Project Paper

On

"THE INFLUENCE OF PSYCHOLOGICAL MOTIVATIONS AND AI RECOMMENDATION QUALITY ON BINGE WATCHING BEHAVIOR AND EMOTIONAL BURNOUT AMONG GENERATION Z OTT USERS"

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Dear Sir,

With due respect, I have a pleasure to submit my project paper on **“The Influence of Psychological Motivations and AI-Recommendation quality on Binge-Watching Behavior and Emotional Burnout Among Generation Z OTT Users"** to fulfill the requirement of the Master's degree under your supervision. I respect you for your important direction. I have tried my best to follow the guidelines you had prescribed me to create my project paper. I believe, the information I have collected, are the most important and necessary. I enjoyed a lot the challenges of preparing the project paper because it has given me, an opportunity to increase my understanding that will help in my future professional life.

I earnestly thankful to you for your guidance during the preparation of this paper. I will be so grateful to you if you accept the paper and all of your support in this regard will be highly appreciated. I shall be satisfied to reply to any inquiry you think fundamental as and when required.

Sincerely yours,

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Student’s Declaration

I declare that the project paper namely, " **The Influence of Psychological Motivations and AI-Recommendation quality on Binge-Watching Behavior and Emotional Burnout Among Generation Z OTT Users**" is completed by me. This project paper is the result of my work and that due acknowledgement has been given in the references to all sources of information be they printed or personal. This paper does not break any existing copyright.

This particular project paper has not been previously submitted to any other University/College/Organization for academic qualification/certificate/diploma or degree. I have prepared it for the academic purpose of the Master of Business Administration (MBA) degree.

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Supervisor's Declaration

This is to declare that the project paper on **"The Influence of Psychological Motivations and AI-Recommendation quality on Binge-Watching Behavior and Emotional Burnout Among Generation Z OTT Users"** in the bona fide record at the report is done by Mimma Akter; Roll No: 22307018, as partial fulfillment of the requirement Master of Business Administration (MBA) degree.

The project paper has been prepared under my guidance and is a record of the bona fide work carried out successfully.

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At the beginning of preparing this project paper, all praises to Almighty Allah who has created me and has allowed me the opportunity to go through the total process of MBA (Master of Business Administration) as well as project program and strength to work. It was a great opportunity for me to get an opportunity to work. Writing this paper emerged to be a great experience for me. If I say that this paper is one of my memorable experiences in student life, then it would not be wrong.

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Abstract

The rapid growth of digital streaming platforms has significantly changed the way people consume entertainment content, especially among younger generations. With the increasing availability of AI-driven recommendations and on-demand access, binge-watching has become a dominant behavior among OTT (Over-The-Top) platform users. The main objective of this study is to investigates the psychological and technological factors influencing binge-watching behavior and its subsequent impact on emotional burnout among Generation Z OTT platform users in Bangladesh. Grounded in the Uses and Gratifications Theory (UGT), the research model integrates traditional user-driven motives entertainment, escapism, and social influence alongside a modern system-driven factor, AI recommendation quality, to explore their direct and indirect effects on binge-watching and emotional outcomes. Using a quantitative research design, data were collected from 302 valid respondents through structured online and offline surveys. SmartPLS 4.0 was employed to analyze the measurement and structural models, testing reliability, validity, and path coefficients. The results show that entertainment, social influence, and AI recommendation quality have a significant positive influence on binge-watching behavior. However, escapism does not show a significant relationship with binge-watching. Most importantly, binge-watching behavior has a strong and direct impact on emotional burnout, indicating that excessive content consumption may lead to negative psychological outcomes. The study contributes both theoretically and practically by bridging user-centered media theories with algorithmic influence, and by identifying binge-watching as a central behavioral mechanism linked to digital mental health concerns. Practical implications include the need for ethical AI design, media literacy education, and interventions promoting mindful media consumption among young OTT users. While the study offers significant insights, it acknowledges, limitations related to sample size, geographic scope, cross-sectional design, and the use of self-reported online surveys. For future research, it is recommended to expand the sample across more diverse regions, employ longitudinal or mixed-method approaches, and explore other relevant psychological or behavioral variables. Data could also be collected through in-person interviews or paper-based surveys for broader insight.

Keywords: Over the Top (OTT), Binge Watching, AI recommendation quality, Emotional Burnout, Gen Z.

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CHAPTER ONE:

INTRODUCTION

1.1 Introduction

Media consumption has undergone significant changes in recent years, driven by technological developments and shifts in cultural dynamics. With the availability of high-speed internet, smart devices, and personalized digital services, traditional boundaries of time, place, and platform have been significantly blurred. The global shift regarding digital media consumption reflects broader socio-economic and technological trends. As digital platforms continue to evolve, media consumption habits will likely become more personalized and on-demand (Travis Akello,2024). New media have brought changes and challenges to traditional media effects theories and models. The public has more choices of what to watch and read and the themes and cultures are presented by various media formats in a more diverse way as well (Don W. Stacks et al, 2015) Consumers now have unprecedented access to a vast amount of multimedia content ranging from news and educational materials to entertainment through digital interfaces that are always connected, highly interactive, and increasingly tailored through artificial intelligence (AI) and algorithmic personalization (Sundar & Limperos, 2013; Head et al., 2020). This transformation has redefined media consumption as an on-demand, user-driven experience. Viewers, particularly digital-native generations such as Generation Z, are no longer passive recipients of scheduled programming but rather active participants in shaping their media experiences, often guided by preferences, peer influences, and AI-curated content suggestions (Deloitte, 2023)

Generation Z, born between 1995 and 2010 (Jayathilake & Annuar, 2020; Agarwal & Vaghela, 2018; Kirchmayer & Fratričová, 2017; Bencsik et al., 2016; Jiri, 2016; Fodor & Jaeckel, 2018; Diaconu & Dutu, 2020; Kirchmayer & Fratričová, 2017, 2018; Huțanu et al., 2018; McKinsey & Company, 2018), represents the first generation to grow up with uninterrupted access to digital technology and social media. This has led to the emergence of a distinctly digital-first, often technoholic mindset (Puiu, 2017). Seemiller and Grace (2016) emphasize that Gen Z has matured in an environment of rapid technological progress, where digital devices and the internet have become integral to everyday life. Often referred to as "zoomers" or digital natives, members of Generation Z have lived in internet-connected environments from birth, making them highly fluent in the use of digital media (Nikolaos Panagiotou et al., 2022).

Their media consumption habits further reflect this digital dependency. According to recent data, 72.9% of Gen Z spends over an hour daily on paid streaming services like Netflix and Hulu, while 81% engage with social media for more than an hour per day, with over half using it for more than three hours. Platforms like TikTok are especially dominant, with 67% of Gen Z preferring comedy and meme-based short-form content, and 42.9% relying on social media for daily news updates 21% of whom identify TikTok as their primary source. Traditional linear television is rapidly losing relevance for this cohort, with nearly one in three reporting that they never watch it. Instead, the majority gravitate toward on-demand streaming platforms such as Netflix, Hulu, and Disney+, with 82% expressing a willingness to pay for such services (Stephanie Rand, 2025). The rise of streaming services, mobile applications, and content-sharing platforms has made it remarkably easy for Gen Z to consume vast amounts of information and entertainment in a highly personalized and compact format. This easy accessibility has increased the rise of binge-watching, a behavior characterized by continuous, on-demand content consumption that aligns closely with the digital expectations and routines of this generation.

The increase of connectivity and technological availability has significantly contributed to the expansion of globalized media consumption, with Over-the-Top (OTT) platforms becoming as a central force in these changes. OTT services commonly known as video-on-demand platforms have grown exponentially worldwide in recent years, bypassing traditional media delivery systems such as cable television, satellite broadcasting, and cinema (Mulla, 2022; Sharma & Lulandala, 2023). According to the United States Federal Communications Commission (FCC, 2017), Over-the-Top (OTT) services are broadly classified into two categories: Multichannel Video Programming Distributors (MVPDs) and Online Video Distributors (OVDs). MVPDs refer to services that deliver multiple television channels over the internet, encompassing platforms such as AT&T TV, Netflix, and YouTube TV. In contrast, OVDs are defined as entities that provide video content particularly live streaming via the internet or other Internet Protocol (IP)-based transmission systems, regardless of whether they own or control the transmission infrastructure. These platforms offer a broad range of digitally streamed entertainment content, including web series, films, reality shows, and television serials, delivered directly via internet networks (Chen et al., 2017). Several factors have accelerated the proliferation of OTT platforms: the widespread availability of affordable internet data, the penetration of smart devices, and ongoing technological innovations that have enhanced network efficiency and accessibility (Lee et al., 2020; Kwak et al., 2021). Unlike easy broadcast systems, OTT platforms allow individuals to exercise complete autonomy in media consumption, enabling them to select, stream, and engage with content at their own way and pace (Puthiyakath & Goswami, 2021). As a result, OTT platforms have emerged as independent digital ecosystems, reshaping the dynamics of global media engagement.

The global Over-the-Top (OTT) video market is undergoing a significant transformation, characterized by a shift toward more intensive and immersive streaming experiences. Contemporary platforms are increasingly integrating features such as live streaming, user-generated content, and real-time audience engagement to enhance user interactivity and personalization. In the Asia-Pacific region, subscription-based models are gaining substantial momentum, offering consumers access to exclusive, regionally tailored content. Conversely, in Europe, there is a marked rise in ad-supported streaming services, which provide free access to diverse content libraries while monetizing through targeted advertising strategies. The surge in online video streaming has dramatically reshaped global media consumption patterns. This growth has been fueled by rapid advances in internet penetration, the proliferation of mobile devices, and a rising preference for on-demand, personalized content experiences. As a result, the global OTT industry has witnessed unprecedented expansion over the past decade. According to Statista, worldwide revenue in the OTT video market is projected to reach USD 343.82 billion by 2025, up from an estimated USD 288 billion in 2023, with the United States contributing the largest share of this global revenue. Over The Top or OTT are the young and new players in the content delivery market and diffusion indicates accessible services or applications on the web that do not require hardware support (Suman Kumar et al, 2023). The OTT media market is flourishing day by day and there is possibility to grow more in future. (Ghalawat et al., 2021a).

The digital entertainment industry in Bangladesh has undergone a transformative evolution over the past decade, spurred by technological advancements, increased internet penetration, and the rapid adoption of smartphones. The Over-the-Top (OTT) platform industry in Bangladesh is emerging as a dynamic sector, reflecting the global trends of content digitization and personalized entertainment consumption. According to the Bangladesh Telecommunication Regulatory Commission (BTRC, 2024), internet penetration in Bangladesh stands at approximately 76%, with over 131 million internet users end of December 2023, providing a substantial foundation for the growth of OTT services. Mobile broadband is the primary access point for digital content, with over 120 million smartphone users as of early 2024 (BTRC, 2024).

The rise of local OTT platforms, such as Chorki, Bongo, Bioscope, and Toffee, has been instrumental in popularizing video-on-demand (VOD) culture in Bangladesh. These platforms offer a mix of locally produced web series, movies, dramas, and international content, effectively catering to the linguistic and cultural preferences of Bangladeshi audiences (Rahman, 2023). Several factors have fueled the expansion of the OTT ecosystem in Bangladesh: COVID-19 Pandemic Effect: Lockdowns and social distancing measures significantly accelerated OTT consumption, as users turned to digital platforms for entertainment during home confinement (Islam & Sultana, 2022). Bangladesh has a demographic advantage, with nearly 48% of its population below the age of 25 (World Bank, 2023), providing a vast consumer base that is digitally literate and entertainment-hungry. Despite impressive growth, the Bangladeshi OTT sector faces significant challenges: Piracy Issues: Unauthorized content distribution remains a major problem, undermining the revenue models of legitimate OTT providers (Khan, 2023). Content Regulation: The government has indicated intentions to regulate OTT content to ensure cultural and moral appropriateness, which may affect creative freedom (The Daily Star, 2023).

