Binge-watching: An empirical study of the trigger factors from an economic perspective

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ABSTRACT

This research addresses the motivations driving young adults' binge-watching behavior within the economic theoretical framework. As platforms like Netflix and Amazon Prime become prevalent among youth, one viewing behavior known as “Binge-watching” emerges. Existing research in the relevant field is focused on the media use aspects by adopting Use and Gratifications theory. Following previous research on the economic theory of binge-watching developed by Gaenssle & Kunz-Kaltenhaeuser (2020), this study aims to fill gaps in empirical evidence by examining the triggers enticing young adults to binge-watch. The main research question identifies factors motivating increased binge-watching among young adults. The study outlines research objectives, hypotheses, methods, interpretation of results, discussion, and limitations of the research and conclusion. Hypotheses are derived from economic perspectives, including serialized content, sense of self-administration, short time intervals for reconsideration, and the flat-rate pricing models' influence on binge-watching likelihood. Additionally, the research investigates the economic perspective on gratifications sought — the utility perceived from social engagement, entertainment, stress relief, escapism, and combating boredom—as potential influencers of binge-watching behaviors. Employing a quantitative research method, data collection will involve an online questionnaire. Statistical analysis will use regression models via R-studio, correlating various factors with binge-watching likelihood. The findings indicate that supply-side, serial content, and consumer-side factors, like social interaction and stress relief, are crucial drivers of binge-watching behavior. The sense of administration and flat rate pricing are potentially driving the likelihood of binge-watching. In contrast, entertainment, escape reality, and boredom do not significantly impact binge-watching behavior. The insights of this study have practical implications for the video-on-demand industry, offering valuable guidance to both the platforms and content creators on how platforms can refine their business models and strategies to increase user engagement and expand their revenue streams. The study also appears to have several limitations on both the sample and model aspects. The insignificant factors may be due to the lack of variance of the samples, suggesting a broader population should be obtained for further study on motivations of binge-watching. Future research should adopt qualitative methods to explore additional predictors of binge-watching, providing a deeper understanding of economic and social factors that quantitative methods might neglect.

Keywords: Binge-watching, Video-on-demand, Culture Economics, Viewing behavior, Young adults

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1. Introduction

As for technological innovation in the past several years, the newly-appearing video streaming platform has prevailed. Platforms like Netflix and Amazon Prime are getting more attention than traditional streaming services like television and cinema. This new type of streaming service is known as video-on-demand (VOD) and over-the-top (OTT). With the convenience of this satisfaction in consuming the audio or video content on demand by individual control, a certain behavior was observed, namely binge-watching. The term binge-watching is originally derived from words like “binge-eating” and “binge-drinking.” According to the definition given by Oxford Dictionary (2013), binge-watching refers to “watching multiple episodes of a television program in rapid succession, typically through DVD or digital streaming”. Rubenking and Bracken (2018) describe binge-watching as watching three to four or more thirty-minute series episodes or watching three or more one-hour episodes in a single sitting. According to a report conducted by the European Audiovisual Observatory (2021), Netflix has the largest number of subscribers, followed by Amazon Prime in 2020. A definition provided by Netflix on the term binge-watching is to watch between 2-6 episodes of the same TV show in one sitting. However, the definition of binge-watching is still vague. In brief, binge-watching refers to excessive consumption of audiovisual content.

The word “binge-watching” was originally used to describe a phenomenon of overconsumption on TV programs. Most of the existing definitions carry the common features of “multiple episodes,” “single series,” and “one sitting” (Schweidel & Moe, 2016; Annalect, 2014; Sheehan, 2015; Rubenking & Bracken, 2018). This continuous consumption refers to so-called non-linear television. The term is defined in the media theory as audiovisual media service for simultaneous viewing of programs sequentially, based on a program schedule (Galić, 2016). In a modern context, it relates to the function of video-on-demand, which allows late viewing of the program, and consuming multiple episodes at once (Krstić, 2018). Such service appears on the top and gains attention due to its self-administration and personal autonomy (Gaenssle & Kunz-Kaltenhaeuser, 2020; Granow et al., 2018). According to Chang & Peng (2022), people perceive binge-watching as successively watching episodes with serial content instead based on the time spent watching or the number of episodes. However, the common understanding of binge-watching remains controversial since the concerns brought up by Sung et al. (2018) claim that the duration of one episode varies among different programs. For those who would spend a whole afternoon binge-watching movies for two hours each, the time they spend is different than those who binge-watch animations, which only last 20 minutes for each episode.

Past research analyzed the phenomenon of binge-watching from several different perspectives. The motivation and potential consequences have been studied. Research conducted by Gaenssle & Kunz-Kaltenhaeuser (2020) distinguished four factors that may trigger binge-watching behaviour from an economic perspective, namely the serial content of a single program, non-linear consumption and self-administration, less time for reconsideration between videos, and low full price. Some psychological factors related to gratifications can be motivations for binge-watching. The Use and Gratifications Theory framework, also known as the U&G theory, has been used in various binge-watching studies. The U&G theory is an approach that focuses on the audience and their motivations for using different media and content to satisfy their social and psychological needs (Ruggiero, 2000). Panda &Pandey (2017) indicate that factors like social influence, escape reality, accessibility of TV shows through multiple platforms, and the advertising effectiveness of content providers can be positively related to binge-watching. Studies have also shown that negative gratification can lead to binge-watching as well (Panda &Pandey, 2017). Recent research has also unveiled the fact that gender differences can be one of the factors that influence binge-watching behavior (Qayyoum, 2023).

Research also indicates that binge-watching can lead to negative consequences, such as psychological and physical distortion (Flayelle et al., 2022; Ort et al., 2021). Problematic viewing habits can lead to anxiety, increasing the probability of having health issues due to lack of movement, low sleep quality, less social interaction, and overconsumption as a form of procrastination (Ort et al., 2021).

However, it still requires attention to the empirical evidence on what triggers people to binge-watch. Thus, this study will delve deep into the nature of the phenomenon of binge-watching. It intends to build on the existing economic theories of binge-watching motivation and previous research on physical and psychological motivations to examine further the factors that trigger binge-watching with empirical evidence.

My research question is, what are the factors that motivate young adults to spend more time binge-watching?

The research will introduce a theoretical framework, followed by a systematic review of the existing literature on binge-watching. Section three will present the research hypothesis regarding the research question, later with specific research methodology and results. Finally, a comprehensive conclusion with limitations and future research directions will be discussed.

2. Literature review

2.1 Consumer-side Factors

From a consumer perspective, factors derived from the Uses and Gratifications (U&G) theory can be understood through an economic lens. The U&G framework focuses on the audience's motivations for using different media and content to satisfy their social and psychological needs. Building on an economic framework, U&G theory provides insight into people's needs, the gratifications sought, and the consequences of media use. This approach assumes that individuals seek to maximize their satisfaction, achieving self-satisfaction through media consumption (Elliott & Quattlebaum, 1979). In the work from Katz et al. (1974), the U& G theory is rooted in two main assumptions: (a) The audience is generally active and goal-oriented in its media consumption, and(b) the initiative to choose specific media to satisfy particular needs rests with the audience member. This behavior mirrors economic principles, where individuals make deliberate choices to maximize utility. In this context, viewers actively seek media content that offers the greatest personal satisfaction, whether in terms of entertainment, information, or emotional engagement. The selection process reflects a cost-benefit analysis, where time and attention are treated as valuable resources, and individuals aim to allocate these resources to media options that promise the highest returns in terms of gratification.

U&G theory has evolved significantly since its introduction in the 1940s. Early research was primarily descriptive and qualitative, identifying functions and gratifications of media use such as information, entertainment, escape, and social interaction (Klapper, 1963; Kippax et al., 1980; Mendelsohn, 1964; Katz & Foulkes, 1962; Ruggiero, 2000). McQuail (2010) broadened the theory to encompass five gratifications: education, information, characteristics of the media environment, entertainment, social interaction, and escape. U&G theory thus offers a dynamic view of the interplay between attitudes, actions, and media effects (Pittman & Sheehan, 2015).

2.1.1 Peer Influence and Social Engagement

Peers are people of similar ages and close interests, normally friends or classmates. They can influence people with their attitudes and activities (Dhull & Beniwal, 2017). Peers occupy more of one's life while one is growing up. Individuals are likely to alter their behavior based on what they observe from peers out of curiosity or a desire to be valued and respected (Ngo et al., 2024). The advanced technology and the convenience of accessibility on social media for information acquisition from others may easily lead to imitation of individuals. Research has indicated that a growing frequency of young adults’ social media use may be triggered by peer influence and fears of missing out (Adebiyi, 2019). Due to friends ' suggestions or expectations, young adults may only be stimulated to engage in certain behaviors. Research indicated that peer influence might be the primary factor contributing to college students' binge-watching behavior to maximize their utility in getting involved with the topic for discussion with friends (Fernandes & Pinto, 2020). The utility maximizes under peer influence to achieve a sense of belonging. Research conducted by Ayten et al. (2019) indicates that 76% of binge-watchers confess that they finished the serial video content as soon as possible, only to participate in the chats among friends.

Social media has broadened peer influence online, and young adults may be more likely to encounter people who share their values and interests. Actors and producers, as an extension of the topic regarding a particular series, may lead individuals to binge-watch more series to gain a deeper understanding (Krstić, 2016). Young adults tend to achieve a concept of the Economy via an online platform, part of the gig economy (Ayten et al., 2019).

The social engagement aspect of media consumption emerges as a significant driver in viewer habits, particularly among college students and adolescents. This dimension reflects how individuals use media to foster a sense of connection and community, fulfilling their social needs through shared experiences. Fernandes and Pinto (2020) highlighted that binge-watching serves as a medium for college students to feel a sense of social belonging. This observation underscores binge-watching as a solitary activity that facilitates community and connection among individuals with similar interests, reinforcing social bonds even when viewers are physically isolated. Vaterlaus et al. (2018) state that watching popular series can create inside jokes with old friends and help make new friends.

Expanding on this, Panda and Pandey (2017) identified social interaction as a crucial motivation for binge-watching, illustrating that it allows students to participate in broader conversations and maintain cultural relevancy and social connections. Additionally, Qayyoum and Malik (2023) noted gender differences in the social motivations behind binge-watching, with female teenagers showing a higher inclination towards social interaction and a fear of missing out than males. These studies collectively suggest that social engagement in binge-watching is multifaceted, involving the act of watching and the subsequent social interactions it enables, such as discussions on social media, in-person conversations, and participation in fan communities. This enhances the viewing experience, making it a rich social activity that extends beyond the screen and plays a vital role in the social lives of viewers, especially those in transitional stages such as adolescence and college.

