews.

4.4.4 ***State of Mind and Feelings - Autoplay versus Recommendations***. We define two stages which are important to analyze in a video watching session, the *video selection (interaction) phase* and the *video completion phase.*

Video selection phase – We refer to video selection phase as the phase where users interact with the UI features of streaming platform to select a video for viewing. We use this for analyzing user state of mind.

(1) As observed from Figure 3(a), as users move from the first 2 videos towards the last 2, or as users move from the start of a viewing session towards the end, the percentage of people who view videos mindlessly increases by 24.8% in Autoplay, as compared to the percentage increase in mindless viewing due to Recommendations, which is 3.5%.
(2) As users move from the start of a viewing session towards the end, they move from liking a video suggestion on Autoplay, to mindlessly letting it play, and finally to a margin of uncertainty (somewhere between liking the Autoplay suggestion to mindlessly using it) (Figure 4(a)). The interviews revealed two explanations for this. Firstly, most Autoplay suggestions were used by users to complete a story in a series (continuous content format of story development over multiple episodes). Therefore, even if the user did not like a story, they watched the video so that a closure could be achieved. P6 said when discussing Autoplay, "5 seconds left on Autoplay and then you're like never mind, it has started already. I can't stop it because once the content starts and I'm about to cancel or exit, it feels like you're leaving it midway. There's this strange feeling of missing out on something. It's only later when you have lost a lot of time that you realize that I had no reason to complete the video, maybe other than to watch how the story ends." Secondly, while watching a series, users did not have enough time in the Autoplay timer to pause to reflect and discuss about the recently concluded episode of a story clearly, or to make a conscious decision to stop watching. P8 said, "Watching credits should be default action when one is watching a story. An episode usually finishes at a watershed moment, which requires thinking and discussions with fellow watchers, which are arguably denied by Autoplay after conclusion of an episode. Honestly, this could be avoidable. It ruins the viewing experience."
(3) As users move from the start of a viewing session toward the end of a viewing session, they move from a margin of uncertainty, to liking a video suggestion through Recommendations, and finally to mindlessly selecting a Recommendation suggestion (Figure 4(a)). The interviews revealed that this might be because most users at the start of the session were not sure of which Recommended video to select in the selection phase. But since Recommendations continuously keeps recommending on the basis of previous watching history after completing each video, people start liking the suggestions as it starts matching their current mood. P5 said, "Recommendations are good to get started with. I get to choose the topic of the videos that I have watched currently." However, towards the end of a viewing session, users are usually exhausted and bored with the presented Recommendations. P4 said, "As you keep selecting the videos from Recommendations in YouTube, it feels like a rabbit hole, you start disliking the viewing experience. I mean it might be good to have a wider range of recommendations at times, like Netflix does."

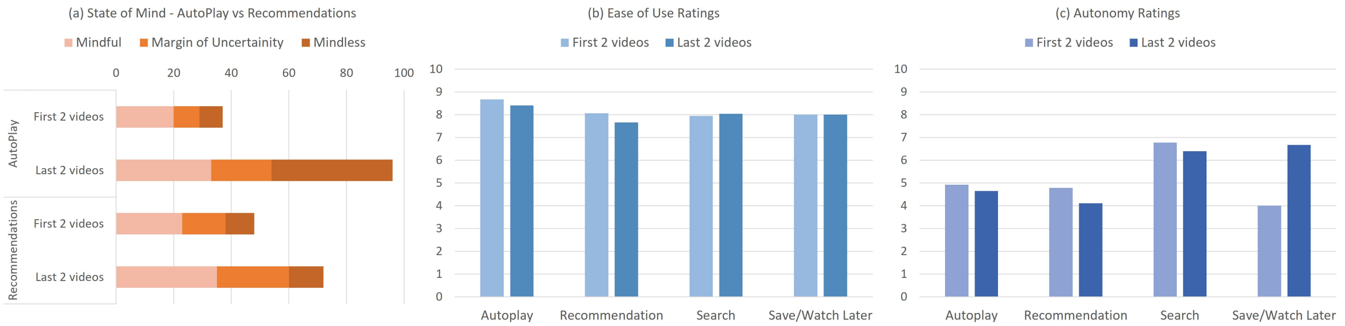

Figure 3: (a) Represents number of sessions in which people were mindless, mindful or in the margin of uncertainty while selecting an interaction to watch a video due to either Autoplay or Recommendation. These classifications are displayed for both start and end of viewing session. We define margin of uncertainty as the state of mind of people in sessions where they were not exactly mindful or mindless, but somewhere in between. (b) Displays the mean ease of use user ratings for the 4 UI features - Autoplay, Recommendations, Search, Save/Watch Later for start and end of a viewing session. (c) Displays the mean autonomy user ratings for the UI features for start and end of a viewing session.