Several OTT platforms have emerged in Bangladesh, each offering distinct features and targeting diverse viewer segments:

- Chorki focuses on original Bangladeshi movies, series, and dramas. It has made significant investments in local productions and has rapidly expanded its subscriber base.
- Bongo was one of the earliest entrants in the market, offering a mix of TV shows, sports content, and movies through both free and premium models.
- Bioscope delivers a combination of live TV and on-demand content, and is particularly popular for streaming sports, especially cricket.
- Toffee, backed by Banglalink Telecom, offers live sports, international movies, and regional content, and is witnessing fast-paced user growth across mobile platforms.

Industry experts forecast that Bangladesh's OTT market will continue expanding at a compound annual growth rate (CAGR) of over 18% from 2023 to 2028 (Rahman & Hossain, 2024). Increasing investment in content diversity, platform innovation, and payment facilitation is expected to further strengthen the sector. Furthermore, with the upcoming rollout of 5G technology, streaming quality and user experience are likely to improve significantly, providing a major boost to OTT platform penetration beyond urban areas into rural and semi-urban regions.

The shift from traditional television to Over-the-Top (OTT) platforms represents one of the most profound transformations in media consumption behavior in recent decades. Historically, traditional television was defined by linear broadcasting, where viewers had limited agency over what and when they watched. Content was curated by networks, and viewers were bound by schedules and geographical broadcast rights (Lotz, 2014). However, with the advent of the internet and digital streaming technologies, OTT platforms disrupted this model, offering on-demand, user-centric alternatives that bypass traditional distribution channels entirely. OTT services, such as Netflix, Amazon Prime Video, Disney+, and their regional counterparts (Chorki in Bangladesh), deliver content via the internet directly to consumers, allowing them to choose their preferred programming, at their preferred time, on a device of their choice (Nieminen, 2020). These platforms eliminate the need for cable subscriptions, offering greater affordability, accessibility, and personalization, which have significantly contributed to their widespread adoption across global markets. A hallmark of the OTT revolution is the emergence of binge-watching culture, defined as watching multiple episodes of a series in a single sitting. This behavior is enabled by entire seasons being released at once and supported by features such as auto-play, which continuously feeds the next episode without user intervention (Flayelle et al., 2020). The transition from a scarcity-driven model (waiting weekly for episodes) to a hyper-abundant media environment has fundamentally altered user behavior and expectations.

Furthermore, AI Recommendation Quality play a key role in sustaining binge-watching habits. By analyzing user data such as viewing history, preferences, and behavior patterns, these systems suggest tailored content, encouraging prolonged engagement (Head et al., 2020). As a result, viewers may enter what has been described as a "digital loop of consumption", where one's intent to casually watch an episode transforms into hours of continuous, often unintentional viewing (Pittman & Sheehan, 2015). Importantly, binge-watching is not merely a technical consequence of platform design it reflects broader cultural and psychological shifts. In contrast to communal family television viewing of the past, today's OTT content consumption is increasingly personalized, private, and mobile, aligning with Generation Z's preference for control, autonomy, and emotional gratification (Deloitte, 2023). Gen Z users, in particular, are drawn to the immersive storytelling, episodic cliffhangers, and on-demand accessibility that OTT platforms offer. This transition has implications beyond convenience. While binge-watching offers short-term enjoyment and escapism, it has also raised concerns related to mental fatigue, sleep disruption, and emotional exhaustion outcomes traditionally not associated with conventional television viewing (Alimoradi et al., 2022). As binge-watching becomes increasingly embedded in the daily routines of younger audiences, understanding its psychological and social impact becomes critical

The global media landscape has undergone a dramatic transformation with the rise of Over-the-Top (OTT) streaming services, which have disrupted traditional television consumption by offering on-demand access to a vast array of content. Platforms like Netflix, Amazon Prime Video, and Disney+, as well as regional services like Chorki, Bongo, and Bioscope in Bangladesh, provide consumers especially younger demographics with unprecedented autonomy, personalization, and convenience (Nieminen, 2020; Rahman, 2023). The integration of AI Recommendation Quality, which analyze user behavior and content preferences, has intensified content consumption by making the viewing experience seamless, engaging, and continuous (Rassameeroj & Wu, 2019; Head et al., 2020). Among the most prevalent behavioral outcomes of this shift is binge-watching, a phenomenon where users consume multiple episodes or extended content in a single sitting. While binge-watching has become normalized and even celebrated in popular culture, a growing body of research suggests that excessive and unregulated binge-watching may have significant psychological costs, including increased fatigue, anxiety, stress, and emotional exhaustion collectively contributing to what researchers now refer to as emotional burnout (Flayelle et al., 2020; Alimoradi et al., 2022).

Despite its rising prevalence, the psychological and emotional consequences of binge-watching remain underexplored in the literature, particularly in non-Western, developing country contexts like Bangladesh. Much of the existing research on OTT services has centered around user adoption, satisfaction, and continued usage behavior, using frameworks such as the Uses and Gratifications (U&G) theory (Sadana & Sharma, 2021; Menon, 2022), Unified Theory of Acceptance and Use of Technology (UTAUT) (Shah & Mehta, 2023), and the Theory of Consumption Values (TCV) (Chakraborty et al., 2023). These studies focus on understanding what drives individuals to start and continue using OTT services, emphasizing motivational variables such as entertainment, escapism, and information seeking. However, they do not sufficiently address what happens after prolonged or excessive use — particularly in terms of emotional health outcomes. Furthermore, while some emerging research has examined binge-watching during the COVID-19 pandemic a period that dramatically increased screen time due to lockdowns and isolation — these studies primarily highlight short-term mental health issues like depression and anxiety without isolating emotional burnout as a distinct and measurable outcome (Raza et al., 2021; Orben, 2020). Burnout, a concept traditionally linked to workplace stress, is now increasingly relevant in leisure contexts, especially when media consumption becomes compulsive and emotionally draining (Pittman & Sheehan, 2015; Alimoradi et al., 2022).

In the Bangladesh context, scholarly attention to the OTT sector is still in its infancy. Despite the rapid growth of platforms like Chorki and Bongo, there exists limited empirical research on user behavior, let alone psychological consequences associated with OTT binge-watching. Bangladesh has a large, youthful, digitally connected population with over 120 million mobile internet subscribers and nearly 48% of the population below the age of 25 (BTRC, 2024; World Bank, 2023). This makes Generation Z a particularly important demographic to study, given their media-rich lifestyles and high susceptibility to algorithmically driven engagement loops. Yet, most existing studies are either media industry reports or qualitative explorations that lack the quantitative rigor needed to establish causal or mediating relationships between binge-watching and emotional burnout.

In addition, very few studies either in Bangladesh or globally have examined AI Recommendation Quality as a potential predictor of binge-watching behavior. Although platforms heavily rely on algorithmic personalization to increase user engagement, no existing quantitative research has tested whether these AI systems indirectly contribute to emotional burnout through their influence on binge-watching habits. This gap is particularly important in light of studies that warn against the "filter bubble" and "digital fatigue" effects caused by hyper-personalized content (Otto & Maier, 2016; Head et al., 2020). Even less is known about how motivational factors such as escapism, enjoyment, and social influence work in tandem with AI systems to drive extended engagement. The existing literature treats these motivations largely in isolation. There is a lack of integrated models that account for both human motives and technological cues in understanding how binge-watching behaviors are formed and sustained, and how they may lead to adverse emotional outcomes.

Therefore, this study seeks to fill several critical research gaps. First, it aims to extend the Uses and Gratifications framework by incorporating AI Recommendation Quality as an external technological cue alongside internal psychological motivations. Second, it introduces binge-watching as a mediating behavioral mechanism that links these motivational and technological antecedents to emotional burnout. Third, it grounds the study in the under-researched context of Bangladeshi Generation Z, providing locally relevant data that can inform both theoretical development and practical interventions. By addressing these gaps, the study contributes to a more holistic understanding of OTT media consumption in the digital age — moving beyond adoption and gratification to examine the emotional and psychological costs of continuous media exposure. It also opens pathways for future research into digital well-being, responsible AI design, and culturally adaptive mental health strategies in emerging economies

1.2 Research Objectives

The general objective of this study is to examine the influence of psychological motivations and AI recommendation Quality on binge-watching behavior and its subsequent emotional burnout among Generation Z OTT users. The study aims to propose and empirically validate a conceptual framework integrating both individual-level motivational factors (from the Uses and Gratifications theory) and technological affordances (such as algorithmic personalization), with binge-watching as a mediating behavioral mechanism. Specifically, this research proposes two specific objectives that will be answered by means of this study.

- To examine how Escapism, Social influence, Entertainment and AI-recommendation Quality influence binge-watching behavior.
- To assess the mediating role of binge-watching between motivational/technological factors and emotional burnout.

1.3 Research Questions

On the basis of the problem statement, following research questions have been developed**.**

RQ1: What are the key factors influencing Gen Z Binge watching behavior and Emotional Burnout?

RQ2: Does binge-watching behavior mediate the relationship between motivations/AI recommendation Quality and emotional burnout?

CHAPTER TWO:
LITERATURE REVIEW

2.1 Theoretical Background

2.1.1Uses and Gratifications Theory

The Uses and Gratifications Theory (UGT) is a foundational media theory that explains why individuals engage with particular media forms based on their psychological and social needs. Originally developed by Katz, Blumler, and Gurevitch (1973), UGT posits that media users are not passive consumers, but rather active agents who consciously choose content that gratifies specific internal needs whether cognitive, affective, personal integrative, or social integrative (Katz et al., 1973). This paradigm marked a shift from behaviorist models that viewed media effects as unidirectional and deterministic, towards a more user-centered perspective of media interaction. UGT has historically been applied to understand motivations for consuming traditional media such as radio, newspapers, and television (Rubin, 1983). Over time, it has been extended to new communication technologies, including the internet, mobile phones, social networking sites, and more recently, Over-the-Top (OTT) streaming platforms (Ruggiero, 2000). This adaptability stems from UGT's ability to account for evolving audience behavior and media affordances.

In the digital era, OTT platforms such as Netflix, Amazon Prime Video, Disney+, and regional services like Chorki have emerged as dominant modes of media consumption. Unlike traditional broadcasting, these platforms provide users with on-demand access to diverse content, enabling greater control over what, when, and how content is consumed. Consequently, UGT has regained prominence as a relevant framework to explore OTT usage patterns, particularly in understanding the motivations behind binge-watching behavior a consumption pattern where multiple episodes of a series are watched in a single session.Moreover, recent research has begun to explore how gratification-seeking can lead to unintended consequences. While UGT traditionally emphasizes active and rational media use, newer studies suggest that gratification-seeking particularly when linked to emotional or escapist motives may also foster compulsive or problematic viewing behaviors (Flayelle et al., 2020). In this light, the theory offers a dual lens: explaining both the deliberate choices behind binge-watching and the potential descent into emotionally taxing usage patterns. Furthermore, in contrast to linear television viewing, OTT platforms grant users unparalleled access to vast content libraries, made more accessible through algorithmically generated recommendations and auto-play features. These AI enhancements arguably deepen gratification by reducing the cognitive effort needed to search for content, thus perpetuating longer viewing sessions (Head et al., 2020). In this way, UGT's focus on gratifications sought and obtained becomes even more nuanced in digital streaming environments where algorithmic curation complements psychological motivation. Contemporary UGT research in OTT environments has identified several recurring motives among viewers: escapism, entertainment, social interaction, habit, and information seeking. Among these, escapism and entertainment are the most frequently cited motivations for binge-watching (Sung et al., 2018; Flayelle et al., 2020).