2.1.2 Entertainment

The word entertainment can be taken as the enjoyment and happiness that people perceive through their behavior. Happiness and pleasure can be derived from picking certain shows that match individual tastes. According to Becker and Stigler (1977), tastes refer to changes that contribute to consuming certain addictive goods, eventually increasing the desire and raising their consumption over time. The marginal utility will rise correspondingly over time as tastes shift in individual favor. Entertainment has been indicated as one of the predictors that drive up people’s video consumption since 1991 by Conway and Rubin (1991) in TV watching. People consume video content for self-amusement. As video-on-demand platforms replaced traditional TV in recent ages, people can decide what program they would like to consume regardless of the timing set by the broadcast channel back in the TV ages. Alongside. the pleasure, specifically the sense of fulfillment and happiness, generated by the extensive watching behavior may also result from the “flow”, according to Csikszentmihalyi (2004). The flow is defined as a state in which people are completely immersed in certain actions, neglecting the sense of passing time.

Fernandes and Pinto (2020) underscored entertainment as a fundamental motivation for college students engaging in binge-watching, emphasizing the pursuit of pleasure derived from compelling and immersive content. This highlights how entertainment is not merely a side effect but the core attraction that drives student engagement with streamed media. Pittman and Sheehan (2015) take another perspective on entertainment as they broaden the concept into engagement with the video content. They implicated two statements in their questionnaire: “I feel more engaged with the characters when I binge-watch” and “It is very entertaining”. The result revealed the fact of the existence of a positive relationship between engagement and entertainment with the frequency of binge-watching.

Further, Rubenking and Bracken (2021) and Panda and Pandey (2017) observed that binge-watching has evolved into a normalized and habitual form of entertainment. This transformation indicates a shift in viewing habits, where binge-watching is no longer an occasional activity but a regular entertainment practice woven into viewers' daily routines. Such habitual engagement suggests that the entertainment value of binge-watching is sufficiently rewarding to encourage frequent and sustained viewing sessions, making it a staple in entertainment diets. Sung et al. (2018) and Qayyoum and Malik (2023) contribute to this narrative by identifying entertainment as a critical predictor and primary motivation for binge-watching across different levels of viewer engagement. Whether viewers engage lightly or immerse themselves in long binge-watching sessions, the entertainment factor remains a consistent draw, reinforcing its role in attracting and retaining viewer interest. This universal appeal underscores the powerful pull of entertaining content in driving the binge-watching phenomenon. Ayten et al. (2019) also suggested that people acknowledge binge-watching as entertainment as they prefer to watch the episodes simultaneously to spare free time.

Moreover, Rubenking and Bracken (2018) delve deeper into the content characteristics that enhance entertainment value, noting that the pursuit of suspenseful and emotionally engaging content particularly resonates with younger audiences. This preference for suspense and emotional engagement indicates that viewers are not just seeking any content but are drawn to narratives that evoke strong emotional responses and keep them on the edge of their seats. This aspect of entertainment not only sustains viewer interest but also amplifies the immersive experience that binge-watching offers, making it a dominant form of modern media consumption.

2.1.3 Stress Relief

In the context of binge-watching, stress relief emerges as a compelling motivation, reflecting how viewers use media consumption to alleviate and detach from the pressures of everyday life. Fernandes and Pinto (2020) and Panda and Pandey (2017) acknowledge stress relieving as a significant factor in binge-watching, where students and other viewers view sessions as a means to step away from their daily stressors momentarily. This usage of binge-watching as an escape mechanism demonstrates how media can serve as a buffer against stress, providing a temporary retreat into worlds and narratives that differ markedly from the viewer's reality. The immersive nature of binge-watching allows for a deep engagement with content, effectively sidelining immediate worries and fostering a sense of mental detachment. Rubenking and Bracken (2018) indicated that people may experience stress relief and emotional satisfaction while intentionally binge-watching. The word restorative experience is introduced as one of the motivations that drives people to binge-watch. Kaplan (1995) notes that restorative experiences are methods through which individuals can rejuvenate mentally. Pang (2014) points out that binge-watching possesses all the elements of such a restorative experience, frequently involving shows with intricate plots that unfold throughout a season and featuring compelling characters in a captivating world distinct from the viewer's own.

Ort, Wirz, and Fahr (2021) further emphasize the role of relaxation in binge-watching, noting it as a motive that can mitigate problematic viewing behaviors. This suggests that binge-watching can be a healthy leisure activity that contributes positively to stress relief when used moderately. The capacity of binge-watching to act as a stress reliever underscores its potential therapeutic benefits, provided it is consumed in a balanced manner without leading to excessive viewing habits that could have counterproductive effects. Feeney (2014) suggests people see binge-watching as a reward in a weekly routine after the hard work of days. Individuals are looking forward and plan in advance for binge-watching.

Thus, the relationship between binge-watching and stress relief is twofold. On the one hand, it offers an effective diversion from the demands of daily life, and on the other, it can encourage a relaxation response that aids in stress management. These insights reveal the dual nature of binge-watching as both a cause for concern when overindulged and a potentially valuable tool for psychological relief when used appropriately. This understanding is crucial for developing a balanced perspective on media consumption habits in contemporary digital culture.

2.1.4 Escape Reality

The motivation to escape reality through binge-watching is deeply intertwined with the psychological benefits that immersive narratives offer. This escapism is not merely about avoiding real-life responsibilities or challenges but involves actively seeking solace and comfort in alternative realities that streaming content provides. This motivation is particularly pronounced in environments where individuals may feel overwhelmed by their daily routines or stressed by external pressures. The appeal of entering a different world, whether the fantastical landscapes of a sci-fi series or the intricate dramas of a period piece, offers a respite that many find therapeutic. Escape as a motive has also been linked to other forms of media use, including online games (Yee, 2006), YouTube (Haridakis & Hanson, 2009), and iPod usage (Ferguson et al., 2007).

Studies such as those conducted by Fernandes and Pinto (2020) and Panda & Pandey (2017) highlight how binge-watching can serve as a modern sanctuary, where viewers find a sense of relief and detachment that is hard to achieve in other facets of their lives. This phenomenon is particularly relevant in today's fast-paced world, where the pressures of productivity and constant connectivity can be mentally exhausting. The ability to "switch off" and dive into a show provides a valuable break for the mind, allowing for mental regeneration.

Moreover, Ort, Wirz, and Fahr (2021) point out the complexity of escapism in the context of binge-watching. While it provides temporary relief, it can also lead to a vicious cycle where viewers become overly reliant on media to escape, potentially neglecting real-world issues or responsibilities. This suggests that while binge-watching can be a positive coping mechanism, it requires moderation and self-awareness to prevent it from becoming a problematic behavior that more deeply entrenches viewers in avoidance patterns. Qayyoum and Malik (2023) explore how escapism through binge-watching can differ based on demographic factors such as age and gender, with varying impacts on emotional well-being. This highlights the need for further research to understand the nuanced ways in which different groups use media to cope with reality and the potential long-term effects on their mental health and social interactions.

2.1.5 Boredom

Boredom as a motivator for binge-watching is closely linked to the modern context of digital media consumption, where the vast availability of streaming content meets viewers' idle moments. This alignment makes streaming platforms an ideal solution to the problem of boredom, offering endless options for engagement at any time and under any circumstances. The literature indicates that the ease of access to these platforms, combined with their rich variety of content, makes binge-watching an appealing choice for filling the void created by unstructured time (Rubenking & Bracken, 2021; Sung et al., 2018).

Rubenking and Bracken (2021) discussed that the increase in viewing during periods such as the COVID-19 pandemic illustrates how societal changes that increase free time can lead to more frequent binge-watching. The relationship between boredom and binge-watching becomes particularly significant in contexts where traditional social and recreational activities are limited, and individuals turn to digital media as a readily available alternative. This shift to media consumption as a primary leisure activity underscores how boredom drives engagement with content that is not only entertaining but also readily accessible and consumable in large quantities at once.

Sung et al. (2018) further elucidate this point by noting that the motivation to pass the time through binge-watching often correlates with higher levels of engagement, particularly among those who might otherwise feel directionless or unoccupied. This suggests that binge-watching serves not just to pass the time but as a way to structure it, providing a framework of activity that can make unstructured time feel more manageable and less daunting. audience members indicated that they used television and radio to escape the boredom of everyday life, to have something to talk about with others, to compare the people and events in the programs with their own experiences, and to keep in touch with the main events in the world (McQuail, 2010).

However, the ease with which binge-watching fills periods of boredom can also have downsides. It may lead to habit formation, where viewers default to binge-watching as their primary method of filling free time, potentially at the expense of more varied or fulfilling activities. This habituation can make engaging in more active or socially interactive pursuits challenging, leading to a cycle where boredom is temporarily alleviated but not genuinely resolved.

Thus, the hypothesis regarding the consumer perspective motivations can be addressed as

H1: Factors (a) social engagement, (b) entertainment, (c) stress relief, (d) escape reality, and

(e) boredom have a positive impact on the likelihood of binge-watching for young adults.

2.2 Supply-side factors

Studies have found that binge-watching can be seen as an addictive behavior (Ort et al., 2021; Chang & Peng, 2022), even without self-realization. A theoretical economic framework for binge-watching has been developed, drawing from multiple theories, including consumption capital theory and consumer decision-making, rational addiction theory, and behavioral economics (Stigler & Becker, 1977; Adler, 1985; Becker & Murphy, 1988; Chaloupka et al., 1999; Vuchinich & Heather, 2003). The economic model contains several factors that raise the likelihood of binge-watching behavior, namely internal factors like self-administration and rational utility maximization, high knowledge absorbing with low opportunity cost, external factors like the sequential plot and content accessibility, flat rate pricing model, and the limited reconsideration time due to autoplay (Gaenssle & Kunz-Kaltenhaeuser, 2020). Switching programs can be troublesome for people, whereas spending time on finishing the series lowers the opportunity cost for viewers, providing more consumption capital. On the other hand, research conducted by Chang & Peng (2022) indicates that people tend to distinguish themselves as behavior from a rational choice to binge-watch. Technology has advanced rapidly, enabling platforms like Netflix to use algorithms that apply auto-play, minimizing the gap between episodes. Furthermore, a flat-rate monthly subscription fee enhances the value for viewers who wish to gain comprehensive knowledge of a series in one sitting (Gaenssle & Kunz-Kaltenhaeuser, 2020).

2.2.1 Serialized Content

Adopting consumption capital theory, past consumption impacts future consumption. The degree to which past consumption increases current consumption defines a good's addictive qualities (Stigler & Becker, 1977; Becker & Murphy, 1988), along with knowing that consumption capital matters for consumption where it consists of specific knowledge (Adler, 1985). Acquisition of specific knowledge may derive from the information gained via different channels. Implementing modern technology, the channel can be realized online and offline (Adler, 2006). Serial viewing is suggested to be the most common predictor of binge-watching for both 2015 and 2020 (Rubenking & Bracken, 2021).