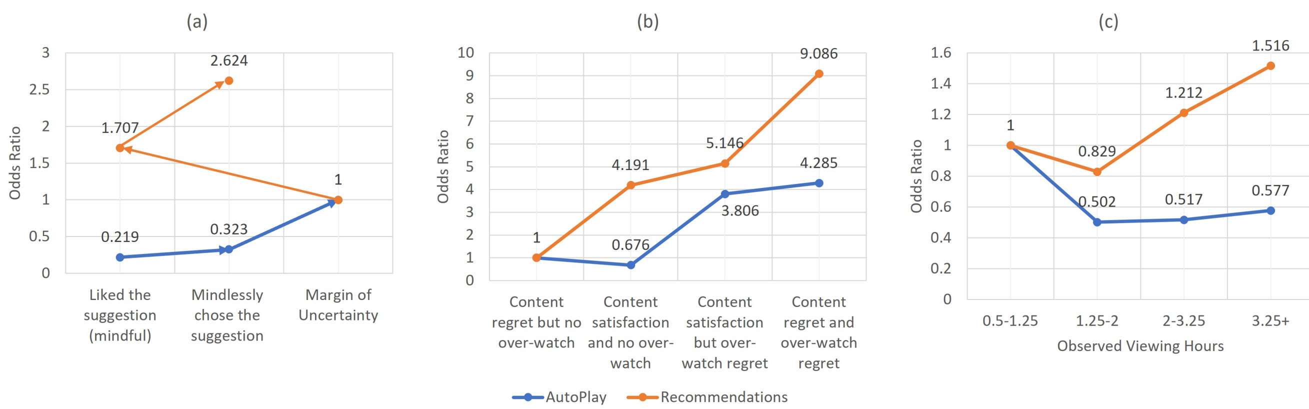

Figure 4: (a) Displays the odds ratio in linear regression values of the three user states of mind (mindful - liked the suggestion, mindless, margin of uncertainty) when using Autoplay and Recommendations, representing trends in user states of mind due to different types of user interaction. (b) Displays the odds ratio in linear regression values of the four types of user feelings when using Autoplay and Recommendations, representing trends in user feelings due to different types of user interaction. (c) Displays the odds ratio in linear regression values of observed viewing hours, representing trends in viewing behavior due to duration of session length.

Video completion phase – We refer to video completion phase as the phase where users conclude watching a video. We use this for analyzing user feelings.

(1) As observed from Figure 5(a), unplanned viewers who tend to extend their viewing sessions increase chances of feeling regret by 34.02% while using Recommendations. The percentage increase in regret due to Autoplay is 19.8%. Although the percentage increase for both Autoplay and Recommendations are high here, the percentage increase in regret due to Recommendations is much higher and much more problematic.

(2) As users move from the start of a viewing session towards the end of a viewing session, there are two most prominent feelings after finishing a video selected using Autoplay. One is a feeling of dissatisfacton due to content and regret of over-watching the amount of content. Second is satisfacton of content but regret of over-watching the amount of content (Figure 4(b)). This result was very significant in our findings. The interviews revealed that the reason behind this could be Autoplay's way of working while users view a series, which is to continuously enforce content to users that they like and force them to watch back to back episodes in a season until they finish the entire season off. P7 said, "It's almost predatory, you can't have any discussions with family or friends, you hardly get any time to interact with the UI in the limited timer, and there you go, another episode starts."

(3) As users move from the start of a viewing session towards the end of a viewing session, the most prominent feeling

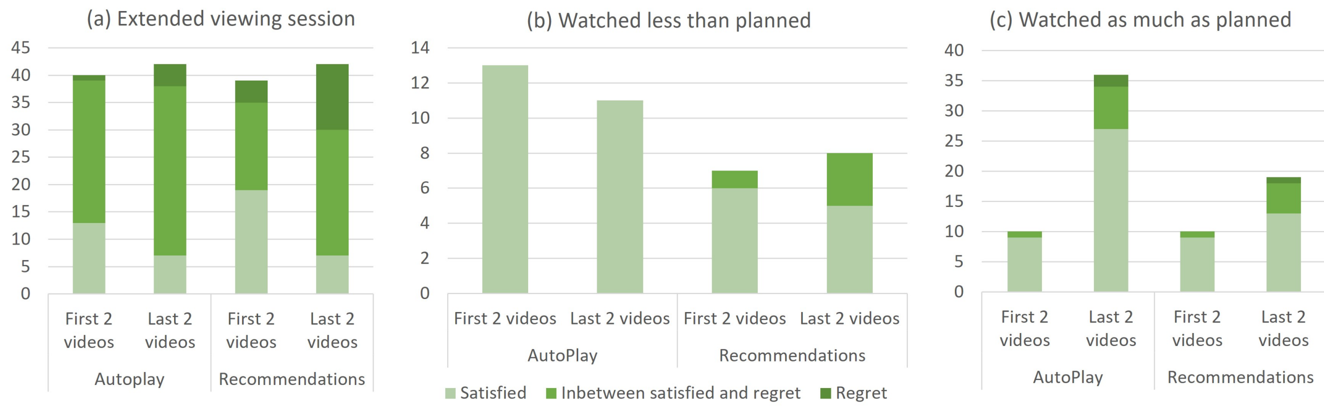

Figure 5: Represents number of sessions in which people were satisfied, regretted or in the margin of uncertainty after watching a video selected due to either Autoplay or Recommendation. These classifications are displayed for both start and end of a viewing session (a) Shows classification of these number of sessions for all extended viewers. (b) Shows classification of the number of sessions for people who watched less than they planned. (c) Shows classification of the number of sessions for people who watched as much as they planned. We define margin of uncertainty as the feelings of people in sessions where they were not exactly satisfied or regretted, but somewhere in between due to watching undesired content for a desired amount time, or watching desired content for an undesired amount of time. The Y-axes have been rescaled in each figure as required to show change in number of sessions across the listed categories.