Escapism refers to the use of media to avoid or temporarily disengage from real-life stressors, responsibilities, or negative emotions (Rubin, 1983). In the OTT context, this often translates into immersive binge sessions, where viewers mentally retreat into fictional narratives to cope with boredom, anxiety, or loneliness (Vaterlaus et al., 2019). While escapism can serve as a functional coping strategy, excessive reliance on it may lead to maladaptive outcomes, including emotional exhaustion and diminished real-life engagement (Starosta & Izydorczyk, 2020).

Entertainment gratification, meanwhile, centers on hedonic consumption seeking fun, pleasure, and relaxation from content. OTT platforms cater well to this need by offering algorithmically curated, high-quality, engaging content across genres (Menon, 2022). Entertainment gratification is typically associated with positive outcomes, such as temporary mood elevation and stress relief. However, studies also suggest that when pleasure-seeking behaviors are sustained over long periods especially in binge-watching, they can contribute to screen fatigue and displacement of important tasks (Merrill & Rubenking, 2019).

Social influence as a motivational factor draws from both UGT's social integrative dimension and technology adoption literature. It captures the role of peer norms, recommendations, and fear of missing out (FOMO) in driving content engagement. As Bastos et al. (2024) show, peer pressure and online buzz significantly enhance viewers' intentions to start and continue binge-watching, especially when the behavior is framed as socially rewarding. Among Generation Z, who are immersed in real-time digital cultures and peer-based sharing, social motives are especially pronounced (Vaterlaus et al., 2019).

While UGT traditionally focuses on psychological motives, the affordances of OTT platforms particularly AI Recommendation Quality also shape binge-watching behavior. These systems personalize content suggestions based on user data, thereby reducing the cognitive effort of content selection and increasing engagement (Head et al., 2020). Features such as autoplay and predictive recommendations effectively sustain users' attention and contribute to passive overconsumption, leading to a “content consumption loop.”

This extension of UGT aligns with evolving scholarship that emphasizes the interaction between user motivations and technological affordances (Sundar & Limperos, 2013). In this view, gratification is not only self-determined but also platform-enabled, suggesting that binge-watching is the result of both psychological needs and external design triggers.

Recent empirical evidence supports this integration. For example, Qiao et al. (2024) found that algorithmically curated entertainment apps heighten user dependency, leading to entertainment fatigue and reduced emotional resilience. Among Gen Z, this creates a feedback loop where motivated viewing (for escapism) is unintentionally prolonged due to persuasive design, eventually contributing to emotional burnout a state of digital fatigue marked by emotional exhaustion, disengagement, and diminished efficacy (Han et al., 2019).

Despite the utility of UGT in understanding OTT behavior, there remains a critical theoretical gap: few studies integrate motivational and platform-level explanations in a single framework. While existing research has explored binge-watching motivations and its negative consequences independently, the combined effect of UGT motives and AI-enabled platform features on emotional burnout is underexplored. This study addresses this gap by proposing a model where UGT-based drivers (escapism, entertainment, and social influence) and AI Recommendation Quality jointly influence binge-watching behavior, which in turn predicts emotional burnout. By doing so, the study extends UGT into a technologically mediated digital environment, offering a more comprehensive understanding of OTT consumption and its psychological outcomes among Gen Z.

2.2 Conceptual Framework

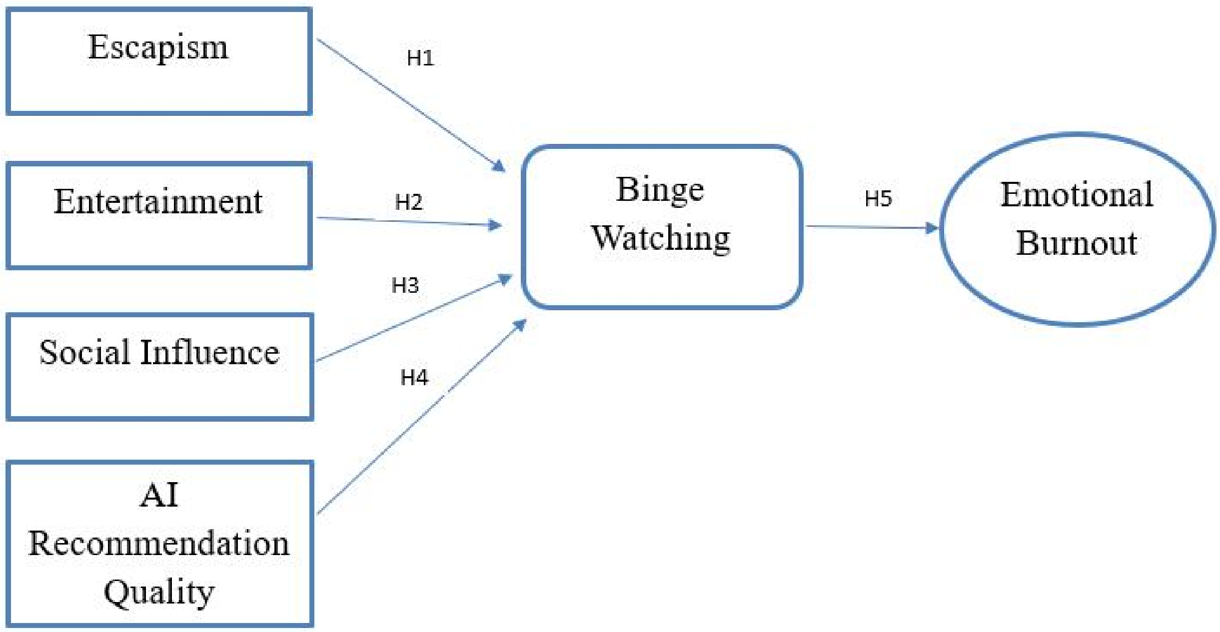


Figure 2.1: The Proposed Model

The proposed framework builds on both classical and modern digital media theories to explain the psychological consequences of binge-watching behavior on OTT platforms, especially in Generation Z users. The model integrates well-established motivational constructs from the Uses and Gratifications Theory (U&G) with the unique technological influence of AI Recommendation Quality, and positions binge-watching as a mediating behavioral pathway that leads to emotional burnout.

2.3Emotional Burnout:

Emotional burnout, traditionally associated with occupational stress, has increasingly been recognized in non-work contexts especially in the digital age. It is broadly defined as a psychological syndrome characterized by emotional exhaustion, cynicism (or depersonalization), and a reduced sense of efficacy, arising from prolonged exposure to emotionally taxing situations

(Maslach & Jackson, 1981). While initially rooted in workplace psychology, the construct has now evolved to encompass stressors emerging from personal and recreational digital engagements, including binge-watching. In recent psychological research, emotional burnout has been linked to digital fatigue an emergent concept encompassing mental depletion from excessive technology use. Han et al. (2019) advanced this framework by adapting the Maslach Burnout Inventory to social media usage. Their adaptation revealed that persistent interaction with digital platforms results in emotional exhaustion, loss of interest, and psychological disengagement, thus mirroring professional burnout symptoms even in recreational environments. This conceptual expansion validates the transposability of burnout to non-occupational domains, particularly those dominated by media consumption.

The implications of such findings become even more salient when contextualized within binge-watching behaviors. During the COVID-19 pandemic, binge-watching surged as a primary coping mechanism and leisure activity. However, evidence suggests it may paradoxically exacerbate emotional strain. Raza et al. (2021) identified binge-watching as a significant predictor of emotional fatigue and disengagement among Gen Z users during lockdowns. These outcomes stress, lack of motivation, and psychological overload are consistent with the clinical symptoms of emotional burnout. Similarly, Orben (2020) in her critical review of adolescent screen time, emphasized the mounting emotional costs of digital overuse. She noted that prolonged screen exposure correlates with rising levels of emotional exhaustion, a key dimension of burnout, thereby underscoring the emotional toll exacted by seemingly passive leisure activities. This is particularly relevant for younger audiences, who are often immersed in screen-based behaviors without adequate regulation or awareness of long-term effects.

Further validation of emotional burnout's relevance to binge-watching is found in Alimoradi et al.'s (2022) comprehensive meta-analysis, which confirmed significant associations between excessive viewing and mental health issues, including anxiety, depression, and insomnia. These manifestations, while categorized under broader psychopathologies, overlap with and often precede emotional burnout, especially when users experience persistent psychological depletion from uncontrollable media habits. Moreover, foundational definitions by Freudenberger (1974) and later expansions by Maslach, Perlman, and Hartman (1982), illustrate how burnout serves as a psychological defense mechanism. When individuals are unable to psychologically disengage from stressful stimuli whether work-related or digital they become emotionally numb, depleted, and withdrawn. In this sense, binge-watching can act as both a coping strategy and a stressor, contributing to a harmful cycle of media-induced exhaustion. Despite the growing body of evidence, emotional burnout remains under-theorized as a direct outcome of binge-watching. While mental health consequences are increasingly acknowledged, few studies frame them explicitly within the burnout paradigm. This research aims to fill that gap by theorizing emotional burnout not merely as an ancillary symptom, but as a core psychological outcome driven by excessive and compulsive digital consumption

2.4 Escapism

Escapism is broadly defined as a psychological mechanism through which individuals divert attention from real-life stressors, self-reflection, and existential concerns by immersing themselves in alternative experiences, particularly within media environments. In the context of digital media consumption and binge-watching behaviors, escapism has evolved into a pivotal conceptual lens to understand why individuals engage in prolonged and immersive viewing of streaming content. Rather than solely reflecting a pursuit of pleasure, escapism frequently signals a relief-oriented motivation an attempt to temporarily withdraw from the demands of reality and internal psychological distress (Baumeister, 1991; Heatherton & Baumeister, 1991).

From a theoretical standpoint, escapism has been robustly anchored in Escape Theory, which asserts that when individuals are faced with perceived self-discrepancies or experiences of personal failure, they may engage in cognitive and behavioral strategies to escape heightened self-awareness (Baumeister, 1991). Within this framework, binge-watching serves not merely as entertainment but as a behavioral conduit for avoiding uncomfortable emotions such as anxiety, guilt, loneliness, or low self-worth states often exacerbated by modern socio-cultural pressures and idealized self-expectations (Donnelly et al., 2016). Recent empirical studies affirm that escapism significantly predicts compulsive and maladaptive digital media behaviors, particularly among adolescents and young adults, who constitute a demographic most heavily engaged in binge-watching. For instance, Jarman et al. (2021) and Liu et al. (2022) found that escapist motives consistently correlate with excessive screen time, impaired daily functioning, and difficulty in emotional regulation. Moreover, such behavior is often not socially collaborative but rather solitary and immersive, further emphasizing its internalized and affect-driven origins

(Weiss & Schiele, 2013). Scholars such as Stenseng, Rise, and Kraft (2012) and later Stenseng et al. (2021) have also advanced the notion of dualistic escapism, differentiating between adaptive and maladaptive forms. Adaptive escapism refers to healthy psychological relief and temporary distraction used to regulate mood and restore well-being. In contrast, maladaptive escapism functions as emotional avoidance, often reinforcing patterns of procrastination, social withdrawal, and digital dependency. This duality is especially relevant in the binge-watching context, where individuals may either recuperate through episodic consumption or become entrenched in passive avoidance of real-world obligations (Hagström & Kaldo, 2014; Kaczmarek & Drążkowski, 2014). Adding historical depth, Katz and Foulkes (1962) were among the first scholars to explore escapism in mass media use, linking it to social alienation, deprivation, and broader societal withdrawal. They argued that media allowed individuals to temporarily suspend reality, but warned of its potential to erode political engagement, interpersonal roles, and community integration. This early skepticism was echoed in later media studies emphasizing the long-term psychological impacts of escapist entertainment, such as reduced life satisfaction, elevated anxiety, and diminished role functioning (Meier, Meltzer, & Reinecke, 2018; Halfmann & Reinecke, 2021). In contemporary media landscapes, binge-watching has become a paradigmatic expression of escapist behavior, enabled by the algorithmic and uninterrupted nature of streaming platforms. Platforms such as Netflix, Amazon Prime, and Disney+ foster a culture of instant gratification and narrative immersion, providing continuous story arcs that minimize self-regulation and time-awareness (Matrix, 2014). According to Castro et al. (2021), many viewers report heightened post-viewing emotional discomfort—such as sadness or emptiness—suggesting that the transition from immersive fiction back to everyday reality can be psychologically jarring and even depressing.