In this way, the serialized content, namely the plot and storyline, can be seen as the specific knowledge from a single program (sometimes strictly defined as a series only). Research has shown that serialized content increases the probability of binge-watching an individual. People accumulate consumption via video streaming platforms to gain future utility. The perceived utility is maximized when people finish the whole season with the plot. Consequently, when the last available season of a series ends, consumers can terminate their binging behavior at a relatively low cost (Clarke & Danilkina, 2006). Based on the theory development from consumer behavior and economic behavior, Gaenssle & Kunz-Kaltenhaeuser (2020) drew a conclusion that serial content increases the possibility of binge-watching. However, binge-watching would not be limited to the genre and platform. The study conducted by Cordts (2019) unveiled evidence that watching behavior may vary from platform to platform. The author makes use of the experience sampling method to gather data from 55 participants in the time span of 2 weeks. Results reveal that if one consumes a huge amount of video content on YouTube, no evidence can prove that the same behavior will occur with PS-ODVSP, like Amazon Prime or Netflix (Cordts, 2019).

2.2.2 Self-administration / Non-linear Video Consumption

According to Gaenssle & Kunz-Kaltenhaeuser (2020), people tend to consume commodities to maximize their utility by taking their personal effort and investment into account. Investment from an economic perspective means the time spent, knowledge gained, and other human capital in general that directly contribute to an individual's utility. The viewing behavior nowadays differs from that of traditional TV, which is non-linear. The video-on-demand platform allows self-administration and non-linear consumption (small/flexible). This convenience and flexibility increase the probability of binge-watching. The availability of (continuous) content in a structure of self-administration gives recipients the choice of binge-watching throughout the desired content. Riddle et al. (2017) found that people may also control their view behavior, namely intentionally or unintentionally. From a user perspective, such video-on-demand services are popular because they increase choice and personal autonomy, allowing them to watch any quantity of content whenever and wherever they like (Granow et al., 2018).

Meanwhile, the open accessibility provided by the video-on-demand platform offers consumers the flexibility to choose shows or series that have been released for a whole season instead of waiting for weekly update episodes. From an economic perspective, consumption capital may decline as people tend to forget or blur their memories as time passes. Flayelle et al. (2017) indicated that people appear to be able to easily abstain from watching VOD content provided that they can watch at a later time, i.e. after the whole season of the series is released. Preference theory can be implemented. According to Gaenssle and Kunz-Kaltenhaeuser (2020), consumption capital can be allocated quicker via binge-watching. For instance, the loss of memory of the previous plot of the show or series can lead to decrement in the consumption capital after one week. Individuals tend to fall myopic on present consumption instead of pleasure in the future, even though the actual utility would be the same. Thus, the factor of self-administration and non-linear consumption contribute to the increment of the possibility of binge-watching by Gaenssle and Kunz-Kaltenhaeuser (2020).

2.2.3 Short Time Interval/ Low Reconsideration Time

Individuals build up their utility based on past values. As time passes without consumption, the built-up stock of consumption capital dissipates (Stigler & Becker 1977; Vuchinich & Heather 2003). It is, therefore, easier to develop a taste (or an addiction, for that matter) when the frequency of consumption is high, or the depreciation rate on the built-up stock of consumption capital is relatively low (Becker & Murphy, 1988). Since time intervals between consumption are short, the depreciation of positive capital stock only occurs in a very short time span, and the depreciation rate loses relevance for decision-making. Also, general structural features of VOD platforms, such as auto-play functions, cliffhangers, or suggestions for related follow-up videos (Flayelle et al., 2017; Rubenking & Bracken, 2018), have been proven to influence the continuous watching process. From a supplier perspective, video-on-demand platforms utilize features like auto-play to facilitate binge-watching (Horeck et al., 2018). De Feijter et al. (2016) indicate that the unintended extended viewing time is the high suspense level, the autoplay feature ("without autoplay, my viewing experience would be disrupted"), the available amount of free time, and the absence of obligations.

Focused consumption refers to the actual act of watching the content rather than only using television as side entertainment or background 'noise'. Serial consumption, uninterrupted in one sitting, translates into continuous repetition of consumption decisions. The number of videos and frequency of usage considered in the literature (Pierce-Grove, 2017; Sung et al., 2018) mean repeated decision-making regarding consuming the next unit in rapid succession. Moreover, research has shown that individuals spontaneously persist in their watching management to achieve utility with accumulative consumption. Platform characteristics like smart recommender systems and auto-play formats decrease the time between consumption decisions and make it harder to decide actively against further consumption. Content providers are incentivized to keep the consumers on the platform using sophisticated algorithms (Budzinski & Lindstädt-Dreusicke, 2020; Gaenssle & Budzinski, 2019).

2.2.4 Flat-rate Pricing Model / Accessibility with Low Cost

Video-on-demand streaming platforms like Netflix and Amazon Video advertise by offering free unlimited access to TV content for a limited period. For instance, Netflix offers a month of free viewing, while Amazon Student provides six months of unlimited content. These platforms also implement pricing promotions, such as discounts for longer subscription packages, where a longer subscription period results in a lower monthly fee than shorter ones. These pricing strategies can encourage viewers to subscribe to these TV streaming services.

Additional factors that enhance well-being (EWB) include the ample free time individuals have (de Feijter et al., 2016) and the easy access to and availability of video content (Panda & Pandey, 2017; Steiner & Xu, 2018). These features are commonly found on platforms like YouTube, Netflix, and Amazon Prime. As Merikivi et al. (2017) state, for a binge-watcher, VOD streaming services are akin to buffet restaurants for food addicts. The combination of cheap and effortless access to a virtually unlimited amount of content and the ability to consume series not only at home but also on mobile devices while commuting or traveling likely facilitates, encourages, or even triggers excessive consumption behaviors (Ort et al., 2021).

Previous literature suggests that the ease of accessibility, abundance, and convenience of available content as facilitating high consumption and the resulting insidiousness of increased watching (Flayelle et al., 2017). Considering the full price and, thereby, the time invested by the consumer, the mere number of videos seems inappropriate when calculating the cost of consumption and its effects. Consequently, the number of videos, and thus the number of consumption decisions, as well as the overall time invested in consumption, is decisive since time makes up most of the consumer's time. Depending on the consumer's occupation, age, and responsibilities, opportunity costs vary a lot. Low opportunity costs decrease the full price; hence, demand increases. Consumers who are small are consequently more likely to binge-watch. The flat rate pricing models commonly used by VoD streaming services decreased. monetary cost per unit and increase the importance of opportunity costs. The monthly paid flat rate price could be considered fixed costs independent of quantity or even sunk costs (Tversky & Kahneman, 1992; Train et al.,1987). From a behavioral economics perspective, flat-rate pricing facilitates binge-watching by bypassing the individual's loss aversion of having to buy single episodes.

H2: The (a) serialized content, (b) sense of self-administration, (c) Short time interval for reconsideration, (d) flat rate pricing model increases the likelihood of binge-watching for young adults;

3. Methods

Behaviors and precedents can vary significantly among individuals, especially in young adults. By adopting a cultural, economic, and behavioral economic theoretical framework, this research aims to explore further the trigger factors that entice young adults to binge-watch, seeking to bridge the gap by investigating and examining the economic theoretical binge-watching framework with empirical evidence. To achieve this goal, the study employs a quantitative research method, considering 9 factors developed in previous research (Gaenssle & Kunz-Kaltenhaeuser, 2020; Flayelle et al., 2017; Fernandes & Pinto, 2020; Panda & Pandey, 2017; Rubenking & Bracken, 2021; Sung et al., 2018; Qayyoum & Malik, 2023) and previous research on binge-watching. The research seeks to delve deeper into the factors that seduce young adults into binge-watching, providing empirical insights into the economic aspect. The research question is as follows:

What are the factors that motivate young adults to spend more time binge-watching?

The sub-objectives of the study are:

- To study the economic nature of young adults' binge-watching behavior;
- To statistically examine various motivations of students that lead to binge-watching behavior.

The aim is to gather diverse data and target young adults. The primary data is collected from an online quantitative questionnaire via Qualtrics, which has 16 questions designed to correspond to the several factors addressed previously, along with demographic questions to draw an overview of the participants. Participants voluntarily participate in the research and can quit the survey at any stage. The survey was spread out via social media platforms, namely WhatsApp groups, WeChat (Chinese social media), Instagram, and Reddit in different communities. Since Reddit includes all types of people online, various communities are built with specific interests in mind. The survey is distributed in specific communities, such as "r/BingeWatching Junkies" and "r/Netflix," but also spread via academic Reddit communities. The raw response's population size is 305. An Excel file is used to store and clean the data. Approximately 91 responses are incomplete. The effective data set of the sample is 214, which is close to the expected sample size.

3.1 Survey Instrument Development

The survey is constructed in three sections: a) demographic questions, b) video viewing behavior, and c) motivations for binge-watching.

The demographic questions collect data that can be used as control variables for the data set. Questions about the participant's age, gender, and nationality are included. The survey also considers their income level, educational background, and households. The investigation of income level measures the purchase ability of participants to distinguish the signal corresponding to the factor of the flat rate pricing model later in the survey.

Video viewing behavior: This study adopted the definition of binge-watching and the economic model developed by Pittman and Sheehan (2015) and Gaenssle and Kunz-Kaltenhaeuser (2020), which the binge-watching behavior is measured with the frequency of viewing and the time spent in one sitting for viewing. Further, the element of time is implemented to measure watching behavior. Participants were asked to estimate how many episodes they typically watched in a single sitting, with options ranging from one episode to 50. It was followed by a question about how long they spent in one sitting viewing video content in hours estimated, with options ranging from 0 to 12 hours. The frequency of each participant's viewing behavior is examined via options from a few times per day, daily, a few times per week, weekly, a few times per month, and monthly. These questions served as a primary screening tool to distinguish binge viewers from non-binge viewers.

Motivation of binge-watching. Participants were asked to indicate their level of agreement with five statements on a 5-point Likert scale for testing the supplier side factors, namely serial content, sense of self-administration, reconsideration time, flat rate of pricing model (Gaenssle & Kunz-Kaltenhaeuser, 2020), ranging from strongly disagree (1) to strongly agree (5) (Wang & Calder, 2009). Every statement offers an extra option for the participant to choose with "No response" if the participant is unwilling to answer the question. These statements included: "I like to watch series", "I would watch the whole season in one sit just to get to know how the plot ends", " I like to watch non-linear content on demand (independent of a broadcasting schedule)", "I like an autoplay mode between videos or episodes to keep watching", "I frequently end up watching more episodes than I initially intended", and "My video consumption increases if all contents are included in my monthly subscription (i.e., Netflix with no additional pay per view)". Five motivations from the consumer side were included: social engagement, entertainment/enjoyment, escape reality, stress relief, and boredom (Rubenking & Bracken, 2018). The factors are also measured via 5 points Likert scale, along with the one additional option, "no response". Statements are taken as follows: "I like to watch video content to be entertained", "I like to watch video content to connect with friends and family", "I like to watch video content to release stress from school/university/work", "I like to watch video content to get a break from reality", "I like to watch video content to pass the time without boredom".