after finishing a video selected using Recommendations is dissatisfaction due to the content watched along with over-watching (Figure 4(b)). This result was very significant in our findings. We also observed that the odds of an extended session is more when a user uses Recommendation than Autoplay, as a user moves from the start to the end of a session. Hence, we conclude that Recommendations causes more regretful extended viewing sessions than Autoplay as with Autoplay suggestions the user watches the desired content which is not the case with Recommendation suggestions. The interviews revealed that this might be because of undesired Recommendations which people end up watching and eventually wasting time on. P12 said, “I usually watch the series recommended by a friend or which is trending, so I don’t have to go through the Recommended videos.” P10 said, “Just because the medium is easy to use, and not as hard to get onto as maybe reading a book, its easy to just start watching whatever Recommendation you get. Its the best time pass, but usually I feel like I could have watched something better, or maybe have done something more productive.”

We conclude that among Autoplay and Recommendations, Recommendations enforces more mindlessness at the interaction (video selection) stage, whereas Autoplay enforces more extended viewing sessions. We noted that high duration viewing sessions were more as a result of Autoplay than Recommendations. Both Autoplay and Recommendations induce increased feelings of regret due to over-watching undesired content at the post-video watching stage towards the end of a session, indicating that these features impose unintended behaviors of over-watching.

4.5 Design considerations for digital wellbeing

Our online diary study data provided initial confirmation for our hypothesis that UI elements are responsible for causing regrettable over-watching behaviors (**H1**). We also found that default UIs generally enhance usability without inducing compulsiveness at the start of a viewing session. However, these features tend to become compulsive as we approach the end time of a viewing session (**H2**). Hence, design safeguards are especially needed as we approach the end of a viewing session in order to reduce mindless viewing. Here we present some ways to enforce more conscious interactions with video streaming platforms that can enhance end user digital wellbeing.

- *Autoplay nudges* - Since Autoplay enforced a drastic (24.8%) increase in mindless behaviors with the progression of viewing duration in a video session, design safeguards like nudges could be particularly useful in prompting a user to make a conscious interaction before continuing to watch more videos [12].
- *Conscious default UI interactions* - The only options available in Autoplay while video watching a series are ‘Watch Credits’ and ‘Play Next’. While currently the default option for video watching is selecting ‘Play Next’ after a brief amount of time, the default option could instead be changed to ‘Skip Credits’ and then require a conscious interaction in order to begin playing the next episode of the series.
- *Varied recommendations* - Netflix is a good case in point for other video streaming platforms in that it tries to maintain categories and introduce varied Recommendations that users can choose from. By effectively categorizing personalized recommendations, the platform helps the user in making a

decision resulting in well informed and better utilization of their engagement times with the platform.

- *Alternative recommendation nudges* - Since suggesting new recommendations currently work on providing video options that extend the user interests and biases over the previous watching history, design safeguards that timely refresh Recommendations randomly and provide nudges for introducing something new after a particular threshold of Recommendations might be helpful to break out of the set list of options that users are engaged in. This can help expose them to new personal interests, potentially enhancing and broadening their interests and moods, thereby reducing mindless viewing.

In analyzing the previous study, we found that current UIs are responsible for a loss autonomy and self control in users while they video watch. While the above mentioned design safeguards could serve as helpful measures to improve the current state of UI on video streaming platforms, we also identify and validate instances of specific problematic design UI patterns that promote inadvertent user watching behaviors, which we discuss in the next section.

5 DARK PATTERNS ON VIDEO-STREAMING PLATFORMS

We categorize dark patterns on video streaming platform UI after analyzing artifacts on YouTube, Netflix, Amazon Prime Video and Disney+ Hotstar. These are patterns that have the potential to promote unintended viewing behaviors in a video watching session.

5.1 Protocol

Based on user insights gathered from the diary study, a team of 4 researchers, including one more senior researcher with extensive UX design expertise, separately analyzed the individual UI features on each of the 4 streaming platforms available across different devices (laptop/PC, mobile/tablet devices, television). All the researchers then presented their findings on each UI element across the 4 platforms, and worked together to identify problematic UI elements. Finally, every researcher independently confirmed that all formulated categories were appropriate. The goal of this categorization process was to reveal certain situations of use and their consequent effect on a user's state of mind. For example, 'extreme countdown' not only represented the timer in an Autoplay functionality, but also the pressure situation induced by it for the users to make a decision. We arrived at a total of 44 UI artifact instances. These are highlighted in Figure 7 through red marked icons. We recruited 15 participants by sending emails across the university for interviews to gather evidence on the selected UI artifacts. The participants were a mix of randomly chosen self-reported bingers and regular viewers in the following categories: 0-3 hrs (3), 3-5 hrs (4), 5-7 hrs (4), and 7+ hrs (4).

5.2 Interview method

We conducted open-ended interviews with each participant asking general UI-related questions, inquiring about interface functionality and effect on video watching. We then showed them our set of screenshots that contained instances of problematic streaming UI artifacts. (Examples of these screenshots are provided in Section 3 of the supplementary materials document). To understand each participant's thoughts about our compiled UI patterns, we encouraged them to speak freely. We asked each participant to recollect their previous viewing experiences in relation to the viewed UI artifact while mentioning the effects of those UI patterns on their viewing habits. After each category of similar type of problematic UIs, we encouraged participants to provide potential suggestions to reduce their addictive viewing effects, if any.