Moreover, studies grounded in Uses and Gratifications Theory have identified escapism as one of the core media gratifications sought by individuals across media types (Katz, Blumler, & Gurevitch, 1973). Whether via traditional broadcast, print media (Vincent & Basil, 1997), or digital streaming, escapist motives remain consistent drivers of content consumption. Pena (2015) noted that viewers often pursue binge-watching for its capacity to relieve stress and provide a temporary sanctuary from life's adversities, reaffirming the critical intersection between emotional need and digital behavior. Additionally, motivations for escapist media use are more predictive of psychological outcomes than sheer time spent online. Kuss et al. (2012) and Sauter et al. (2021) found that individuals driven by escapist motives tend to exhibit more negative emotional consequences including loneliness, depression, and poor self-regulation than those motivated by curiosity, information-seeking, or entertainment alone. This distinction underscores the emotional valence of escapism and highlights its potential to transform binge-watching from a benign habit into a maladaptive coping mechanism. Further reinforcing this perspective, Rubenking et al. (2018) investigated the psychological motivations underlying binge-watching and found escapism to be among the top-reported reasons, along with emotional gratification and immersion. Similarly, Vordere and Hartmann (2009) argued that escapism fulfills the existential desire for alternate realities and imagination, especially during periods of heightened psychological stress or dissatisfaction.

H1: Escapism has a significant positive effect on binge-watching behavior among Generation Z OTT users.

2.5 Entertainment

Entertainment, or hedonic gratification, is another dominant motive driving OTT usage. Within U&G literature, entertainment is considered a content-based gratification, sought for pleasure, amusement, and relaxation (Rubin, 1983; Gan, 2017). Streaming services such as Netflix and Amazon Prime design their interfaces to optimize content discovery and viewer enjoyment, often through autoplay features, personalized trailers, and humor-oriented content curation (Sundar & Limperos, 2013). Sung et al. (2018) found that entertainment was as influential as escapism in motivating binge-watching, particularly when viewers sought relaxation after a long day or used shows as mood boosters. Unlike escapism, entertainment-driven binge-watching tends to have more positive connotations, such as enjoyment, stress relief, and immersion in narratives (Walton-Pattison et al., 2018). Entertainment has long been recognized as a primary driver of media consumption, particularly within the framework of the Uses and Gratifications Theory (UGT). Rooted in audience-centered approaches, UGT posits that individuals actively seek out media to fulfill specific psychological and social needs, including entertainment, escapism, information, social interaction, and identity formation (Katz, Blumler & Gurevitch, 1974; Ruggiero, 2000). Among these, entertainment defined as the pursuit of enjoyment, relaxation, and emotional diversion emerges as one of the most influential variables motivating binge-watching behavior in the digital streaming era.

With the rise of on-demand video platforms like Netflix, Amazon Prime, and Disney+, binge-watching has become a dominant mode of content consumption. Scholars define binge-watching as watching multiple episodes of a television series in a single sitting (Pittman & Sheehan, 2015; Shim & Kim, 2018). This behavior is often voluntary and goal-oriented, with users actively engaging in prolonged viewing sessions to achieve certain gratifications, primarily entertainment (Flayelle et al., 2020). In this context, entertainment serves not merely as a passive outcome but as a key motivator that drives individuals to repeatedly engage in binge-watching behavior. Empirical studies consistently underscore the centrality of entertainment in binge-watching motivations. For instance, Panda and Pandey (2017) found that entertainment was the most cited reason among college students for engaging in binge-watching. Participants reported that binge-watching served as an emotional outlet, offering relaxation and a means to escape from everyday stress. Similarly, Walton-Pattison et al. (2018) confirmed that the entertainment gratification derived from watching serialized content influenced both the frequency and duration of viewing sessions. Viewers experiencing higher emotional pleasure from content were more likely to repeat such behavior, forming habitual viewing patterns. Additionally, the variable of perceived usefulness, originally conceptualized in the Technology Acceptance Model (TAM) by Davis (1989), has been adapted to contextualize entertainment-based media use. In traditional TAM applications, perceived usefulness refers to the degree to which a user believes that a technology will enhance their performance. However, when extended to entertainment media, it reflects the degree to which viewers believe that binge-watching effectively satisfies their entertainment needs (Hsu & Lu, 2004). This shift illustrates how cognitive evaluations—viewing binge-watching as "useful" for achieving enjoyment—interact with emotional gratifications to reinforce the behavior.

The entertainment gratification also contributes to satisfaction, a key mediator between media exposure and behavioral intention. According to Zabel et al. (2025), viewers who find content emotionally satisfying are more likely to form a binge-watching tendency. Satisfaction not only reinforces the likelihood of repeating the behavior but also strengthens the perceived value of the activity. This leads to a self-reinforcing cycle, where positive viewing experiences heighten expectations of future entertainment, thereby increasing the intention to binge-watch again (Shim & Kim, 2018). From a psychological standpoint, entertainment serves several deeper functions in binge-watching contexts. It offers a form of emotional regulation, allowing users to manage stress, boredom, and loneliness (Rubenking & Bracken, 2018). Flayelle et al. (2020) developed the Watching TV Series Motives Questionnaire (WTSMQ), which identified entertainment and escapism as top motivational factors in binge-watching. Their findings highlight how individuals may use binge-watching to cope with emotional challenges, reinforcing the behavior as both a hedonic and functional activity. Entertainment-driven binge-watching is also influenced by content characteristics such as narrative complexity, cliffhangers, and character development. Pittman and Sheehan (2015) note that when users find the content immersive and enjoyable, they are more inclined to watch multiple episodes in succession. This aligns with the concept of flow, a state of deep absorption and pleasure during media use, which is tightly linked with entertainment motivation (Csikszentmihalyi, 1990; Hsu & Lu, 2004).

Moreover, demographic and personality factors modulate how entertainment influences binge-watching. Cha and Chan-Olmsted (2025) found that entertainment motives were particularly salient among younger viewers and females, who often cited "fun" and "relaxation" as primary gratifications. Other studies point to traits like sensation-seeking and emotional responsiveness as predictors of entertainment-driven binge behavior (Starosta et al., 2021). Importantly, the entertainment motive also carries implications for problematic use. When the pursuit of entertainment becomes excessive or compensatory for unmet emotional needs, it may contribute to problematic binge-watching patterns. Starosta (2020) caution that while entertainment serves a valid psychological function, over-reliance on binge-watching for emotional gratification can lead to disrupted routines, procrastination, and even symptoms akin to behavioral addiction.

In conclusion, entertainment is a multifaceted and deeply influential variable in binge-watching behavior. It not only initiates engagement but also sustains and reinforces it through satisfaction and emotional gratification. Its integration with perceived usefulness enhances the explanatory power of both UGT and TAM in understanding digital media consumption. As platforms continue to design content for immersive, enjoyable experiences, understanding entertainment as a core motivational force becomes essential for both researchers and media designers aiming to predict, influence, or moderate viewer behavior.

H2: Entertainment has a significant positive effect on binge-watching behavior among Generation Z OTT user

2.6 Social Influence

Social influence is a critical psychological and environmental factor shaping digital content consumption, particularly binge-watching behavior on Over-the-Top (OTT) platforms among Generation Z. Social influence refers to the way individuals' behaviors, attitudes, or beliefs are shaped by others, especially peers, family, and media communities (Cialdini & Goldstein, 2004). In the context of digital media, especially for Gen Z a generation deeply immersed in online and social media cultures peer norms, viral trends, and social validation significantly determine viewing choices and engagement depth (Vaterlaus et al., 2019).

Within the Uses and Gratifications Theory (UGT) framework, social interaction and integration are well-documented motives for media use (Katz et al., 1973). For Gen Z, the need to participate in communal experiences such as watching trending series or discussing plot developments on social media translates into binge-watching as a socially rewarding activity. According to Sung et al. (2018), binge-watching is not only driven by entertainment and escapism but also by social drivers such as peer recommendations, show popularity, and social media buzz. From the Technology Acceptance Model (TAM) perspective, Venkatesh and Davis (2000) explain that social influence affects users' perceived usefulness of a technology or platform. In OTT streaming, if influential peers or digital communities endorse binge-watching, individuals are more likely to perceive the activity as beneficial or normative, thus encouraging adoption and repetition. This aligns with research by Beldad and Hegner (2018), who found that perceived peer usage significantly influenced attitudes toward digital media platforms.

In addition, social identity theory suggests that individuals derive part of their self-concept from group membership (Tajfel & Turner, 1986). Watching and discussing the same shows as one's peer group helps reinforce social bonds and a sense of belonging—key psychosocial needs, especially for adolescents and young adults. As noted by Shim and Kim (2018), shared media consumption leads to social gratification, making individuals more likely to binge-watch in order to maintain their place within their digital or offline social groups. Empirical studies further validate the role of social influence. For instance, Karahanna and Straub (1999) highlighted that subjective norm (beliefs about what others expect or do) strongly predict technology usage intentions. Applying this to OTT platforms, it becomes evident that the popularity of a show within a social network can lead to herd behavior—users binge-watch to conform, engage in conversations, or avoid social exclusion (Bastos et al., 2024). Thus, social influence operates as both a direct motivator for media consumption and an indirect reinforcer, shaping users' attitudes and perceived expectations. This influence is particularly pronounced among Gen Z, who are socially interconnected and actively seek validation and identity reinforcement through shared digital experiences.

H3: Social influence has a significant positive effect on binge-watching behavior among Generation Z OTT users

2.7 AI Recommendation Quality

Artificial Intelligence (AI)- recommendation Quality have emerged as transformative forces within digital content platforms, particularly in the realm of video streaming, where they have significantly influenced user engagement patterns, including the phenomenon of binge-watching. AI technologies not only enable personalized content delivery but also fundamentally reshape consumer behavior by reducing cognitive effort, triggering emotional responses, and sustaining prolonged engagement. In the context of over-the-top (OTT) services, binge-watching defined as the continuous viewing of multiple episodes or content units in a single sitting is no longer merely a user-driven habit but an AI-mediated outcome (Panda & Pandey, 2017; Ahmed & Aziz, 2024). At the core of these systems lies the capacity to analyze user data viewing histories, search behaviors, interactions, and preferences to predict and suggest content that resonates with individual tastes (Nilashi et al., 2016; Stoica & Chaintreau, 2019). This functionality exemplifies weak AI, wherein algorithms augment user experience rather than simulate human cognition (Searle, 1980; Al-Rifaie & Bishop, 2014). The evolution of these systems from basic collaborative filtering and content-based filtering to sophisticated deep learning architectures and hybrid models has amplified their effectiveness (Zhang et al., 2022). Leading platforms such as Netflix, YouTube, and Disney+ employ these technologies not just to curate personalized libraries, but to engineer viewing pathways that nudge users toward extended engagement (Covington et al., 2016; Raji et al., 2024).