We define the independent variable for each hypothesis as the various factors: serial content, sense of self-administration, reconsideration time, rate of pricing model, social engagement, entertainment, stress relief, escape reality, and boredom. The dependent variable will be the likelihood of young adults spending time binge-watching. The moderate variable will be intentional and unintentional binge-watching.

The data analysis will utilize R-studio software and employ the regression model to examine the correlation between the dependent and independent variables. A statistical overview will be presented before the regression results to give the audience an understanding of the respondents. The robustness of the models is tested via correlation tests and variance inflation factors. Further, three regression models with all nine factors, both the consumer and supplier sides and the three dependent variables, are tested to extend the model's explanation power. The overview of the robustness of models is presented at the end of the robustness section.

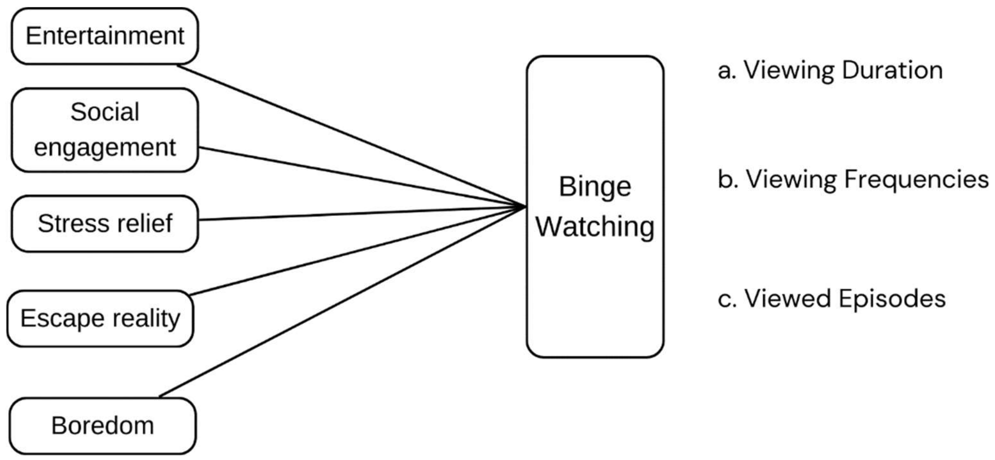
3.2 Model development

Based on the theory developed in the literature review, this study's regression model can be developed based on three dependent variables that represent binge-watching: viewing duration, viewing frequencies, and viewed episodes.

On both the supplier and customer sides, the independent variables are examined with three different regression models: viewing duration, viewing frequency, and the episodes consumed. The ordinary linear regression model is implemented to test the continuous numerical data for the viewing duration. Corresponding to my hypothesis, which is separated by supplier and customer perspectives, the multilinear regression model can test the relationship between multi-factors and the dependent variable, the viewing duration. On the other hand, logistic and ordinal logistic regression models are implemented to test the dependent variables, viewing frequencies, and viewed episodes. The ordinal logistic model is to examine the ordinal dependent variable, which reflects categories with a natural order but an unknown interval between categories. In the case of viewing frequencies, it used to be measured from six different categories, namely from viewing daily to monthly. The six viewing levels in frequency are converted into a numerical scale from 1 to 6. The variance inflation factors test previously proved that there is no risk of multicollinearity with each side of the factors, which falls under the assumption of ordinal logistic regression. The strength of the ordinal logistic regression model is that it can be utilized to test with both continuous and categorical independent variables. The logistic regression model provides a robust test environment for binary dependent variables.

The number of episodes watched in a single sitting was categorized under three episodes viewed as not binge-watching and three episodes viewed and above as binge-watching. More recently, one study reported empirical results demonstrating the important difference in psychological reaction for the exposure to two versus three episodes (Song et al., 2022). The results are categorized into binary data. The logistic regression model is relatively more robust in dealing with outliers than the ordinary linear regression model. This model allows both continuous and categorical independent variables. The results will most likely be valid and accurate because this study has utilized the strengths of all the regression models used.

Figure 1. Models of consumer side factors



The regression equations for the three models on the consumer side factors can be derived as follows:
Model 1: Viewing duration (OLS):
$View\_Duration = \beta 0 + \beta 1 \cdot ENT + \beta 2 \cdot SOCIAL + \beta 3 \cdot STR\_R + \beta 4 \cdot ESC + \beta 5 \cdot BOR + \epsilon$

Model 2: Viewing Frequency (Ordinal Logit):
$\log(P(FreQ \leq j) / P(FreQ > j)) = \beta 0j + \beta 1 \cdot ENT + \beta 2 \cdot SOCIAL + \beta 3 \cdot STR\_R + \beta 4 \cdot ESC + \beta 5 \cdot BOR$

Model 3: Viewed Episodes (Logit):
$\log(P(Epi=1)/ 1-P(Epi=1)) = \beta 0 + \beta 1 \cdot ENT + \beta 2 \cdot SOCIAL + \beta 3 \cdot STR\_R + \beta 4 \cdot ESC + \beta 5 \cdot BOR$

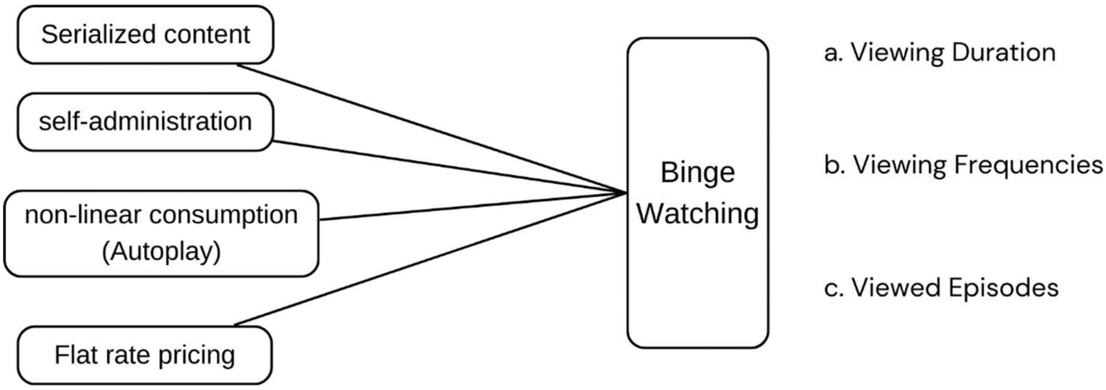
Term explanation:

- Abbreviations: FreQ = Viewing Frequency; Epi = Viewed episodes; ENT = entertainment; SOCIAL= social engagement; STR_R= stress relief; ESC=escape reality; BOR=boredom
- In the second model, which examines **FreQ**, $\log(P(FreQ \leq j) / P(FreQ > j))$ represents the log odds of the ordinal outcome being less than or equal to a particular category j. In this study, the categories range from 1 to 6. Each category j has its intercept term $\beta 0j$.
- In the third model, which tests **Epi**, $\log(P(Epi=1)/ 1-P(Epi=1))$ represents the log odds of the binary outcome being 1.
- $\beta 0$ or $\beta 0j$ are the intercept terms.
- $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, and $\beta 5$ are the coefficients of the independent variables Entertainment, Social

Engagement, Stress Relief, Escape Reality, and Boredom.

- ϵ is the error term in the ordinal least squares regression model.

Figure 2. Models of supplier side factors



The regression equations for three models on the supply side factors correspondingly can be derived as follows:

Model 1: Viewing duration (OLS):

$$View\_Duration = \beta0 + \beta1 \cdot SERI + \beta2 \cdot S\_ADMIN + \beta3 \cdot AUTOP + \beta4 \cdot Price + \epsilon$$

Model 2: Viewing Frequency (Ordinal Logit):

$$\log(P(FreQ \leq j) / P(FreQ > j)) = \beta0j + \beta1 \cdot SERI + \beta2 \cdot S\_ADMIN + \beta3 \cdot AUTOP + \beta4 \cdot Price$$

Model 3: Viewed Episodes (Logit):

$$\log(P(Epi=1)/ 1-P(Epi=1)) = \beta0 + \beta1 \cdot SERI + \beta2 \cdot S\_ADMIN + \beta3 \cdot AUTOP + \beta4 \cdot Price$$

Term explanation:

- Abbreviations: SERI = Serial Content; S-ADMIN = Self-administration; AUTOP=Autoplay; Price = Flat rate pricing.
- In the second model, which examines **FreQ**, $\log(P(FreQ \leq j) / P(FreQ > j))$ represents the log odds of the ordinal outcome being less than or equal to a particular category j. In this study, the categories range from 1 to 6. Each category j has its intercept term $\beta0j$.
- In the third model, which tests **Epi**, $\log(P(Epi=1)/ 1-P(Epi=1))$ represents the log odds of the binary outcome being 1.
- $\beta0$ or $\beta0j$ are the intercept terms.
- $\beta1$, $\beta2$, $\beta3$, and $\beta4$ are the coefficients of the independent variables serial content, self-administration, non-linear consumption, and flat rate pricing.
- ϵ is the error term in the ordinal least squares regression model.

4. Results

4.1 Demographic

The overview of the respondents can be drawn from the answers to the demographic questions. Regarding the gender distribution of the data set, females occupied most of the observations. Females aggregated over 60 percent of the sample while occupied 35 percent. The participants' ages vary from the youngest, 15, to the oldest, 49. Most participants are gathered from 15 to 30, occupying approximately 83 percent of the data set. The average age of the participants is 25; therefore, the sample meets the requirement of the target group of the research, meaning young adults. Over half (53.4 percent) of the data set are around age 20 to 25. Young adults, especially teenagers, tend to binge-watch, specifically from 15 to 30 (Budzinski et al., 2021; Divya, 2020; Matrix, 2014; Steiner & Xu, 2018; Ayten et al., 2019).

Following the sample's age range, the survey also gathers the participants' educational background. The results indicate that over half of the sample has a master’s degree (52.6 percent). Bachelor’s degree participants occupy nearly 40 percent of the sample. A relatively small observation group contains either a secondary degree (age 15-18) or PhD. Binge-watching is particularly relevant for college students with a large audience segment (Chaudhary, 2014). Research indicates that nine out of ten college students frequently use Netflix and engage in binge-watching TV shows (Solis, 2014).