5.3 Analysis

All interviews were recorded and transcribed. Each interview lasted for an average of 25 minutes. Three different researchers separately inductively coded UI pattern themes which cause unintended viewing on video streaming platforms. After analyzing these 3 separate sets of codes, we came up with 8 distinct themes. We finally converged these 8 categories into 5, after analyzing the formulated definitions and resolving overlapping categories. We then present 5 dark pattern themes to describe their long-term negative capabilities as observed from the participant interviews (see Figure 6 and Figure 7). Our analysis of these interviews provide an initial confirmation of our hypothesis that UI dark patterns impact aspects of user wellbeing, including user autonomy and self-control (**H3**).

5.4 Feature fog

"Feature fog" refers to UI patterns that induce unawareness by reducing autonomy of monitoring user time spent, and is related to Brignull's "hidden information" [6] and Gray's "interface interference" [24]. These UI patterns are designed so that the user less able to get feedback on time spent engaged in a viewing session. For example, the time elapsed feature that lets you monitor how much time has elapsed since the start of video is missing from Netflix. Upon showing the time elapsed feature (Figure 1), 12 out of the 15 participants agreed that this feature has the potential to enforce unawareness of sense of time spent on the platform. As observed from our previous user study, we can say that over time such a pattern becomes more prominent in enforcing extended viewing sessions. 6 out of 15 participants were unaware if this pattern even existed. P09 says, "I never paid attention to this. This does definitely seem deceptive to me." P12 says, "Usually, I can subtract the time elapsed from the actual length of the time to know how much time I have spent. But other times, I am like let's just complete the movie or episode. It does lead to an extension of over half an hour to 1 hour in my viewing experience."

This pattern leads to a sense of time unawareness persuading users to watch more, irrespective of the time spent already. P04 says, "I tend to forget to keep track of time and it (Netflix) doesn't help me at all." This is similar in effect to the psychological trick used by restaurants called 'menu engineering,' where they hide the costly items so that they customers not in direct visual contact of customers [33]. Similarly, in video streaming platforms it can be argued that the time elapsed feature is intentionally hidden from the default UI so that users don't exit by seeing it. Ideally, this can be fixed by incorporating both time elapsed as well as time remaining for a video with a scope of enhancement by adding a 'Time watched' feature as seen in YouTube.