From a behavioral standpoint, AI-driven recommendations lower the decision-making burden by offering a narrowed set of high-probability choices that cater to both explicit preferences and latent psychological needs (Nilashi et al., 2016). This creates a "choice architecture" where users feel in control, while the underlying algorithm orchestrates the flow of content (Sunstein, 2016). By leveraging real-time analytics, platforms can strategically present cliffhanger-driven narratives or auto-play mechanisms, pushing users toward consuming multiple episodes without actively choosing to do so (Tefertiller, 2018). Consequently, binge-watching is no longer a mere consequence of narrative structure; it is the result of an algorithmic loop designed to maximize watch time (Ahmed & Aziz, 2024). Moreover, the psychological mechanism of perceived serendipity the feeling that a recommendation unexpectedly matches one's hidden interest plays a critical role in sustaining binge behavior (Kwon et al., 2021). Users interpret algorithmic suggestions as meaningful coincidences, reinforcing trust in the platform and increasing the likelihood of continuous engagement. AI systems now incorporate contextual factors such as time of day, mood inferred from browsing speed, and device type to fine-tune these suggestions (Kulkarni & Rodd, 2020). This level of contextual intelligence reinforces platform stickiness and encourages longer, more frequent viewing sessions.

Recent scholarship emphasizes the role of recommendation agent value in fostering user satisfaction and repeated usage. Kwon et al. (2021) demonstrated that dimensions such as match-score accuracy, diversity of recommended content, and even thumbnail attractiveness significantly influence perceived diagnostic the user's belief that the recommendation is helpful in content selection. These dimensions, in turn, feed into decision satisfaction and continuous intention to use, key drivers of binge-watching behavior. Thus, binge consumption is not merely a habit; it is a design outcome deeply embedded in the technical and psychological architecture of AI-powered systems. As competition among streaming platforms intensifies, companies are innovating beyond basic personalization. Netflix, for instance, has begun testing next-generation AI systems that adapt not only to user history but also to momentary behavioral signals such as pause times and rewinds (Agency Staff, 2025). Similarly, platforms like Pix and Likewise are experimenting with hybrid AI models that incorporate both algorithmic predictions and crowd-sourced human recommendations to create a more engaging, socially aware recommendation interface (CNET, 2024). These advancements are indicative of a larger trend AI systems are becoming *proactive curators* of experience, capable of anticipating not only what users want but when and how they prefer to consume it. While these developments enhance user satisfaction and loyalty, they also raise critical questions about the ethical dimensions of engineered binge behavior. The persuasive design of AI systems often leads users to underestimate their screen time, contributing to negative consequences such as sleep disruption, reduced productivity, and emotional fatigue (Flayelle et al., 2020; Tefertiller, 2018). The opaque nature of algorithmic processes further complicates user awareness, making it difficult to distinguish between autonomous choice and nudged behavior (Mittelstadt et al., 2016). Nonetheless, the business logic is clear: AI-based recommendation systems are instrumental in increasing watch-time metrics, a key performance indicator for platforms monetized through subscription or ad-based models (Smith & Linden, 2017). From the perspective of platform economics, encouraging binge-watching through finely tuned algorithms enhances retention and reduces churn (Zhou et al., 2010). As such, AI systems are not just passive tools but active agents shaping how, when, and how much users consume.

AI Recommendation Quality have redefined the contours of digital consumption by enabling hyper-personalized, context-aware content curation. Their role in fostering binge-watching behavior is multifaceted, extending from cognitive load reduction and emotional gratification to strategic content sequencing and predictive modeling. As AI technologies continue to evolve, understanding their influence on user behavior becomes critical not just for academic discourse, but for ethical platform design and responsible technology use.

H4: AI Recommendation Quality has a significant positive effect on binge-watching behavior among Generation Z OTT users

2.8 OTT Binge – Watching Behavior

Binge-watching is commonly defined as watching multiple (usually 2–6 or more) episodes of a TV series in a single sitting, often facilitated by the autoplay features of OTT platforms (Pittman & Sheehan, 2015). The term gained scholarly traction around 2013 with the emergence of the "Netflix era," which revolutionized television consumption by making entire seasons available on-demand. According to Jenner (2016), binge-watching signifies more than a new mode of viewing it represents a cultural shift toward personalized, immersive engagement with narratives. While there is no universally agreed-upon threshold for binge-watching, researchers often rely on the 2+ episode criterion in one sitting (Flayelle et al., 2020). This behavioral pattern distinguishes itself from traditional television watching by its intensity, autonomy, and lack of temporal constraints, allowing users to watch content at their own pace and for extended durations. Since its mainstream emergence, binge-watching has become increasingly prevalent.

The Netflix model, launched in 2007 but gaining cultural dominance after 2013, reshaped viewer expectations by encouraging consumption of entire series arcs without interruption (Matrix, 2014). OTT platforms leverage algorithms and autoplay features to foster continuous watching, making binge-viewing the default behavior rather than the exception. Among Generation Z (born between 1997 and 2012), binge-watching has become a normative leisure activity. A survey by Deloitte (2021) found that 90% of Gen Z respondents reported binge-watching regularly. For this cohort, streaming content serves not only as entertainment but also as a social and emotional outlet, deeply intertwined with identity and peer engagement.

While binge-watching can be enjoyable and socially enriching, it also raises concerns about its impact on mental health, sleep, productivity, and self-regulation. Academic literature often portrays binge-watching as a double-edged sword both a pleasurable pastime and a potential behavioral concern. On the positive side, binge-watching is often associated with heightened enjoyment, escapism, and increased narrative engagement. According to Walton-Pattison et al. (2018), viewers often report greater immersion and satisfaction when consuming content in longer sessions. Watching entire story arcs without long breaks enables stronger emotional connections to characters and plots, enhancing the overall entertainment experience. Moreover, social binge-watching, where viewers watch content together physically or via virtual platforms, promotes bonding and shared cultural experiences. Social media interaction surrounding shows also creates fandom communities, where viewers exchange interpretations, theories, and fan content. As noted by Flayelle et al. (2020), these interactions can enhance belongingness and viewer satisfaction. However, excessive binge-watching is associated with problematic behaviors. According to several types of research, binge-watching can be harmful to an individual's general well-being because it has a tendency to be addictive (Chaudhary, 2014). According to Starosta & Izydorczyk (2020), binge-watching can be both "adaptive and entertaining" and "obsessive and compensatory." In cases of compulsive viewing, individuals may use binge-watching as a coping strategy for negative emotions or life dissatisfaction, which can foster dependency. Research by Exelmans & Van den Bulck (2017) found a strong correlation between binge-viewing and poorer sleep quality, as late-night sessions often interfere with natural sleep cycles. Their study showed that binge-watchers were more likely to experience next-day fatigue and cognitive impairment due to insufficient rest.Further, Walton-Pattison et al. (2018) explored the psychological mechanisms underlying binge-watching, identifying a pattern of self-regulation failure and anticipated regret. Their findings revealed that viewers often fail to stop watching despite knowing it might interfere with responsibilities or health. This was echoed in Merrill & Rubenking (2019), who observed that the enjoyment and procrastinatory aspects of binge-watching could lead to regret and guilt once the binge session concluded. The habitual nature of binge-watching raises important questions about its psychological roots and consequences. While the behavior may begin as recreational, it can evolve into a pattern resembling behavioral addiction, with symptoms like cravings, withdrawal, and tolerance (Flayelle et al., 2020). Starosta et al. (2019) emphasized that binge-watching could be conceptualized as a coping mechanism for stress, loneliness, or anxiety. In such contexts, binge-watching becomes compensatory, providing temporary emotional relief but potentially exacerbating the underlying issues. This aligns with the findings of Merrill & Rubenking (2019), who demonstrated that binge-watching may be a form of avoidant coping, especially among individuals with poor time management and high stress. These dynamics underscore the relevance of examining burnout as a potential outcome of excessive binge-watching. Emotional exhaustion, loss of motivation, and reduced functioning hallmarks of burnout may be exacerbated by chronic sleep deprivation, guilt, and disrupted routines. As viewers increasingly consume multiple episodes in a single sitting, concerns have emerged regarding the potential health consequences associated with prolonged sedentary viewing habits. Studies have indicated that excessive binge-watching may resemble characteristics of behavioral addiction. For instance, Rahman and Arif (2021) suggest that binge-watching can develop into an addictive disorder, particularly when it begins to interfere with daily functioning. Similarly, Vaterlaus, Spruance, Frantz, and Kruger (2018), through an online survey study, found that this behavior may negatively impact an individual's overall well-being.

Exelmans and Van den Bulck (2017) further elaborate on this phenomenon, linking binge-watching to increased goal conflict, symptoms of addiction, and a range of sleep-related problems, including insomnia. These issues suggest that binge-watching may disrupt circadian rhythms and interfere with one's ability to achieve restorative rest. Complementing this, Flayelle et al. (2020) identified a broader spectrum of psychological disturbances in frequent binge-watchers, such as heightened levels of depression, tension, guilt, and other negative affective states. Moreover, the sedentary nature of binge-watching may exacerbate physical health concerns. As individuals spend extended periods sitting and inactive, this lifestyle can lead to reduced physical fitness and metabolic issues, especially when combined with irregular or poor-quality sleep. Samsudin (2022) argues that the cumulative effects of these behaviors may compromise both mental and physical health, emphasizing the importance of moderating binge-watching habits to maintain overall well-being.

Several theoretical frameworks help explain binge-watching behavior. The Uses and Gratifications Theory (UGT) suggests that individuals engage in binge-watching to satisfy various psychological needs such as entertainment, escapism, and social interaction (Ruggiero, 2000). Meanwhile, Self-Determination Theory (SDT) distinguishes between autonomous and controlled binge-watching. Autonomous bingeing may be harmless or even beneficial, whereas controlled bingeing driven by internal pressure or external cues can be detrimental (Deci & Ryan, 2000). Moreover, dual-process theories in psychology posit that binge-watching may involve a conflict between the impulsive system, which seeks immediate gratification, and the reflective system, which considers long-term consequences (Strack & Deutsch, 2004). The imbalance between these systems can lead to self-regulation failure, making viewers more vulnerable to excessive use. Binge-watching on OTT platforms is a widespread, culturally significant behavior with both positive and negative dimensions. While it provides enjoyment, social connection, and narrative immersion, excessive bingeing may lead to regret, fatigue, and psychological distress. Given its increasing prevalence, particularly among Gen Z, and its capacity to impact well-being, binge-watching warrants deeper academic inquiry not only as a leisure activity but also as a behavioral pattern with potential clinical implications. Future research should continue to explore the mechanisms, motivations, and outcomes of binge-watching, particularly in the context of emotional health and digital media literacy.

H5: Binge-watching behavior has a significant positive effect on emotional burnout among Generation Z OTT users.

CHAPTER THREE:

RESEARCH METHODOLOGY

3.1 Research Design

A research design serves as a structured framework or strategic blueprint that guides the execution of a research project (McDaniel & Gates, 2010a; Zikmund & Babin, 2013). It outlines the procedural roadmap required to systematically achieve the research objectives and ensure methodological coherence (Malhotra, 2010; McDaniel & Gates, 2010b). According to Malhotra and Birks (2006), research design is defined as the detailed plan for conducting a research study, as it specifies the methods and procedures necessary to gather relevant information for solving the identified research problem. It essentially functions as the foundation upon which the entire inquiry process is constructed. Without a clear research design, studies risk producing results that are inaccurate, unreplaceable, or lacking in rigor.