The income level distribution reflects a similar conclusion with the sample demographic; half of the observation falls in the category with income lower than 2,500, with 33.8 percent earning less than 1,000 euros per month and 15.4 percent earning 1,000 to 2,500 euros per month. The income is measured with the individual's gross income earned per month. This may contribute to the consumer's purchasing power and potentially affect the later study. Meanwhile, around 15 percent of the participants earn more than 2,500 euros but less than 3,500 euros per month, which is almost the same percentage in income level, 3,500 to 4,500 euros gross per month. Only a few observations indicate they earn more than 4,500 euros gross per month. The insights derived from the income level may contribute to the analysis of how an individual’s decision-making is affected by the restricted resource, meaning the amount of money they are available to spend every month.

Due to the distribution channels used for the online survey, most of the observations (64.5 percent) are gathered within a range of Western Europe, mainly the Netherlands. Almost half of the sample currently resides in the Netherlands (45.3 percent), and around 15 percent of the observations are from Germany. Observations from China occupy nearly 30 percent of the remaining samples due to distribution via WeChat. To gain a more comprehensive overview of the observations, a few participants currently reside in the United States. Zoomed into the sample set from a perspective of the country of residence instead of the nationality of the participants to adopt the factors influencing people’s taste and taste formation (Stigler & Becker, 1977).

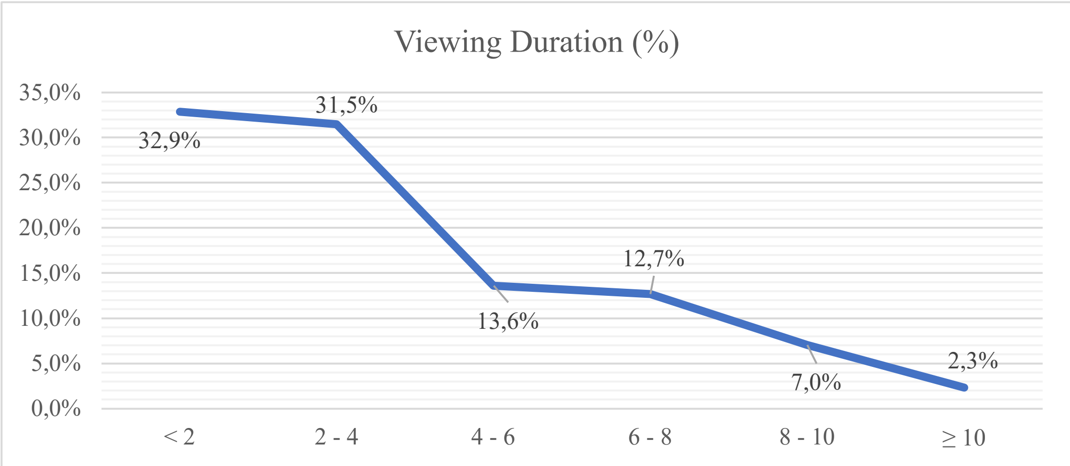
Table 1. Respondents' demographic profiles (N =234)

Measure	Item	Frequency	Percentage
Age			
	18 or below	8	3.4%
	19-30	200	85.5%
	31-40	23	9.8%
	41 and above	3	1.3%
Region			
	Netherlands	106	45.3%
	China	65	27.8%
	Germany	31	13.2%
	Other	32	13.7%
Gender			
	Female	141	60.3%
	Male	80	34.2%
	Non-binary	8	3.4%
	Prefer not to say	5	2.1%
Education			
	Without educational degree	4	1.7%
	Secondary School	14	6.0%
	Bachelor	83	35.5%
	Master	123	52.6%
	PhD	9	3.8%
	Prefer not to say	1	0.4%
Monthly Gross Income			
	Less than 1000	79	33.8%
	1000-2500	36	15.4%
	2500-3500	35	15.0%
	3500-4500	39	16.7%
	More than 4500	23	9.8%
	Prefer not to say	22	9.4%

4.2 Viewing Behavior

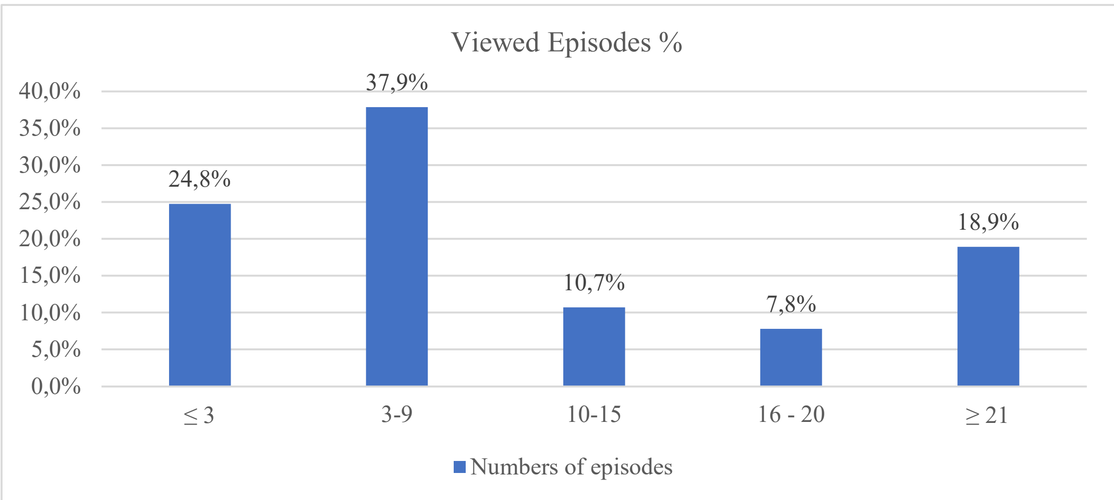
The viewing behavior is measured from three different dimensions: the viewing duration in one sit, the episodes consumed in one sit, and the viewing frequency. The average viewing duration of the sample is 3.56 hours in one sitting, which indicates that half of the participants are likely to engage in binge-watching. Over half of the observations (57.7 percent) were spent in a range of 2 hours to 8 hours in one sitting to watch video content, with 31.5 percent of participants watching between 2 to 4 hours and 13.6 percent of the participants watching 4 to 6 hours video content in one sit. Observations watched for more than 6 hours are categorized into three levels. Results indicate that 12.7 percent of participants watched 6 to 8 hours of video content in one sit. In comparison, approximately 10 percent of participants watched more than 8 hours in one sitting, including 2.3 percent of the participants stating that they watched more than 10 hours on average in one sitting in estimation.

Figure 3. Respondents Viewing Duration in one sitting



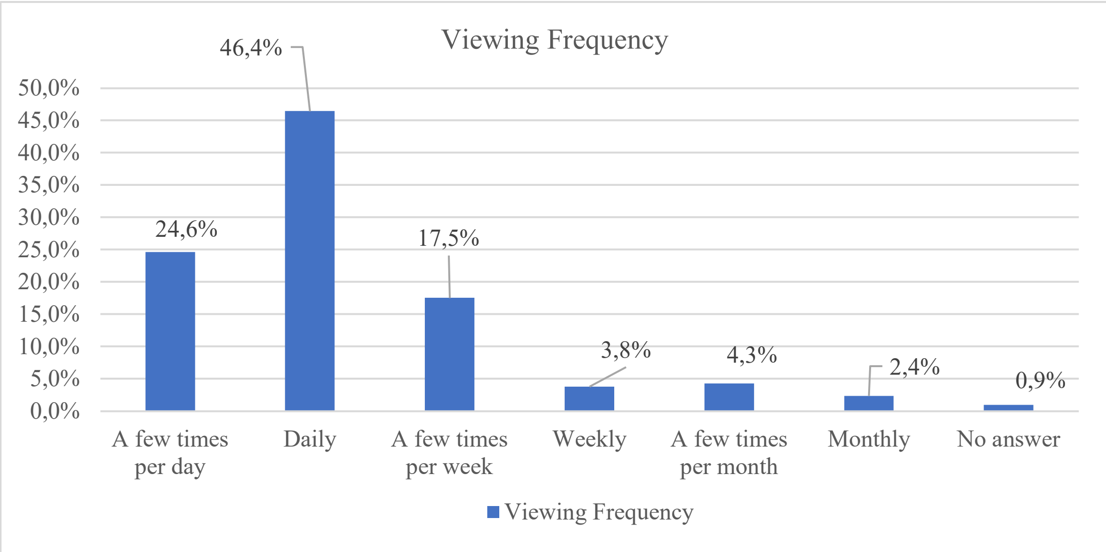
This is followed by measuring the consumed quantity, namely the episodes of the videos that participants consumed in one sitting, which can be interpreted in two ways. According to previous research, people who consume more than 2 episodes in one sitting can be considered binge-watching or “heavy consumption” (Panda & Pandey, 2017; Netflix, 2013). 75.2 percent of the participants fall into the categories that consumed more than 3 episodes in one sitting. Specifically, 37.9 percent of the sample stated that they watched from 3 to 6 episodes. 18 percent of the samples claim they consume 10 to 20 episodes in one sitting. More surprisingly, participants who noted consuming more than 20 episodes occupied 18.9 percent of the sample.

Figure 4. Respondents viewed episodes in one sitting



Regarding viewing frequencies, the participants are divided into 6 categories: a few times per day, daily, a few times per week, weekly, a few times per month, and monthly. The results indicate that most of the participants fall into the category that they consume video content daily, which occupied approximately 46.4 percent of the observations. Meanwhile, approximately 24.6 percent of the participants stated that they consume video content more than once per day. In total, over half of the sample appears with the feature of binge-watching. Schweidel and Moe (2016) suggest that a high consumption rate is the most critical factor in determining whether someone will binge-watch. The rest of the sample reported as less frequent viewers compared to the previous two categories. Only 17.5 percent of the participants claimed they only consume video content a few times weekly, while 3.8 percent stated they watch video once weekly. Only 6.6 percent of the observations state that they watch videos monthly.

Figure 5. Respondents' viewing Frequency



4.3 Motivation of Binge-watching:

4.3.1 Motivations from the Consumer Side Factors

The factors on the consumer side, namely entertainment, social engagement, stress relief, escape reality, and boredom, are recorded as ENT, SOCIAL, STR_R, ESC, and BOR. The regression test is implemented on three dependent variables: viewing duration, viewing frequency, and estimated episodes. The results from the regression analysis depicted in the first model in Table 2 investigate the impact of five predictors: ENT, SOCIAL, STR_R, ESC, and BOR on View Duration. In terms of coefficients, the intercept is statistically significant ($p < 0.05$), indicating a baseline View Duration of 3.10 units when all predictors are zero. Among the predictors, only social interaction shows a statistically significant positive effect ($\beta = 0.48$, $p < 0.05$), suggesting it positively relates to the View Duration. Other variables, including

Entertainment, Stress Reduction, Escape, and Boredom, do not significantly influence View Duration, as evidenced by their high p-values. In the last column of the table, the variance inflation factor (VIF) of the five independent variables is presented, with values well below the commonly used threshold of 5. This suggests that each predictor contributes independently to the model, enhancing the reliability of the regression results.