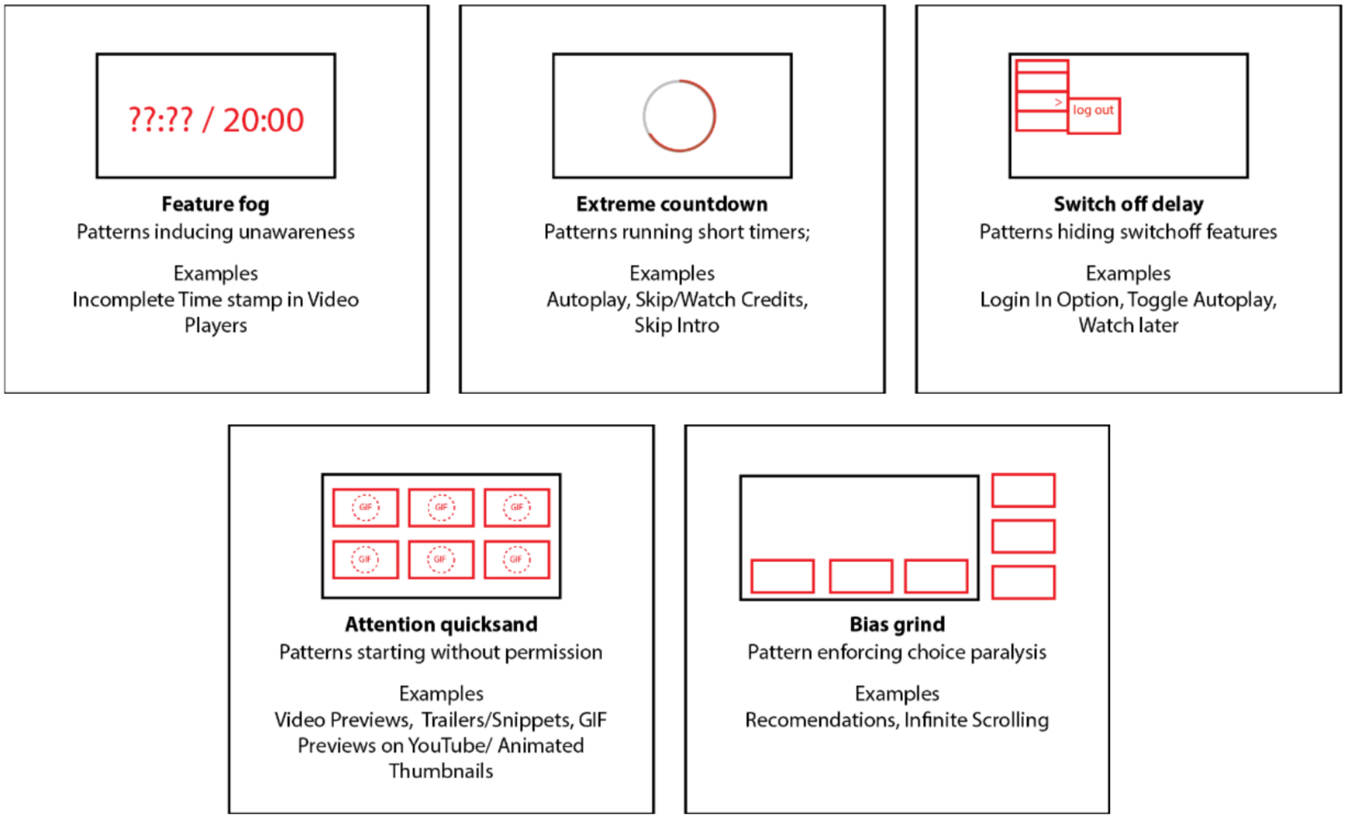

Figure 6: Types of dark patterns on video streaming platforms as observed from a user-centric digital wellbeing viewing behavior. These dark patterns are analyzed and compiled after analysis of 4 popular video streaming platforms Netflix, Disney+ Hotstar, YouTube and Amazon Prime Video through the use of mobile/tablet devices, laptop/PC and television.

5.5 Extreme countdown

“Extreme countdown” refers to UI patterns that have a timer and that execute automatically if not interrupted within the short period of time. Upon showing examples of such UI features (Figure 1) on all platforms, all except 2 participants agreed that such patterns cause unintended behaviors of over-watching. Participants pointed out how such patterns induce pressure situations, especially when present socially, to make a decision within the given time. We can say from our previous study that such patterns reduce user autonomy in making conscious decisions, especially as time increases in a video watching session. P3 says, “Autoplay does not give you time to think, you are still contemplating about the last episode, and then the next episode starts.” P5 describes how Netflix’s Autoplay does not provide an easy way out, “It happened many times when I wanted to stop Autoplay but either I could not find how to cancel it and had to exit the app completely, or it had been too late to grab the remote.” Though such a pattern is useful when watching the desired content, it is also responsible for enforcing a sunk cost fallacy [3] when users have invested some time in a season that they might not necessarily even enjoy watching.

Participants suggested that there should be more degree of freedom in timer-countdown related features by incorporating accessible settings to turn off those features or customize the timer duration. P7 talks about the Autoplay of YouTube, saying, “Although the Autoplay recommendation on YouTube is very compelling, I still find it better because it cancels automatically if you’re reading the comments section or just simply click the cancel button on the screen, unlike Netflix or Amazon Prime Video where you have almost zero control.” We conclude that these patterns enforce a biased choice architecture [48], as users have less time to make a decision. They go with the most prominent option available in front of them, which happens to be the default next Autoplay video. It would serve users better if the choice architecture afforded by such video streaming platforms is more open-ended in terms of providing user autonomy of choice.

This dark pattern is similar to those found on shopping websites that tempt users by offering special discounts that are only available until a timer runs out, though generally those timer are much longer in length (hours rather than seconds). Moreover, the video watching timers take an action unless you explicitly interrupt it, while shopping timers produce no actions when they expire.

5.6 Switchoff delay

“Switchoff delay” refers to UI patterns that promote strategies of hiding restrictive usage features in the default UI, and can be considered a variant of Brignull’s “hidden information” or Gray’s “interface interference” categories. For example, the ‘Log out’ feature in most video streaming platforms not readily available on many platforms.