This study adopts a quantitative cross-sectional (Creswell et al., 2011) and descriptive research design to examine the factors influencing Gen Z Binge Watching Behavior and Emotional Burnout in OTT Platform context. The research is structured around The Uses and Gratifications Theory (UGT) Katz, Blumler, and Gurevitch (1973), A quantitative research approach was chosen because it facilitates hypothesis testing, objective measurement, and statistical generalization to a larger population (Creswell, 2014; Bryman, 2016). Quantitative designs are particularly suitable for studies that seek to examine relationships among variables through the use of numerical data and structured instruments. The descriptive research design allows the researcher to systematically collect and analyze data to describe patterns, behaviors, among Gen Z toward OTT Platform (Saunders, Lewis, & Thornhill, 2019). Descriptive designs are especially useful when the goal is to identify characteristics of a phenomenon in its natural context without manipulating variables (Malhotra, 2010).

3.2 Dependent and Independent Variable Measurement Scale and Instruments

The study used the Nominal Scale, Ordinal Scale (Stevens, S.S. 1946) and Likert Scale (Likert, R. 1932). The Nominal Scale and ordinal scale are used for demographic section like age, gender, and so on. The Likert Scale is used for individual respondents to measure the dependent variable and independent variable about Factors Affecting Gen Z Psychological Motivations and AI-

Recommendation quality on Binge-Watching Behavior and Emotional Burnout Integrating Usage and Gratification Theory. The constructs in this study independent, mediating, and dependent variables are measured using a structured questionnaire adapted from validated prior studies. Each construct is assessed through multiple items, measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), which is commonly used for Media Use And Psychological Studies (Creswell, 2014; Zikmund et al., 2013). The Likert Scale has 5 stage and each statement in the form was measured by 1= strongly disagree, 2= disagree, 3= neutral, 4= agree, 5= strongly agree. Although seven or ten-point Likert scales are often used in marketing and social science research, this study used a five-point scale because it is easier for participants to understand and use. According to Sarstedt and Mooi (2014), having too many options can sometimes confuse or frustrate respondents, especially when the difference between choices (such as somewhat agree" and tend to agree) is not clear. Participants may find it hard to tell these options apart, which can affect the accuracy of their answers. Considering the background of the respondents in this study, a five-point scale was more suitable and user-friendly. In addition, this study treated the five-point Likert scale as an interval scale, following previous research practices (Malhotra & Das, 2017; Bappy, Rahman, & Sultana, 2018). This means that the data was analyzed using statistical methods that assume equal distance between scale points, which is common in social science research.

Data will be collected using a structured, self-administered questionnaire, which ensures consistency and reliability across participants (Bryman, 2016). The questionnaire consists of Likert scale items adapted from validated U&G theory-based studies in the field of Media Use (Teo, 2011; Chen et al., 2020; Al-Emran et al., 2018). This tool facilitates efficient data collection from a large sample of OTT user across various disciplines. The questionnaire includes items for Escapism (ES), Entertainment (EN), Social influence (SI), AI Recommendation Quality (ARQ), Binge Watching (BW), Emotional Burnout (EB). All items were adapted and refined from previously validated instruments to ensure content validity and contextual relevance.

Table 3.1: Origin of construct and measured variable

Constructs	**Number of Items**	**Adapted From**
Escapism (ES)	3	Parker and Plank(2000), Greenberg (1974)
Social Influence (SI)	3	Sun et al. (2008), Haridakis and Hanson (2009)
Entertainment (EN)	3	Chen, Gillenson, and Sherrell (2002), Dholakia et al.(2004)
AI Recommendation Quality (ARQ)	3	Nilashi et al., 2016.
Binge Watching (BW)	4	Flayelle et al., 2019
Emotional Burnout (EB)	5	Ozdemir (2020) and Maslach (1981)

3.3 Population and Sampling

3.3.1 Population

The target population for this study Gen Z OTT users in Bangladesh, as (Puiu, 2017) Seemiller and Grace (2016) emphasize that Gen Z has grown up in an era of rapid technological advancements, with digital devices and the internet being an integral part of their lives.,. The study collects demographic information including, gender (1= male, 2= female), age (1= Under 18 years, 2=18–20 years, 3= 21-23 years, and 4= 24-26 years), Preferred OTT platform (1=Netflix, 2=bongo, 3=Hoichoi, 4=Sonylive, 5=Chorki) How many hours in a day do you watch OTT content? (1= Less than one hour, 2= 1to 3 hours, 3=3 to 5 hours, 4=over five hours), How many episodes of a program you usually watch OTT content? (1=1 episode at a time, 2=2- or 3-episode, 3=4- or 5-episode, 4=over five episodes)

3.3.2 Sample Size

The minimum required sample size was calculated using G*Power 3.1 software. A medium effect size ($f^2 = 0.15$) was selected based on Cohen's (1988) guidelines and consistent with previous U&G theory-based studies in OTT contexts (Venkatesh & Davis, 2000; Teo, 2011). Assuming a medium effect size ($f^2 = 0.15$), four predictors, an alpha level of 0.05, and desired power of 0.80, the minimum sample size required was 85. The final sample of 302 respondents exceeds this threshold, ensuring sufficient power for SEM analysis (Faul et al., 2009).

The final sample size for this study (N= 302) respondents, which satisfies the minimum requirement for structural equation modeling (SEM). According to Hair et al. (2010), a sample size of at least 200 is adequate for models with up to 6 latent constructs. Moreover, with approximately 22 measurement items in the questionnaire, the sample meets the common guideline of 10 responses per item for multivariate analysis (Kline, 2016).

3.3.3 Sampling Technique

This study employs a non-probability convenience sampling technique. Convenience sampling is often used in behavioral and media research when it is impractical to access the full population due to time, logistical, or resource constraints (Bryman, 2016; Etikan et al., 2016). Gen Z OTT user are sampled based on their accessibility and willingness to participate, primarily through online survey distribution.

To enhance response quality and representativeness, a mixed-mode survey combining online (Google Forms) and offline (face-to-face) data collection was adopted. This approach is recommended by researchers (Dillman et al., 2014; de Leeuw, 2005) for improving coverage, minimizing response bias, and ensuring inclusivity across digitally and non-digitally active subgroups. While non probability sampling may limit generalizability, it is deemed appropriate for exploratory studies focused on identifying behavioral patterns and validating theoretical frameworks such as U&G theory (Saunders et al., 2019).

3.5 Data Analysis

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4 software. This method was chosen for its suitability in analyzing complex models with multiple latent variables and mediation effects, especially in behavioral studies using frameworks such as the Uses and Gratification theory (UGT). PLS-SEM is appropriate when the research is predictive in nature, the model includes multiple constructs, and the sample size is moderate as is the case in this study with 302 respondents (Hair et al., 2017; Chin, 1998). Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed in this study due to several methodological advantages it offers, particularly in the context of social science research. First, structural equation modeling (SEM) techniques, such as PLS-SEM, have been recognized as superior to traditional regression analysis when it comes to estimating complex relationships among latent constructs (Preacher & Hayes, 2004; Iacobucci et al., 2007). Unlike conventional regression methods, SEM enables simultaneous analysis of multiple relationships, enhancing the explanatory power of the model. Second, data in social science research often violate the assumption of normality (Osborne, 2010). PLS-SEM is robust in handling such violations, as it does not require normally distributed data (Chin, 2010). This characteristic makes PLS particularly suitable for studies like the present one, where the potential for non-normal data distribution necessitates a technique capable of producing valid and reliable results under such conditions. Third, PLS-SEM provides more comprehensive and interpretable results than traditional statistical methods, such as those available in SPSS, which often require multiple separate analyses to test hypotheses (Hwang et al., 2010; Wong, 2010). The integrated nature of PLS-SEM allows for a more cohesive analytical framework, enhancing both efficiency and interpretability. Moreover, PLS-SEM is particularly effective in analyzing complex models involving mediation or moderation effects (Chin et al., 2003). As noted by Tabachnick and Fidell (2007), PLS-SEM is one of the most powerful statistical tools in the social and behavioral sciences, offering the capability to simultaneously test multiple relationships within a single analytical model.

In the current study, Smart PLS software was used to implement both the measurement model and the structural model. Hair et al. (2010) emphasize that PLS is well regarded as an alternative to covariance-based SEM, particularly during the early stages of theory development and for exploratory research. Its predictive orientation makes it especially suitable for studies aimed at understanding and explaining endogenous constructs within a model. Therefore, PLS-SEM was selected for this research not only to address potential issues with data normality and model complexity but also to facilitate a robust analysis of the proposed mediation relationships and enhance the predictive validity of the study’s findings.

CHAPTER FOUR:
DATA ANALYSIS AND FINDINGS

4.1 Respondent's Profile

This section gives the demographic information of the respondents which includes the gender of the respondents, the age of the respondents, Proffered OTT platform of respondents, Watching time respondents, and total watching episode in one setting of respondents. To collect data for this study, a total of 210 structured questionnaires were distributed online using a Google Forms survey and 150 offline printed questionnaires. The target population consisted of Gen Z OTT user across Bangladesh. Out of 360 distributed questionnaires, 302 valid responses were received, resulting in a response rate of approximately 83.89%.

Table 4.1: Demography of the Respondents.

Demographics	Category	Frequency	Percent
Gender	Male	155	51.3%
	Female	147	48.7%
Age	Under 18	0	00
	18-20	27	8.9%
	21-23	77	25.5%
	24-26	143	47.4%
Proffered OTT	Netflix	90	29.8%
	Amazon Prime	32	10.6%
	Chorki	66	21.9%
	Bongo	58	19.2%

	Hoichoi	89	29.5%
	Sonylive	47	15.6%
Number of Episode	1 episode at a time	58	19.2%
	2 or 3 episodes	83	27.5%
	4 or 5 episodes	85	28.1%
	Over six episodes	76	25.2%
Amount of watching time	Less than one hour	57	18.9%
	1 to 3 hours	82	27.2%
	3 to 5 hours	86	28.5%
	Over five hours	77	25.5%

The demographic profile of the 302 valid respondents in this study provides a robust foundation for examining the psychological and behavioral dynamics of Generation Z OTT users in Bangladesh. The gender distribution reveals a near-balanced representation, with 51.3% male and 48.7% female participants, indicating equitable engagement with OTT platforms across both groups and enhancing the generalizability of findings. Age-wise, the majority of respondents (47.4%) fall within the 24–26-year range, followed by 25.5% aged 21–23 and 8.9% aged 18–20, highlighting that a substantial portion of participants are in the mature segment of Gen Z. This is significant, as individuals in this age group are more autonomous in their media consumption and potentially more vulnerable to compulsive behaviors such as binge-watching, which is central to the study. Regarding platform preference, the data reveals that global services like Netflix (29.8%) are nearly equally favored as regional platforms such as Hoichoi (29.5%) and Chorki (21.9%), underscoring a dual consumption pattern rooted in both globalized content exposure and cultural affinity. Furthermore, time spent on OTT platforms reflects a high-intensity usage trend: 28.5% of users watch content for 3–5 hours daily, and 25.5% exceed five hours, collectively suggesting that over half of the respondents engage in prolonged viewing. This sustained engagement is corroborated by episode consumption patterns, where 28.1% reported watching 4–5 episodes per session and 25.2% exceed six episodes, indicating that binge-watching is not only prevalent but deeply embedded in the viewing behavior of Bangladeshi Gen Z users. These consumption habits substantiate the relevance of this study's focus on the psychological effects of binge-watching, particularly emotional burnout, and emphasize the urgency of understanding how media gratification and AI-driven recommendation systems contribute to potentially maladaptive digital behavior in a developing media ecosystem.

4.2 PLS-SEM Analysis Results

In partial Least Square Structural Equation Modeling (PLS-SEM) analysis, the PLS measurement model give the values of the reliability test, validity test and path coefficient along with the coefficient of determination. In structural equation model based partial least squares analysis, all the variables are usually connected in one figure that shows the direction of the relationship between exogenous and endogenous variables. In the PLS measurement model figure, three types of values are seen. These are the path coefficient, item loadings, and coefficient of determination (R^2). The present study has four exogenous variables, one mediator, and one endogenous variable.