Regarding model performance metrics, the residual standard error is 2.67 with 160 degrees of freedom, the Multiple R-squared of 0.051 implies that only about 5.08 percent of the variability in View Duration is accounted for by this model, and the Adjusted R-squared of 0.02 further indicates limited explanatory power after adjusting for the number of predictors. Moreover, the F-statistic of 1.71 with a p-value of 0.13 fails to reject the null hypothesis that the model does not explain a significant portion of the variance in the response variable, collectively suggesting that the model may not be the best fit for the data. This analysis underscores the importance of Social Interaction in determining View Duration while highlighting the need for a potentially more robust model to understand the dynamics of the remaining predictors better.

The results displayed in the second model in Table 2 provide insights from a logistic regression model exploring the relationship between the frequency of a behavior (FreQ) and five predictors: Entertainment (ENT), Social engagement (SOCIAL), Stress Relief (STR_R), Escape (ESC), and Boredom (BOR). The logistic model, characterized as 'flexible logit,' was evaluated on 164 observations and indicated a model fit with a log-likelihood of -210.09, an AIC (Akaike Information Criterion) of 440.18, and convergence achieved after 6 iterations with a maximum gradient near zero, suggesting a satisfactory model fit.

Regarding the coefficients for the independent variables, none except stress relief shows a significant impact. Factor stress relief has a positive coefficient of 0.45 ($p = 0.02$), indicating it significantly increases the frequency of binge-watching. Other predictors such as entertainment, social engagement, escape, and boredom show non-significant z-values, indicating no apparent effect on the frequencies. Entertainment and social engagement have negative coefficients, suggesting potential decreases in binge-watching frequency, though these effects are not statistically significant.

The model also includes threshold coefficients for the ordered categories, reflecting the log odds of transitioning between ordinal outcomes. These thresholds do not achieve statistical significance, except for the transition between categories 5 (daily) and 6 (a few times per day) (coefficient = 3.00, z-value = 2.80). This might suggest notable differences in the probabilities of achieving higher categories relative to others. Overall, the regression analysis suggests a limited influence from most entertainment and social factors on the frequency of the behavior, except stress relief, which appears to be a significant predictor. The model's overall performance, represented by the AIC and convergence indicators, shows adequacy but also suggests the potential for model refinement or the need for additional or different predictors to thoroughly capture the dynamics affecting behavior frequency.

Results on the regression model on viewed episodes of the participants and five independent factors fail to reveal significant outcomes. The intercept from this model, with a coefficient of 1.62 and a standard error of 1.22, has a z-value of 1.33 but is not statistically significant ($p = 0.19$). This suggests that the log odds of observing EPI is about 1.62 without all predictors, though this is not a reliable estimate. The factor entertainment shows a negative relationship with consumed episodes, with a coefficient of -0.36; however, this is also not statistically significant ($p = 0.13$). SOCIAL exhibits a potentially positive impact on EPI, indicated by a coefficient of 0.27 and a z-value of 1.59, but this, too, fails to reach statistical significance ($p = 0.113$). STR_R, ESC, and BOR all have negligible and statistically insignificant coefficients, suggesting they do not affect EPI.

Model diagnostics show a null deviance of 206.40 on 165 degrees of freedom compared to a residual deviance of 200.56 on 160 degrees of freedom. This indicates only a slight improvement in the model over the null hypothesis, with the predictors offering limited enhancement of the model fit. The Akaike Information Criterion (AIC) is 212.56. The regression analysis indicates that the model has limited explanatory power for EPI, as none of the independent variables achieves statistical significance. The slight reduction in deviance from the null to the residual model and the overall high AIC value suggest that the model might not effectively capture the underlying dynamics of EPI, potentially requiring a re-evaluation of the variables included or consideration of interaction effects among the predictors.

Discussion according to the results in Table 2 and the interpretations, hypothesis H1, that factors such as social engagement, entertainment, stress relief, escape reality, and boredom positively impact the likelihood of binge-watching for young adults can be evaluated.

For entertainment (ENT), we do not reject the null hypothesis for any model, as there are no significant positive impacts. For social interaction (SOCIAL), the null hypothesis is rejected for view duration, as there is a significant positive impact (coefficient = 0.48, $p < 0.05$). However, the null hypothesis for frequency and the number of viewed episodes is not rejected, as no significant effects are observed.

For stress relief (STR_R), the null hypothesis is rejected for frequency as there is a significant positive impact (coefficient = 0.45, $p < 0.05$). However, the null hypothesis is not rejected for view duration and the number of episodes watched, as no significant effects are found. For the factors escape reality (ESC) and boredom (BOR), the null hypothesis is not rejected for any model, as there are no significant positive impacts.

The null hypotheses regarding social interaction's impact on view duration and stress relief's impact on binge-watching frequency are rejected. However, we do not reject the null hypothesis regarding all other factors and models.

Table 2 Results of Regression on Binge-watching Behavior with Consumer Side Factors

	View Duration Model 1 OLS regression	Frequency Model 2 Ordinal Logistic regression	Episodes Model 3 Logistic regression	VIF
ENT	-0.22	-0.08	-0.36	1.21
	(0.28)	(0.20)	(0.24)	
SOCIAL	**0.48***	-0.18	0.27	1.06
	(0.21)	(0.15)	(0.17)	
STR_R	-0.49	**0.45***	-0.05	1.36
	(0.27)	(0.20)	(0.22)	
ESC	0.28	0.16	0.01	1.34
	(0.22)	(0.16)	(0.18)	
BOR	0.06	0.06	0.004	1.23
	(0.21)	(0.15)	(0.17)	
Estimates	**3.10****		1.62	
	(1.43)		(1.22)	
1|2		-1.80		
		(1.10)		
2|3		-0.85		
		(1.06)		
3|4		-0.51		
		(1.05)		
4|5		0.70		
		(1.05)		
5|6		3.00		
		(1.07)		
Adjusted R-squared	0.02	-	-	
Observations	214	214	214	

Notes: Reported effects are standardized (Beta) coefficients. Controlled for the age, gender, educational level of respondents, and country of residence. Standard errors are entered in parentheses.

Significance levels: ~ p<.10 * p< .05 ** p< .01 *** p< .001.

4.3.2 Motivations from the Supplier side factors

Table 3 outlines the results of regression models analyzing the influence of four predictors—SERI, S_ADMIN, AUTOP, and Price on View Duration. The model's residuals, which provide insight into the distribution around the predicted values, range from -3.88 to 8.36, highlighting the presence of outliers, especially on the higher end. Most residuals cluster between -1.87 and 1.45, around the median of -0.74, indicating a moderate spread. Regarding the coefficients, while none of the predictors are significantly impactful at the conventional 0.05 alpha level, S_ADMIN and Price are on the cusp of significance, with p-values just slightly above the threshold. Specifically, S_ADMIN shows a positive effect (estimate = 0.3983, p-value = 0.053), suggesting it might slightly increase View Duration, and Price also indicates a potential positive impact (estimate = 0.46, p-value = 0.054), implying that higher prices could be associated with longer view durations. Conversely, SERI and AUTOP do not significantly influence View Duration, as reflected by their higher p-values.

The first model's overall fit is relatively weak, with a residual standard error of 2.6 on 161 degrees of freedom and a modest R-squared value of 0.06, adjusted to 0.04. This suggests that the model explains only a tiny portion of the variability in viewing Duration. Nevertheless, the F-statistic of 2.60 with a p-value of 0.04 indicates that the model is statistically significant, albeit with limited explanatory power. This highlights a need to incorporate additional predictors to better capture the viewing duration's determinants.

Model 2 delves into the logistic regression analysis that evaluates the impact of four variables on the dependent variable, viewing frequencies, through a flexible link logit model based on 214 observations. The model outputs reveal that the variables have varying but primarily minimal effects on viewing frequencies. Specifically, serialized content has a slight positive influence, although not statistically significant, suggesting it has a minor role in affecting frequency. While showing a more notable positive estimate, the sense of self-ministration still falls short of statistical significance, hinting at a possible but unconfirmed impact. AUTOP's negative coefficient indicates a potential decrease in viewing frequencies associated with this variable, but like the others, this effect is not statistically significant. PRICE, in particular, shows almost no influence with its negligible coefficient and extremely high p-value.

The model's fitness indicators, such as the Akaike Information Criterion (AIC) of 447.15 and the residual deviance, point to a decent but imperfect model fit. The threshold coefficients provide some of the most meaningful insights from this analysis, clearly delineating significant transitions between specific categories, such as from the lowest to the mid and higher levels. These transitions are statistically significant between categories 1 and 2, 2 and 3, and particularly notable at the transition from categories 5 to 6. These thresholds suggest where significant changes in behavior frequency occur, offering a clearer picture of how different viewing frequency levels are separated.

The analysis, therefore, underscores some critical points about the factors influencing viewing frequencies and their limited explanatory power. It also highlights significant categorical shifts that may warrant further investigation to understand underlying behaviors better or refine the model. The model could benefit from including additional variables or interaction terms to enhance its explanatory capability, potentially capturing more nuanced dynamics that the current predictors fail to elucidate.

Model 3 summarizes the findings of a logistic regression model evaluating the impact of four predictors on the variable EPI. The analysis reveals varying degrees of influence from these predictors, as indicated by their coefficients, standard errors, z-values, and p-values.

Among the predictors, SERI stands out with a coefficient of 0.67 and a remarkably low p-value of 0.00, indicating a strong and statistically significant favorable influence on EPI. This suggests that individuals who prefer serialized content are likelier to consume episodes in one sitting. In contrast, S_ADMIN and Price, though they have positive coefficients of 0.20 and 0.28, respectively, do not reach statistical significance, with p-values of 0.26 and 0.18, indicating that their effects on EPI are not conclusively different from zero in this model. AUTOP shows a negative coefficient of -0.07 and a high p-value of 0.68, suggesting it does not significantly affect the likelihood of consuming more episodes.

After introducing the predictors, the model's overall fit is quantified through the null and residual deviance, with values decreasing from 206.40 to 177.84. This indicates an improved fit from the null model to the model with predictors. The Akaike Information Criterion (AIC) for the model is 187.84, which aids in comparing this model's quality to other models not shown here.