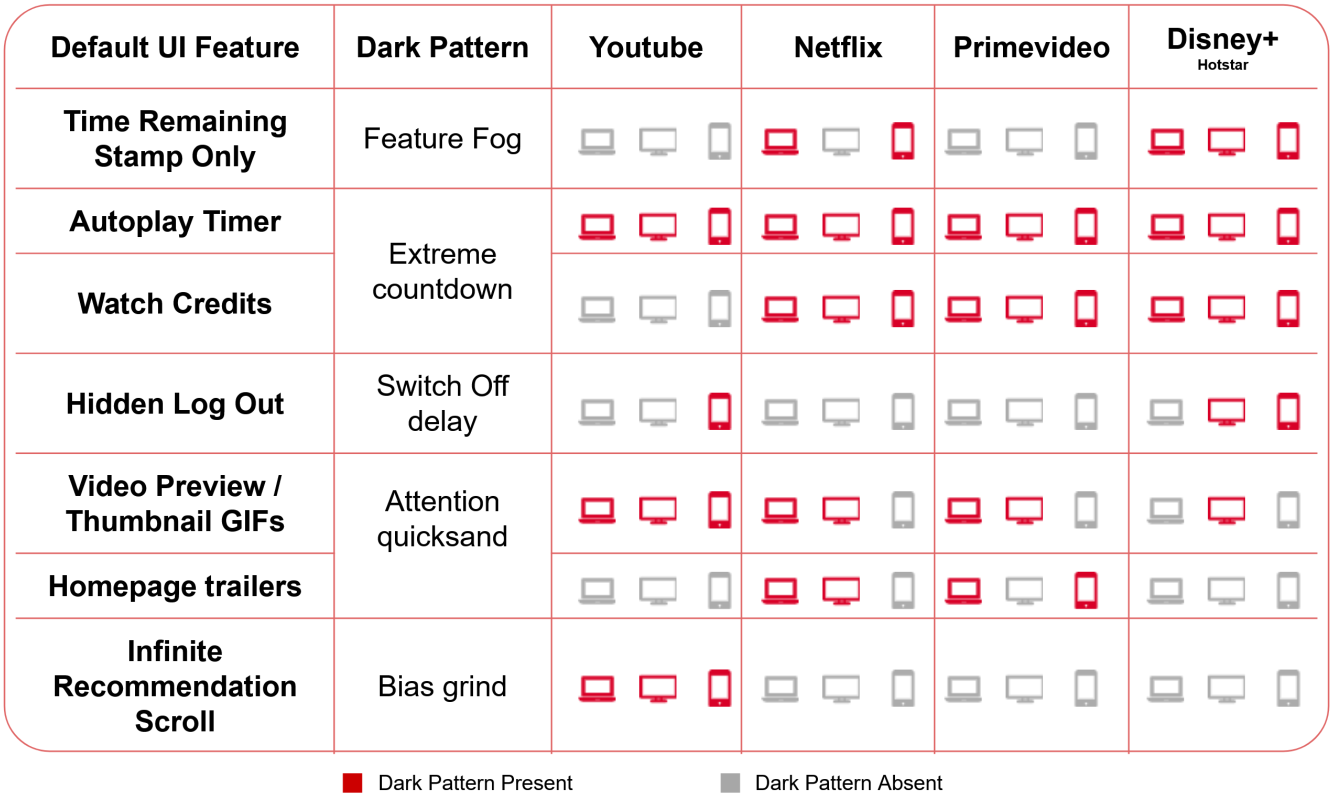

Figure 7: Compiled list of 5 categories of dark patterns — "feature fog", "extreme countdown", "switchoff delay", "attention quicksand", and "bias grind", on each of the 4 popular video streaming platforms - YouTube, Netflix, Disney+ Hotstar and Amazon Prime Video, portraying dark pattern over the 3 types of viewing platforms - mobile/tablet devices, laptop/PC and television.

Upon showing examples of such patterns (Figure 1) on the 4 video streaming platforms, 8 participants agreed that more visibility of such options could help to break mindless extended viewing patterns. These participants pointed how they have been discouraged to log out due to the unavailability of logout on the main landing page. P8 says, "I would rather just quit the app than go and search for the logout option." There are advantages to logging out on video streaming platforms in that the Recommendations become neutral and become less potent in enforcing compulsiveness. As observed from our previous user study, Recommendations enforce extended viewing due to user specific (based on watch history) Recommendations over long video sessions. P1 says, "Logging out is really hidden inside Amazon Prime Video. I wanted to restrict my viewing by logging out, but it was an effort to find it, so I decided not to."

4 participants appreciated Netflix for promoting different profile structure on their home page. P5 says, "The default option for Netflix is to log you out of your account whenever you close the app." Such UI interventions act as design frictions in viewing that reduce unnecessary viewing behaviors by giving some time to think [12]. Rather than just landing on Homepage Recommendations and start watching unnecessarily, a user is supposed to make a conscious decision to login into the type of account that they would like to use. This process is useful as it allows a design friction (like in Extreme Countdown and Feature Fog) before beginning to view videos. We conclude that unavailability of hidden UI cause unawareness in viewing behaviors. Availability of such restrictive design elements can help reduce unnecessary over-watching behaviors if presented on the default UI of video streaming platforms.

5.7 Attention quicksand

"Attention quicksand" refers to UI patterns that instantly start without conscious user action. They instantly grab user attention and divert them from what could otherwise be a different online behavior. Example of this pattern is instant GIF starter on video thumbnails upon mouse hover or single touch scroll on mobile devices. Upon showing examples of such artifacts (Figure 1) on the 4 selected platforms, all participants agreed that they are specifically attention-catching and have diverted them more than once in their viewing sessions. P9 says, "GIF previews on YouTube immediately capture my attention. On a laptop device, they get active whenever I hover my mouse over thumbnails. There's hardly any space on the screen where I can place my cursor so that there is no animation. It is so annoying at times!" P13 says, "They are specifically irritating on mobile devices as you have no option to avoid looking at the video GIFs when you scroll on the touch-screen." These patterns are concerning as they use the unique attention captivating quality inherent in videos, thereby violating the user attention from what their original intent. Video watching has been termed as borderline addictive which means psychologically, these platforms use the power of animated visual content consumed through the path of least cognitive resistance that causes instant gratification through a simple hover interaction [21, 32]. This seems unethical as pointed out by most participants. P15 mentions another instance of such a pattern on Netflix, “Whenever I log into Netflix, trailers of popular shows/movies start automatically, specifically those of Netflix Originals. Almost half of the screen is covered by trailers, it gets very annoying!” This pattern also supports biased choice architecture [48] and makes people regret watching things they would have otherwise not watched.

Participants suggested that there should be a separate category for trailers and previews since they would want to watch them only when they are looking for something new. We inferred that participants wish for a more conscious interaction method instead of videos starting automatically. P4 suggested possible changes to such a pattern that can be useful, “It would be such a nice feature if on a single click or finger tap, a GIF or trailer starts on a thumbnail and on a double mouse click/tap, the entire video starts.” P5 also mentions that “platforms should add a mute button to these previews as seen on the thumbnails on Amazon Prime Video.” We conclude that a more conscious interaction to start a trailer and video can help in reducing unnecessary diverted attentions of users.