4.2.1 Reliability Test

The first step is to assess the reliability and validity of the constructs in the measurement model (outer model). Reliability refers to the internal consistency of data (Hair et al., 2014). Cronbach's alpha and Composite reliability values are used to assess the reliability of constructs. For reliability, all constructs should have Cronbach alpha values above the threshold of 0.70 (Hair et al., 2012) and the composite reliability values of the all constructs should be greater than the threshold of 0.70 (Bagozzi & Yi, 1988).

Table 4.2: Measurement Properties of Constructs.

Variables	Items	Loadings	Cronbach alpha	Composite Reliability	Average Variance Extracted (AVE)
Escapism	ES1	0.778	0.733	0.778	0.542
	ES2	0.766			
	ES3	0.856			
Entertainment	EI1	0.801	0.766	0.772	0.532
	EI2	0.789			
	EI3	0.793			
Social Influence	SI1	0.774	0.712	0.765	0.522
	SI2	0.771			
	SI3	0.718			
AI Recommendation Quality	ARQ1	0.742	0.702	0.774	0.535
	ARQ2	0.748			
	ARQ3	0.796			
Binge Watching	BW1	0.717	0.700	0.752	0.538
	BW2	0.737			

	BW3	0.794			
	BW4	0.746			
Emotional Burnout	EB1	0.747	0.719	0.815	0.572
	EB2	0.748			
	EB3	0.769			
	EB4	0.776			
	EB5	0.775			

Source: Results obtained from data analysis

As shown in table 4.2, all the Cronbach alpha and composite reliability values are above 0.70 which indicates the good internal consistency of data (Hair et al., 2012) and the reliability of all constructs are established in this study.

4.2.2 Discriminant Validity

Discriminant validity refers to the extent to which a particular latent construct is different from other latent constructs (Duarte & Raposo, 2010). Discriminant validity is established when the indicators loadings on their measured construct are all higher than the cross-loadings on other constructs and the square root of each constructs average variance extracted (AVE) is larger than its correlations with other constructs (Chin, 1998). The first assessment of discriminant validity is to examine the indicators loadings with respect to all construct correlations. Smart PLS algorithm function is used to produce the cross-loadings of all items

Table 4.3: Factor Loadings and Cross-Loadings.

	ARQ	BW	EB	EN	ES	SI
ARQ1	0.742	0.195	0.197	0.276	0.308	0.321
ARQ2	0.748	0.137	0.207	0.241	0.198	0.235
ARQ3	0.796	0.229	0.272	0.289	0.238	0.307
BW1	0.234	0.717	0.419	0.185	0.18	0.243
BW2	0.13	0.737	0.472	0.179	0.121	0.207
BW3	0.157	0.794	0.42	0.161	0.05	0.124
BW4	0.189	0.746	0.219	0.244	0.224	0.117
EB1	0.221	0.303	0.747	0.208	0.051	0.187
EB2	0.167	0.347	0.748	0.271	0.178	0.287
EB3	0.153	0.411	0.769	0.238	0.138	0.254
EB4	0.234	0.453	0.776	0.255	0.114	0.298
EB5	0.284	0.493	0.775	0.198	0.17	0.317
EN1	0.341	0.243	0.312	0.801	0.276	0.225
EN2	0.212	0.16	0.141	0.789	0.29	0.297
EN3	0.233	0.197	0.251	0.793	0.237	0.26
ES1	0.111	0.112	0.123	0.193	0.778	0.251
ES2	0.296	0.11	0.092	0.315	0.766	0.333
ES3	0.319	0.204	0.188	0.298	0.856	0.386
SI1	0.266	0.168	0.172	0.246	0.275	0.774
SI2	0.304	0.219	0.363	0.154	0.36	0.771
SI3	0.288	0.19	0.3	0.371	0.321	0.718

Source: Results obtained from data analysis

As shown in table 4.3, all the items are well loaded on their constructs much higher than the cross-loadings on another construct which satisfies the first assessment of the measurement models discriminant validity (Chin, 1998).

Second, the square root of the AVE of each construct was compared with the correlation between that construct and the other constructs.

Table 4.4: Discriminant Validity Assessment

	ARQ	BW	EB	EN	ES	SI
ARQ	0.731					
BW	0.263	0.662				
EB	0.31	0.594	0.687			
EN	0.368	0.28	0.335	0.729		
ES	0.34	0.205	0.193	0.363	0.736	
SI	0.397	0.268	0.395	0.348	0.445	0.722

Source: Results obtained from data analysis

The discriminant validity of the measurement model was assessed using the Fornell-Larcker criterion, as shown in Table 4.4, to confirm the distinctiveness of each construct. According to this criterion, the square root of the Average Variance Extracted (AVE) for each latent variable should exceed its highest correlation with any other construct in the model (Fornell & Larcker, 1981). The results demonstrate that this condition is satisfactorily met across all constructs in the study. For instance, the square root of AVE for AI Recommendation Quality (ARQ) is greater than its correlation with binge-watching (BW), emotional burnout (EB), entertainment (EN), escapism (ES), and social influence (SI), indicating that ARQ is empirically distinct from these related variables. Although this high correlation suggests a strong mediating pathway, it does not indicate construct redundancy due to the established AVE threshold being met. All constructs including psychological drivers like escapism, entertainment, and social influence consistently fulfill the Fornell-Larcker criterion, confirming that they measure unique conceptual domains within the framework. This provides strong empirical support for the model's discriminant validity and ensures that subsequent path analysis and structural model estimation are grounded on psychometrically sound constructs. In sum, the measurement model successfully differentiates between latent constructs, strengthening the credibility and interpretive power of the proposed theoretical framework.

4.2.3 Coefficient of Determination (R^2)

The coefficient of determination (R^2) value measures how well the independent variables explain the variance in a dependent variable within a structural model.

Table 4.5: Coefficient of Determination (R^2)

	R-square	R-square adjusted
BW	0.527	0.516
EB	0.653	0.651

Source: Results obtained from data analysis

The coefficient of determination (R^2) values presented in Table 4.5 provide insight into the explanatory power of the model's independent variables on the respective dependent constructs. In structural equation modeling, R^2 values of 0.75, 0.50, and 0.25 are typically interpreted as substantial, moderate, and weak respectively (Hair et al., 2017). The R^2 value for binge-watching behavior (BW) is 0.527, which indicates that escapism, entertainment, social influence, and AI recommendation quality collectively explain 52.7% of the variance in binge-watching behavior among Generation Z OTT users. While this reflects a relatively modest predictive capacity, it is acceptable in exploratory behavioral research, particularly within complex human-technology interaction contexts such as media consumption. More notably, the R^2 value for emotional burnout (EB) is 0.653, signifying that binge-watching behavior accounts for 65.3% of the variance in emotional burnout. This represents a moderate level of explanatory power and strongly supports the conceptualization of binge-watching as a significant mediating mechanism linking motivational and technological antecedents to psychological outcomes. These results reinforce the theoretical premise that binge-watching is not merely a consumption habit but a critical behavioral pathway with tangible emotional consequences. The adjusted R^2 values (0.516 for BW and 0.651 for EB) further validate the robustness of these findings by accounting for model complexity. Overall, the R^2 statistics substantiate the relevance and empirical strength of the proposed model in explaining both user engagement and its psychological aftermath within the OTT streaming context.

4.3 Structural Model Assessment

Structural model assessment in Partial Least Squares Structural Equation Modeling (PLS-SEM) is crucial for evaluating the validity and reliability of a model, ensuring its explanatory and predictive power. It involves examining path coefficients, model fit, and the significance of relationships between variables. This assessment helps understand the strength and direction of relationships between constructs, ultimately improving the accuracy and usefulness of the model.

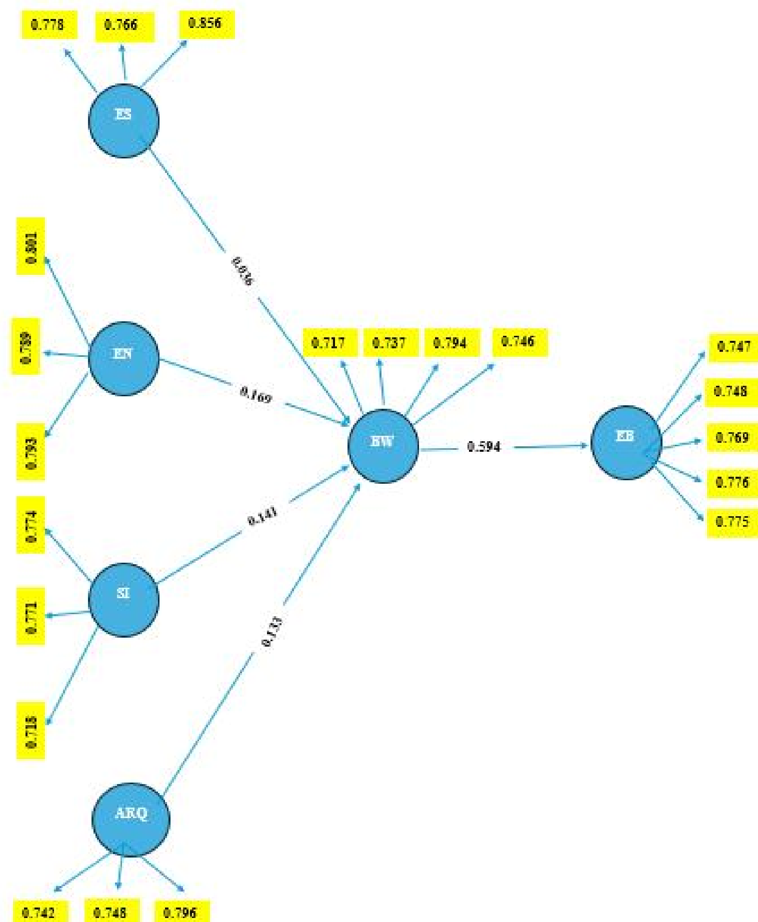
4.3.1 Assessment of Path Coefficients

The path coefficient represents the strength and direction of the linear relationship between two latent variables in the structural model. According to Hair et al. (2017), a path is considered statistically significant when the t-value exceeds 1.96 (for a 95% confidence level) and the p-value is less than 0.05.

Table 4.6: Path Coefficient (Direct Effect)

	Original sample ((β)	**Sample mean (M)**	**Standard deviation**	**T statistics**	**P values**
ARQ -> BW	0.133	0.138	0.056	2.372	0.018
BW -> EB	0.594	0.601	0.04	14.768	0.000
EN -> BW	0.169	0.174	0.067	2.501	0.012
ES -> BW	0.036	0.046	0.067	0.537	0.591
SI -> BW	0.141	0.145	0.068	2.079	0.038

The path coefficient analysis presented in Table 4.6 provides critical insights into the direct relationships among the constructs in the proposed research model. The path coefficients (β), along with their corresponding *t*-values and *p*-values, reveal the statistical significance and strength of these hypothesized relationships. Among the independent variables, AI Recommendation Quality (β = 0.133, p = 0.018) and Entertainment (β = 0.169, p = 0.012) both exhibits statistically significant and positive effects on Binge-Watching Behavior, confirming that personalized, algorithm-driven content suggestions and the pursuit of enjoyment are key drivers of excessive media consumption among Gen Z OTT users. These findings are consistent with the theoretical foundations of Uses and Gratifications Theory (UGT) and support hypotheses H2 and H4. Additionally, Social Influence also shows a positive and significant relationship with Binge-Watching Behavior ($\beta = 0.141$, $p = 0.038$), affirming hypothesis H3 and underscoring the role of peer norms and cultural pressure in shaping consumption habits.