While SERI is a strong predictor of EPI, indicating a significant effect, other variables like S_ADMIN, AUTOP, and Price do not significantly contribute to the model. This suggests that while some factors like SERI1 are critical in influencing EPI, others might require reevaluation or the inclusion of additional variables to capture their potential effects better. The overall observations of the three models show relatively minor differences. The number of observations varies from 207 to 214. The variance inflation factors of the four independent variables appear within the range from 1 to 2, specifically from 1.07 to 1.11. The results state the reliability of the four independent variables with no risk of multicollinearity.

Reflecting on the results provided on the supply side, an overview of hypothesis H2, which posits that factors such as serialized content, sense of self-administration, short time interval for reconsideration, and flat rate pricing model, increase the likelihood of binge-watching for young adults, can be drawn.

For serial content (SERI), the null hypothesis is rejected for the dependent variable of viewed episodes, as there is a significant positive impact (coefficient = 0.67, $p < 0.01$). However, the null hypothesis for view duration and frequency is not rejected, as no significant effects are observed.

For the sense of self-administration (S_ADMIN), the null hypothesis is marginally rejected for view duration, with a positive impact that is near significance (coefficient = 0.40, $p < 0.10$). However, the null hypothesis is not rejected for frequency and the number of episodes watched, as no significant effects are found. The same outcome is observed in the flat-rate pricing (PRICE) factor. The null hypothesis is marginally rejected for view duration, with a positive effect that is also near significance (coefficient = 0.46, $p < 0.10$). The null hypothesis is not rejected for flat-rate pricing's impact on frequency and viewed episodes, as no significant effects are observed. This situation is caused by the relatively low explanation power of the model, as the sample size is limited. Both factors appear to be statistically significant in the models with a total of nine independent variables, as the explanation power of the model grew with the number of independent variables (see Section 4.4). For the short time interval for reconsideration (AUTOP), the null hypothesis is not rejected for any model, as there are no significant positive impacts.

The null hypothesis is rejected for serialized content's impact on the number of episodes watched. The null hypothesis is marginally rejected for the sense of self-administration's impact on view duration and the flat rate pricing model's effect on view duration. For all other factors and models, the null hypothesis is not rejected.

Table 3 Results of Regression on Binge-watching behavior with Supply Side factors

	View Duration Model 1 OLS regression	Frequency Model 2 Ordinal Logistic regression	Episodes Model 3 Logistic regression	VIF
SERI	0.1809	0.03	**0.67****	1.07
	(0.18)	(0.13)	(0.17)	
S_ADMIN	**0.40 ~**	0.20	0.20	1.11
	(0.20)	(0.15)	(0.18)	
AUTOP	-0.17	-0.07	-0.07	1.11
	(0.18)	(0.13)	(0.17)	
Price	**0.46 ~**	-0.004	0.28	1.08
	(0.24)	(0.18)	(0.21)	
Constant	0.23	-	**-2.65****	
	(1.12)	-	(0.97)	
1|2	-	-2.94	-	
		(0.88)		
2|3	-	-2.02	-	
		(0.81)		
3|4	-	-1.70	-	
		(0.80)		
4|5	-	-0,53	-	
		(0.78)		
5|6	-	(1.69)	-	
		(0.80)		
Adjusted R-squared	0.03	-	-	
Observations	214	214	214	

Notes: Reported effects are standardized (Beta) coefficients. Controlled for the age, gender, educational level of respondents, and country of residence. Standard errors are entered in parentheses.
Significance levels: ~ p<.10 * p< .05 ** p< .01 *** p< .001.

4.4 Robustness Checks and Limitations.

To test the robustness of the models in this study, the correlation between the nine independent variables in the separation of consumer and supplier sides. The correlation analysis of consumer-side factors reveals several significant relationships. Firstly, entertainment exhibits a significant positive correlation with stress relief (cor = 0.33, p = 0.012), escapism (cor = 0.22, p = 0.003), and boredom (cor = 0.30, p = 0.0001), indicating that entertainment content is associated with higher levels of stress relief, escapism, and alleviation of boredom. Additionally, social engagement demonstrates a significant positive correlation with stress relief (cor = 0.21, p = 0.005), suggesting that engaging in social activities is linked to stress relief. Furthermore, stress relief shows a significant positive correlation with escapism (cor = 0.41, p < 0.001) and boredom (cor = 0.17, p = 0.03), indicating that stress-relieving activities may also contribute to feelings of escapism and alleviation of boredom. Lastly, boredom exhibits a significant positive correlation with escapism (cor = 0.48, p = 0.001), highlighting a relationship between boredom and the desire to escape reality. These findings provide insights into the interplay between consumer-side factors and their potential impact on motivation.

The correlation analysis of supplier-side factors reveals several significant relationships. Serial content demonstrates a positive and statistically significant correlation with both self-administration (cor = 0.23, p = 0.003) and price (cor = 0.16, p = 0.039), indicating that platforms offering serial content are more likely to involve user self-administration and command higher prices. Self-administration exhibits a significant positive correlation with autoplay (cor = 0.24, p = 0.002), suggesting that platforms allowing users more control over their experience are also inclined towards autoplay features. Additionally, autoplay shows a significant positive correlation with price (cor = 0.23, p = 0.003), implying that platforms with autoplay functionality tend to charge higher prices. However, the correlation between serial content and autoplay is weak and non-significant (cor = 0.10, p = 0.18).

Table 4: Correlation of consumer side factors

	SOCIAL		STR_R		ESC		BOR	
	COR	p-value	COR	p-value	COR	p-value	COR	p-value
ENT	-0.01	0.86	0.33	1,19E-02***	0.22	0.003**	0.30	0.0001**
SOCIAL			0.21	0.005*	0.048	0.53	-0.05	0.55
STR_R					0.41	5.08e-08***	0.17	0.03*
ESC							0.36	1,50E-03***

*ENT = entertainment; SOCIAL= social engagement; STR_R= stress relief; ESC=escape reality; BOR=boredom

Table 5: Correlation of Supplier side factors

	S-ADM		AUTOP		PRICE	
	COR	p-value	COR	p-value	COR	p-value
SER	0.23	0.003*	0.10	0.18	0.16	0.04*
S-ADM			0.24	0.002*	0.08	0.30
AUTOP					0.23	0.002*

*SER = serial content; S-ADM = self-administration; AUTOP=autoplay

To ensure the robustness of this study, additional regression analyses were conducted with the independent variables from both sides, namely entertainment, social interaction, stress relief, escape reality, boredom, serial content, sense of self-administration, autoplay, and flat rate pricing. The results are presented in Table 5.

The results generally reveal a higher power of explanation for the impacts of multiple factors with significant outcomes. Factors significant in the previous tests, such as social interaction and stress relief, stay significant. Furthermore, the factors not significant in the previous tests, namely entertainment, a sense of self-administration, and the pricing model, appear to have significant impacts on binge-watching. This finding supports the statement that factors may overlap and influence one another. At the same time, factor serial content appears insignificant in any of the models.

Zoom into details, serialized content, short reconsideration time interval, escape reality, and boredom fail to show significant impacts on any of the models, namely on the viewing duration, viewing frequency, and viewed episodes of binge-watching.

Entertainment (ENT) shows a negative impact across all models. In the third model, the coefficient of entertainment appears to be negative and statistically significant in the impact on the number of episodes watched (coefficient = -0.60, p-value < 0.05). Social interaction (SOCIAL) appears marginally positive and significant in Model 1 on the impact of viewing duration (coefficient = 0.39, p-value < 0.1). It indicates a potential positive impact on view duration. However, social interaction fails to be significant in the other two models. Stress relief (STR_R) is positive and statistically significant in model 2, indicating that stress relief increases the frequency of binge-watching. No significant impact on viewing duration and viewed episodes for stress relief. Sense of self-administration (S_ADMIN) shows a positive statistically significant impact on the viewing duration (coefficient = 0.41, p-value < 0.5). This factor also shows a positive but insignificant impact on viewing frequency and the viewed episodes. The flat rate pricing model (PRICE) is positively related to the viewing duration and viewed episodes, and it appears statistically significant (coefficient model 1= 0.48, p-value < 0.05; coefficient = 0.50, p-value < 0.05).

While the models provide insights into the factors influencing binge-watching behavior and the explanation power grows significantly, several limitations should be noted. The adjusted R squared value for the OLS regression model is relatively low, stating that a significant portion of the variability in view duration remains unexplained. It suggests that alternative models or additional variables may better capture this variability. Another limitation of the model may be that logistic regression models do not report adjusted R-squared values, which are not applicable. The models report pseudo-R-squared or AIC, which is still limited compared to adjusted R-squared.

However, the variance inflation factors value is below the standard threshold of 10, indicating that multicollinearity is not a severe issue. Values close to 1 are optimal. The potential existence of some collinearity among predictors can still inflate standard errors and affect the reliability of coefficient estimates. Endogeneity issues might exist where some independent variables could correlate with the error term, leading to biased and inconsistent estimates. For example, stress relief (STR_R) and escape reality (ESC) could be endogenous if individuals with certain unobserved traits are more likely to experience stress or seek escapism, affecting their binge-watching behavior.

Table 6: Results of Regression on Binge-watching behavior with all independent variables

	View Duration Model 1 OLS Regression	**Frequency Model 2 Ordinal Logistic Regression**	**Episodes Model 3 Logistic Regression**	**VIF**
ENT	-0.42	-0.09	**-0.60***	1.21
	(0.28)	(0.21)	(0.26)	
SOCIAL	**0.39~**	-0.18	0.18	1.06
	(0.21)	(0.15)	(0.18)	
STR_R	-0.42	**0.45***	-0.07	1.36
	(0.26)	(0.20)	(0.24)	
ESC	0.23	0.14	0.01	1.34
	(0.22)	(0.16)	(0.19)	
BOR	-0.04	0.06	-0.12	1.23
	(0.21)	(0.15)	(0.19)	
SERI	0.27	0.01	0.24	1.07
	(0.20)	(0.15)	(0.17)	
S_ADMIN	**0.41***	0.13	**0.30~**	1.11
	(0.20)	(0.15)	(0.18)	
AUTOP	-0.17	-0.07	0.10	1.11
	(0.18)	(0.13)	(0.16)	
Price	**0.48***	0.04	**0.50***	1.08
	(0.24)	(0.17)	(0.21)	
Constant	1.38	-	-0.39	-
	(1.54)	-	(1.33)	-
Thresholds	-	-1.57	-	-
	-	(1.19)	-	-
	-	-0.62	-	-
	-	(1.15)	-	-

	-	-0.28	-	-
	-	(1.15)	-	-
	-	0.94	-	-
	-	(1.15)	-	-
	-	3.25	-	-
		(1.17)	-	-
Adjusted R-squared	0.07			
Observations	214	214	214	

Notes: Reported effects are standardized (Beta) coefficients. Controlled for the age, gender, educational level of respondents, monthly income, and country of residence. Standard errors are entered in parentheses.
Significance levels: ~ $p<.10$ * $p< .05$ ** $p< .01$ *** $p< .001$.