5.8 Bias grind

“Bias grind” refers to UI patterns that disproportionately overload user interests and biases, and is related to Brignull’s “aesthetic manipulation.” An example of this pattern is providing an infinitely long scroll of Recommendations based on previous watching history (see Figure 1). It is important for video platforms to take care of user wellbeing by analyzing user context and thereby presenting relevant options to user. Further, choice overload is a phenomenon of presenting too many choices to users, which has been associated with unhappiness, decision fatigue, choosing the default option, and choice deferral [44]. From our diary study, we find that Recommendation features enable compulsiveness, especially as the viewing time of a session increases. Users appreciate a variety of options on any platform, but the default UI of Recommendations provides so many options that sometime users fall into an endless list of irrelevant videos. 12 participants agreed on the adverse effects of providing too many options to select from. By not effectively categorizing the recommendations, such patterns further make the users regret watching something they could have avoided had they had limited choice options or effective choice categories. P11 points out how YouTube recommendations enforce this pattern, “YouTube really just provides all the options of what you like, and you feel like you can watch something from the recommendations but are never satisfied.” P5 says, “It’s easy to just click on any video and keep on watching. It’s not that you pay attention all the time, unlike reading a book. There is a responsibility of video platforms to provide content that helps avoid choice paralysis.”

P1 notes how Netflix successfully reduces this pattern “I think Netflix has a huge issue of choice overload, but it effectively manages categorizing their recommendations. They segment their recommendations for each category by providing not more than around 20 options in each category, which seems optimum.” These patterns need to be restricted as they enforce the users’ biases and interests [4] through unlimited choice availability, as on Netflix. Hence, it is difficult for users to make the right choice if these patterns are not optimized and effectively categorized. P2 suggested, “I think some additional interactions after you have viewed some choices, like an additional slide interaction along with the normal scroll or button press, that takes more time than normal could be useful in recommendations to reduce choice overload.” We conclude that such patterns enforce choice paralysis and need to be restricted as done by Netflix by making effective categorisations of the available choices. Further, including more interactions that take time to unlock more choices can act as effective design frictions [12] for reducing unnecessary over-watching.

6 DISCUSSION

We hope that this work is helpful in raising awareness in the HCI community on potential design malpractices that go unnoticed while offending and intruding user attention on digital user interfaces. Attention is an important digital wellbeing parameter that is directly linked to autonomy and privacy, and should be respected. As pointed out by Lukoff et al. [35], promoting more autonomy should be an active goal of video streaming platforms. Our work extends these efforts and provides pointers that raise the need for protecting user autonomy which is easily exploitable through presently unregulated UI designs on digital platforms. Our work also calls for future researchers to highlight issues of user privacy, as all user viewing history is readily available to all video streaming platforms, which in turn is used by recommendation algorithms that have the potential to encourage unhealthy user behaviors. This can have detrimental effect on ways in which people, and especially children, use online platforms, and needs to be studied in more detail for enhancing digital wellbeing of the upcoming digital generation. We notice that dark patterns are designed from the same psychological rulebooks that are used to enhance ease of use. However, a usable design does not always imply an ethical one. The pervasiveness of these designs makes it harder to spot, coercing users to continue using these patterns. At some point, the platform designers should pay attention to the long-term customer interaction and provide ways to mitigate compulsive viewing by using features that enhance instead of diminish wellbeing. Therefore, this calls for defining ethical boundaries of persuasion and deception along with a more meaningful public discourse regarding ethics and condemning these designs by making the practicing community more aware of how persuasion through ease of use techniques may turn “dark” [55]. We need to re-evaluate ease of use as not just providing convenient functionality rather how it affects us as individuals.

Our work therefore initiates a discussion on the close correlation between ease of usability and dark persuasive patterns. We have come across many features in online video streaming platforms that have detrimental effect on the digital wellbeing of a user and might evolve into dark patterns employing backfiring or favoring techniques as mentioned by Widdicks et al. [61]. These UI features are functional and helpful to use, but after prolonged use, transition into compulsive habit-forming designs. This trade-off between ease of use and persuasion is critical because there exists ambiguity regarding the designer's intention. Nonetheless, if a design is negatively affecting the end-user, we need to reappraise the same to offer technology that nourishes rather than distract users. Hence, as they stand presently, these UI features require some surveillance or nudges that minimize the possibility of backfiring. Through our user study, we found participants suggesting more time providing interactions to unlock more autonomy, enhance choice architecture and enable better control for them. One way to achieve that is by introducing effective design frictions [12] for reducing unnecessary over-watching. Other ways to make users more aware of their viewing behavior than presently afforded is by introducing more conscious interactions on the default UI. Further, some features like Recommendations could be presented to enhance more diversity of choice, while enabling better state of mind by reducing unnecessary and unlimited recommendations. Future work can focus on designing and evaluating such UI interventions that help reduce the long-term mindlessness imposing viewing effects on video streaming platform features.

From the follow-up diary study interviews, we also gain an insight into how various platforms execute the same interactions differently. While the patterns classified in the previous section exist in nearly all the mentioned platforms, there have been attempts to alleviate this problem. Netflix has introduced an option "Watch something new," which provides random Recommendations and takes users away from their previously defined biases and interests. Netflix further included a pop-up that asks "Are you still watching?" when the Autoplay automatically plays itself for a fifth consecutive time. However, this only occurs when the user leaves the interface idle, therefore it does not necessarily stop binge-watching, as seen in the interviews. YouTube uses some in-built digital wellbeing prompts such as "Remind me to take a break," and "Remind me when it's bedtime" that help check mindless viewing. Further, it also provides a reasonably accessible Autoplay toggle-off button. Lately, YouTube also included a hover interaction on video thumbnails, which observes a certain time delay before animating the GIFs on them. It now also has a 'Play Now' and 'Watch Later' feature on thumbnails for introducing more custom controls to advanced users. Although these features are a step in the right direction, YouTube removed the unlike feature from its latest update, which could have negative over-watching influences on children, who might not be very mature about judging what to watch. For these purposes, future work can also focus on classifying dark patterns from a perspective of UI design which might expose a target audience, like children, to offensive content. YouTube further removed the time elapsed feature from their default UI in the latest update and changed its location, putting it over the toggle interaction. As observed from our dark pattern study, this causes unawareness of the sense of time passed among users and induces unintended over-watching behaviors. Efforts should be made by these platforms to enable healthy viewing environments for more sustainable engagements and building long-term trust with users. Considering the addictive nature of binge-watching, video streaming platform should constantly innovate and employ workarounds to design and develop specifically for the binge-watching context.

Throughout the discussion we assume that regretful and mindless viewing experiences triggered by dark UI patterns are indicators of bad experiences and users should be safeguarded against them on video streaming platforms. However, there are some mindless behaviors which users happily do and those are worth conserving. For example, through our interviews we found that people liked video watching mindlessly before sleeping irrespective of what they watched as it helped them sleep better. Some participants also liked watching sitcoms mindlessly while studying as it helped them concentrate better. Hence, there is value in some contextual video watching behaviors and they are worth preserving while designing controls for these platforms. We also observed a margin of uncertainty in terms of user state of mind when they select a type of UI interaction, and user feelings after they have watched the video as seen in Figure 3(b),(c) and Figure 5(a),(b),(c). This margin of uncertainty reflects an undecided state of user choice, which eventually translates into feelings of regret/satisfaction and mindless/mindful state of mind and could be an interesting topic for exploration in future work. Design of future studies should specifically focus on exploring such transition areas that might be critical in finding triggers, interactions and feelings that cause unintended viewing behaviors.

Apart from identifying mindless and regretful behaviors in individuals, our work has several social implications as well. In this regard, the results of this study are generalizable to the context of an Indian university. Since video watching is also done as a group activity with family and friends, it serves as a cultural artifact that needs to be ideally curated as it has the power to modify social behaviors. If enough space is not provided to a group of people while video watching to talk and interact, for example when skipping credits and playing next episode, it might ruin the viewing experience and result in non-communicative unhealthy social behaviors. This again raises importance of designing the default UI of these platforms in a way that supports active disengagement from the platform, whenever required, to encourage healthy usage in long-term. Future work should explore user responses to video streaming interfaces across a wider demographic. Stepping aside from conventional streaming platforms, another interesting future work direction could be investigating live-streaming apps like Amazon's Twitch that uses incentives for making people stay on the livestream through virtual "channel points" which can be claimed for in-app rewards.

Our study was conducted at Indraprastha Institute of Information Technology, Delhi, India. Although our results point out psychological human tendencies and behaviors which are extendable for more general inferences across populations, some cultural behaviors and preferences in the target population might not be generalizable to viewers across the world. Further, for our diary study participants were specifically instructed to comment on feelings that arose due to UI interactions and not because of content. While some participants did view education related videos, the majority of people watched entertainment related content (95.6%). Hence, all our results are generalizable mostly for low cognitively loaded story-based content. We provided weekly prompts to users through emails regarding the status of their current progress in terms of the number of video sessions watched versus sessions remaining, and reminding them to complete entries following end of viewing sessions. Potentially, these reminders and restricting participants to a 20-day time frame could influence the natural viewing behavior of participants, and our future studies will focus on how to mitigate this shortcoming. Future work will also focus on the analysis of YouTube as compared to other popular streaming platforms. Figure 7 provides evidence for dark UI patterns on YouTube that are somewhat distinct from the rest, which makes sense as YouTube is also unique in terms of the content it offers, enabling access to an enormous number of interactive content makers. Furthermore, YouTube features mainly shorter, standalone videos as compared to other streaming platforms, which contain mainly longer episodes that are part of a season of videos. Although we did include some user excerpts which point out such platform-related insights, we plan to investigate these differences more thoroughly in a subsequent investigation.

7 CONCLUSION

Through our online diary study, we performed an in-depth analysis of UI features, specifically Autoplay and Recommendations, on popular online streaming platforms in India. We studied their impact on the user's state of mind measuring their level of awareness and feeling of satisfaction while selecting and completing a video for watching. We also included contextual effects of individual characteristics and viewing preference as additional factors that also have a tendency to influence user behaviors. We have centered our analysis on the relation of UI interactions' ease of use and autonomy affordability and their temporal effect on the user's feelings, mostly over-watching and regret. We observed that although these features enable ease of use, they enforce compulsive behaviors on long term usage. We have identified these results from a life-fulfilling wellbeing framework as provided by Peters et al. [40], focusing on user priorities, watching intentions, work and social behaviors, individual motivations, goals, and context of usage. We further analyzed the underlying patterns of deceptive designs that affect the user's digital wellbeing. We identified five design types — "feature fog", extreme countdown", "switchoff delay", "attention quicksand" and "bias grind", from several psychological factors and user responses that contribute and provide evidence in terming these types of design elements as dark patterns in the binge-watching scenario.

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