5. Discussion and Limitation

This study aimed to explore the triggers of binge-watching behavior among young adults from an economic perspective. The primary hypotheses tested were entertainment, social interaction, stress relief, escape reality, and boredom positively impact binge-watching, and serial content, self-administration, sort reconsideration intervals, and flat rate pricing increase the likelihood of binge-watching. The key findings of this study are that social interaction, stress relief, and the accumulation of knowledge are the main predictors of young adults' binge-watching behavior. Current approaches are more focused on media use (Ayten et al., 2019; Panda & Pandey, 2017; Fernandes & Pinto, 2020; Rubenking & Bracken, 2018; Qayyoum & Malik, 2023; Pang, 2014; Pittman & Sheehan, 2015) and the psychological aspects of binge-watching (Ort et al., 2021; Ahmend, 2017). Merely some studies explored the business nature of binge-watching (Song et al., 2022). Following the previous pilot research of the economic theoretical framework on binge-watching (Gaenssle & Kunz-Kaltenhaeuser, 2020), this exploratory study further tests the economic factors in the framework of Gaenssle and Kunz-Kaltenhaeuser (2015), combining with the five perceived utilities that derived from previous studies (Panda & Pandey, 2017; Fernandes & Pinto, 2020; Rubenking & Bracken, 2018).

On the consumer side, five factors are derived from the individual perceived uses and gratifications, namely entertainment, social interaction, stress relief, escape reality, and boredom. The results on all three models appear to be different factors that are statistically significant in the impact of dependent variables. The result states that the need for social interaction can trigger motivation to increase the viewing duration of video content. Due to the sense of belonging and fears of missing out on social networks, people are willing to spend more time binge-watching series. Consistent with previous literature, individuals' need for social interaction is crucial and, in a way, grants greater opportunities to other viewers (Fernandes & Pinto, 2020; Panda & Pandey, 2017; Rezende & Gomide, 2017; Rubenking & Bracken, 2018; Rubenking et al., 2018; Anghelcev et al., 2022). Pittman and Sheen (2015) state that people tend to plan specific periods to binge-watch to be engaged in conversation with friends and family. Harris (2013) also suggested that the current prevalent use of social media is simulating people to binge-watch. On the other hand, the second model revealed that stress relief is positively related to the frequency of viewing video content, suggesting people tend to seek pleasure in relieving stress. Fernandes and Pinto (2020) suggested that social belonging and interaction are presented to be one of the most crucial predictors of binge-watching for college students.

On the other hand, stress relief appears to positively impact binge-watching frequency. This finding is supported by Wang (2019) and Rubenking and Bracken (2018) in the way that individuals tend to utilize binge-watching to fulfill emotional needs. Binge-watching video content can alleviate stress and fade the shade of the current issue (Sulkowski et al., 2011). Wang (2019) also addresses that people use binge-watching as an avoidance coping mechanism for stress. This funding is also supported by Anghelcev et al. (2020) and Pitman and Sheehan (2015), who indicated that individuals use media consumption as a shelter for stress. The role of stress relief as a motivator is consistent across studies, suggesting a universal tendency for individuals to turn to media to relax. Streaming platforms can use this funding to develop specific programs or sections, like sharing remote e-viewing rooms for watching series with friends and specific relaxation or mindfulness series channels.

Contrary to previous research (Panda & Pandey, 2017; Rubenhke & Bracken, 2018; Song et al., 2022), entertainment, escapism, and boredom features are not significantly related to binge-watching. The discrepancies might be due to differences in sample demographics or the measurement of these factors. The measurement for entertainment in this study can be too broad for participants to distinguish or to relate the feeling of being amused or purely killing time. The same situation can happen with the other two factors.

However, the supplier side factors revealed that none of the factors, namely serialized content, self-administration, non-linear viewing consumption, and flat rate price model, are significantly related to binge-watching in all three models. The serialized content is the only motivation on the supplier side to binge-watching episodes, meaning that individuals tend to consume more episodes only because accumulated knowledge is high. Worth mentioning is that, though previous research elaborates on the feature of rational addiction, in a way that consumer is notified of the consumption, and they are willing to binge-watch as they can stop if they want. However, self-administration is relatively irrelevant to binge-watching as viewing duration and viewing frequency appear statistically insignificant. It may be due to the sample's demographic, as this study is focused on young adults who rarely reflect on it. On the same level, flat-rate pricing did not significantly affect the possibility of binge-watching. Previous studies suggested that the price of a subscription to a VOD platform can be a consequence of binge-watching behavior instead of an antecedent. Song et al. (2022) suggested binge-watching behavior negatively affects paid subscriptions. Having consumers watch more chapters before the payment requirement makes them more likely to buy the following episodes. Instead of price, accessibility can be the factor that affects binge-watching. According to Panda & Pandey (2017), factors of price and accessibility are tested at the same time, and the results revealed that instead of pricing, factor accessibility appears to be statistically significant to binge-watching. Further research can delve into the relationship between accessibility and binge-watching further.

This study aims to expand the understanding of the motivations behind binge-watching from an economic perspective. The observations are primarily gathered in the Netherlands and Germany and partially from China. The platform chosen for this study was Netflix, the most prevalent choice of all observations (60 percent). The reason why Netflix can be the top option for consuming videos has been discussed through several pieces of literature. Some literature has found that Netflix contributes to the binge-watching phenomenon among people via affordability and accessibility (Jenner, 2019). Viewers can consume series episodes without disruption, i.e., commercials between episodes. The autoplay feature of Netflix makes the cost of quitting watching outweigh the cost of staying (Pittman & Eanes, 2015; Pittman & Sheehan, 2015). However, the findings of this study showed that, in reality, the autoplay feature is not statistically significant relative to individuals' binge-watching behavior. The results revealed a unique perspective of viewing behavior, showing the challenges of previous research.

This exploratory study is exposed to several limitations, which are reflected in the results of the analytical models. As a result, several factors appear to be significant. The limited sample population size can address the reason. Due to the time constraint, the online survey is only open for data collection for three weeks. The distribution of the survey is limited as well. More exposure can be expected via expanded distribution channels. The limited observation may also be due to the specific target group, as this study investigates binge-watching behavior among young adults. A previous study suggests that the insignificant results on escapism can be due to the limited sampling in age groups, as middle-aged people may be more likely to be exposed to pressure from reality.

In addition, only social engagement and stress relief on the consumer side appear significant, while only the serialized content on the supplier side is significant. The regression analysis showed low explained variance, indicating that other predictors may exist to motivate young adults to binge-watch. Further research can delve into the potential motivations via in-depth interviews to explore more aspects missed in current research.

This study contributes to broadening the understanding of economic factors influencing binge-watching behavior among young adults. By analyzing the empirical data, the results found that consumer and supply motivations positively impact binge-watching behavior. Individuals tend to consume more video content and binge-watch due to accumulated knowledge of serialized content, social interaction, and stress relief. These findings conflict with previous studies, suggesting a need for further research but also requiring critical thinking on the other premises of binge-watching.

Furthermore, this research addresses a gap in empirical evidence supporting the theoretical frameworks of economic theory on binge-watching. The findings indicate that supply-side factors like pricing strategies and content availability and consumer-side factors like social motivations and stress relief are crucial drivers of binge-watching behavior. These insights have practical implications for the video-on-demand industry, providing valuable insight into how platforms can refine their business models and strategies to increase user engagement and broaden their revenue stream. Future research should adopt qualitative methods to explore additional predictors of binge-watching, offering a deeper understanding of economic and social factors that quantitative methods might overlook.

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Appendix 1: Survey questions

Welcome!

The survey serves a Master's student from Erasmus University Rotterdam, majoring in Cultural Economics and Entrepreneurship. This research aims to understand video consumption behaviour among young adults. The questionnaire consists of 14 questions, each designed to understand the various aspects that influence your video content viewing habits. This survey approximately will occupy you no longer than 10 minutes. Please answer each question based on your experiences and preferences. There are no right or wrong answers, and your responses will be kept confidential and used solely for research purposes. Participation in this study is completely voluntary. You can stop at any time and would not need to provide any explanation.

If you are ready, please click "Next" or "->" to start! :)
Thank you for your time and participation.

Demographic Information
How old are you?
[text box]
Country of residence?
[text box]
How many people live in your household? (including you)
[text box]

2, **What is your gender:**
Male
Female
non-binary
Prefer not to say

3, **What is your educational level?**
Without educational degree
Secondary School
Bachelor
Master
PhD
Prefer not to say

4, What is your Income? (gross income in euro per month)

Less than 1000

1000-2500

2500-3500

3500-4500

More than 4500

Prefer not to say

Now, please consider your personal habits regarding the consumption of video content and VoD-streaming services such as Netflix, Disney+, Amazon Prime & Co, etc...

5. How long on average do you spend in one sitting watching video content? (Please estimate!)

A Slider from 0 to 12, and option is not applicable

6.How many episodes do you consume on average in one sitting? *(Please estimate!)*

Slider from 0 to 50, and option not applicable.

7.How frequently do you watch video content? *(Please estimate!)*

A few times per day

Daily

a few times per week

weekly

a few times per month

month

no answer

8.When I consume video content..

I like to watch series.

Strongly disagree 1

Disagree 2

Neutral 3

Agree 4

Strongly agree 5

No response 6

I would watch the whole season in one sit just to get to know how the plot ends.

Strongly disagree 1

Disagree 2

Neutral 3

Agree 4

Strongly agree 5

No response 6

I like to watch non-linear content on demand (independent of a broadcasting schedule).

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

I like an autoplay mode between videos or episodes to keep watching.

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

I frequently end up watching more episodes than I initially intended.

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

9. I like to watch video content to...

…be entertained

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

… connect with friends and family

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

… release stress from school/university/work

Strongly disagree 1

Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

…get a break from reality

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

…pass the time without boredom

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

10. What video-on-demand platform you normally consume with?

Netflix
Amazon Prime
Disney+
Apple TV
HBO
Other, please specify

11. To what extent would you agree...

My video consumption increases if all contents are included in my monthly subscription (ie., Netflix with no additional pay per view)Strongly disagree 1

Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

I'm more inclined to watch more video content when I have spare time than when I'm busy.

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5

No response 6

After excessively watching video content, I feel better to go back to work.

Strongly disagree 1
Disagree 2
Neutral 3
Agree 4
Strongly agree 5
No response 6

12. In your opinion, what can be described as “Binge-watching”? (optional)
[Textbox]

Thank you so much for your time and participation! This is the end of the survey. Please click "Next" or "->" to submit and record your answer.

Have a good day!