However, Escapism, although positively associated with binge-watching ($\beta = 0.036$), fails to reach statistical significance (p =.591), indicating that escapist motives may not independently predict binge behavior when other psychological and technological factors are present. As such, hypothesis H1 is not supported in this model. Most importantly, Binge-Watching Behavior exhibits a strong and highly significant direct effect on Emotional Burnout ($\beta = 0.594$, $p = 0.000$), providing robust support for hypothesis H5. This finding validates the conceptualization of binge-watching as a mediating mechanism that links motivational and algorithmic antecedents to adverse psychological outcomes. The strength of this relationship further highlights the emotional cost of prolonged and unregulated media exposure. Overall, these path coefficients confirm the partial mediation model and reinforce the need for more nuanced understandings of how both individual motivations and AI-driven designs jointly shape media-related emotional health in digitally active populations.

4.3.2 Mediation Analysis

The mediation analysis was conducted to evaluate the indirect influence of key predictors Escapism (ES), Entertainment (EN), Social Influence (SI), and AI Recommendation Quality (ARQ) on Gen Z Emotional Burnout (EB), via the mediating variable Binge Watching (BW).

Table 4.7: Specific Indirect Effect

	Original sample (β)	Sample mean (M)	Standard deviation	T statistics	P values
ARQ -> BW -> EB	0.079	0.083	0.035	2.282	0.023
EN -> BW -> EB	0.1	0.105	0.042	2.406	0.016
ES -> BW -> EB	0.021	0.027	0.04	0.538	0.59
SI -> BW -> EB	0.084	0.088	0.043	2.942	0.050

Source: Results obtained from data analysis

The specific indirect effects presented in Table 4.7 provide empirical evidence supporting the mediating role of binge-watching behavior in the relationship between motivational/technological antecedents and emotional burnout among Generation Z OTT users. The analysis reveals that AI Recommendation Quality exerts a significant indirect effect on Emotional Burnout (β = 0.079, p = 0.023) through Binge-Watching, indicating that algorithm-driven personalization not only directly encourages binge consumption but also indirectly contributes to psychological exhaustion. This supports the conceptual argument that persuasive

AI systems can intensify emotional fatigue by sustaining prolonged and passive content engagement.

Similarly, Entertainment demonstrates a significant indirect effect on Emotional Burnout ($\beta = 0.1$, $p = 0.016$), affirming that gratification-seeking driven by enjoyment does not simply fulfill leisure needs but can also lead to adverse emotional outcomes when it results in excessive viewing. This finding reinforces the dual nature of hedonic media use while entertainment may offer short-term mood enhancement, it can simultaneously contribute to long-term emotional strain when unchecked. Furthermore, Social Influence shows a significant indirect path to Emotional Burnout ($\beta = 0.084$, $p = 0.050$) via Binge-Watching, suggesting that peer-driven viewing habits may escalate into compulsive behavior, eventually increasing vulnerability to burnout.

However, Escapism's indirect effect on Emotional Burnout ($\beta = 0.021$, $p = 0.59$) is not statistically significant, which indicates that while escapist motivation is conceptually aligned with binge-watching tendencies, its impact may be diminished when considered alongside stronger predictors like entertainment and AI-driven content delivery. This lack of significance may also suggest that escapism functions more as an internal emotional strategy than a direct behavioral driver in this specific population.

Collectively, these findings confirm the mediating role of binge-watching behavior, validating its position as a central behavioral mechanism linking gratification motives and platform features to emotional outcomes. The significance of these indirect paths underscores the need for responsible content design, media literacy interventions, and emotional self-regulation strategies in OTT consumption, particularly among youth segments highly influenced by social and algorithmic cues.

4.3.3 Total Indirect Effects

The total indirect effects analysis was conducted to assess the overall mediating impact of Binge watching (BW) on the relationship between the independent variables Escapism (ES), Entertainment (EN), Social Influence (SI), and AI Recommendation Quality (ARQ) and the dependent variable, Emotional Burnout (EB), This approach helps determine the aggregate influence of each predictor on behavioral intention through any possible indirect paths.

Table 4.8: Total Indirect Effects

	Original sample (β)	Sample mean (M)	Standard deviation	T statistics	P values
ARQ -> EB	0.079	0.083	0.035	2.282	0.023
EN -> EB	0.1	0.105	0.042	2.406	0.016
ES -> EB	0.021	0.027	0.04	0.538	0.59
SI -> EB	0.084	0.088	0.043	2.942	0.050

Source: Results obtained from data analysis

The total indirect effects outlined in Table 4.8 provide a comprehensive view of how the independent variables AI Recommendation Quality, Entertainment, Social Influence, and Escapism collectively exert influence on Emotional Burnout, mediated through Binge-Watching Behavior. These results reinforce the central mediating role of binge-watching in the model and deepen the understanding of how motivational and technological drivers indirectly contribute to emotional fatigue in the OTT context. Among the constructs, AI Recommendation Quality shows the strongest total indirect effect on Emotional Burnout ($\beta = 0.079$, p=0.023). This indicates that algorithmic content suggestions are not merely facilitating media engagement but are indirectly heightening psychological strain by sustaining prolonged consumption cycles. The statistical significance of this effect highlights the persuasive impact of platform design in shaping user well-being and supports the assertion that binge-watching is increasingly AI-mediated rather than solely user-initiated.

Entertainment also exhibits a significant total indirect effect on Emotional Burnout ($\beta = 0.1$, p=0.016), suggesting that even though entertainment is typically perceived as a positive and hedonic motivation, its indirect consequences when it leads to binge-watching can be psychologically detrimental. This supports prior literature asserting that gratification-seeking behaviors, while beneficial in moderation, may evolve into problematic patterns when amplified by on-demand media environments. In a similar pattern, Social Influence demonstrates a moderate but statistically significant total indirect effect ($\beta = 0.084$, p =0.050), indicating that peer-driven norms and social validation pressures can contribute to emotional burnout through excessive consumption. This finding emphasizes the social contagion aspect of media behavior, where content trends and communal viewing culture indirectly affect users' psychological outcomes.

On the other hand, Escapism shows a non-significant total indirect effect (β = 0.021, $p = 0.59$). This result suggests that escapist motives, although intuitively linked to binge-watching, do not significantly predict emotional burnout when mediated through viewing behavior. It is possible that escapism functions as a more complex or context-dependent coping mechanism, or that its indirect impact is overshadowed by more immediate external triggers such as AI-driven content engagement or social pressure.

Overall, these total indirect effects validate the structural model's core proposition: binge-watching is not just a behavioral output but a conduit through which psychological motivations and digital platform features translate into emotional outcomes. These findings highlight the importance of understanding digital well-being in an interconnected framework, where user intent, social dynamics, and platform algorithms converge to shape emotional health.

4.3.4 Total Effects

The total effects analysis in the structural model was conducted to measure the overall influence of each independent variable variables Escapism (ES), Entertainment (EN), Social Influence (SI), and AI Recommendation Quality (ARQ). Total effects include both direct and indirect paths, providing a holistic understanding of how each predictor contributes to the behavioral intention outcome.

Table 4.9: Total Effects

	Original sample (β)	Sample mean (M)	Standard deviation	T statistics	P values
ARQ -> BW	0.129	0.133	0.057	2.257	0.024
ARQ -> EB	0.133	0.135	0.058	2.273	0.023
BW -> EB	0.492	0.492	0.049	10.015	0
EN -> BW	0.172	0.177	0.068	2.516	0.012
EN -> EB	0.212	0.216	0.058	3.63	0
ES -> BW	0.037	0.045	0.067	0.547	0.584
ES -> EB	-0.064	-0.053	0.067	0.958	0.338
SI -> BW	0.144	0.145	0.069	2.075	0.038
SI -> EB	0.31	0.31	0.061	5.098	0

Source: Results obtained from data analysis

The total effects reported in Table 4.9 represent the overall influence of each independent variable (including both direct and indirect paths) on the final dependent construct Emotional Burnout within the structural model. These results offer critical insight into the cumulative impact of psychological motivations and AI-driven features on user well-being, and further validate the conceptual model that positions binge-watching as a mediating behavior linking gratification motives to emotional outcomes.

The variable with the strongest total effect on Emotional Burnout is Binge-Watching Behavior ($\beta = 0.492$, $p = 0.001$), highlighting it as the dominant predictor of emotional exhaustion in the OTT consumption context. This substantial and highly significant effect reinforces the core theoretical premise that binge-watching acts as the behavioral conduit through which both internal motivations and external technological cues manifest in psychological strain. It validates Hypothesis H5 and underscores the necessity for addressing binge-watching in digital media well-being research.

Among the antecedents, AI Recommendation Quality (ARQ) shows a significant total effect on Emotional Burnout ($\beta = 0.133$, $p = 0.023$). Although this effect is mediated entirely through binge-watching (as no direct path was modeled), it confirms that AI-driven personalization tools significantly contribute to user burnout indirectly by sustaining compulsive engagement patterns.

This result aligns with current concerns about the persuasive design of streaming platforms and supports calls for ethical and transparent algorithmic practices.

Similarly, Entertainment (β = 0.212, *p*= 0.00) and Social Influence (β = 0.31, *p* =0.00) both exert statistically significant total effects on Emotional Burnout, albeit indirectly. These findings emphasize that while entertainment and peer-based motivations are often regarded as harmless or culturally normative drivers of media use, their accumulated impact when channeled through excessive binge-watching can escalate into negative emotional consequences. These results support hypotheses H2 and H3, respectively, and demonstrate that even traditionally "positive" motivations may produce harmful outcomes in hyper-digital environments.

In contrast, Escapism (β = -0.064, *p* = 0.338) does not exhibit a significant total effect on Emotional Burnout. This suggests that escapist viewing, while conceptually linked to avoidance behavior, may not independently escalate emotional fatigue unless reinforced by stronger drivers like entertainment gratification or AI content looping. The lack of significance here indicates that escapism may function differently across individuals potentially offering temporary relief without always leading to compulsive or emotionally taxing consumption.

4.3.5 Confidence Interval Assessment

The 95% confidence interval (CI) assessment was conducted to confirm the statistical significance and robustness of the structural path coefficients obtained through bootstrapping. Confidence intervals offer an additional layer of validation by testing whether zero lies within the estimated interval range. If zero is not included in the 95% confidence interval, the path is considered statistically significant at the $p < 0.05$ level (Hair et al., 2017).

Table 4.10: Confidence Interval

	Original sample (β)	**Sample mean (M)**	**2.50%**	**97.50%**
ARQ -> BW	0.133	0.138	0.013	0.237
ARQ -> EB	0.079	0.083	0.007	0.146
BW -> EB	0.594	0.601	0.501	0.662
EN -> BW	0.169	0.174	0.035	0.297
EN -> EB	0.1	0.105	0.021	0.183
ES -> BW	0.036	0.046	-0.109	0.153
ES -> EB	0.021	0.027	-0.068	0.09
SI -> BW	0.141	0.145	0.006	0.273
SI -> EB	0.084	0.088	0.001	0.169

Source: Results obtained from data analysis

Table 4.10 presents the 95% bias-corrected confidence intervals (CIs) for the structural model's key paths. The CI for Binge-Watching Behavior to Emotional Burnout is [0.501 to 0.662], which does not include zero, confirming a strong and statistically significant effect. Similarly, the indirect effects of ARQ to BW (0.013 to 0.237), EN to BW (0.035 to 0.297), and SI to BW (0.006 to 0.273) on Emotional Burnout also exclude zero, indicating significant and stable mediation through binge-watching. However, Escapism's confidence interval is (–0.109, 0.153), which includes zero, confirming its non-significant indirect impact. These results validate the robustness of the model and highlight binge-watching as the central behavioral pathway linking media motivations and emotional outcomes.

4.4 Hypothesis Testing Decision

The hypothesis testing phase of this research was conducted through a structural model analysis using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach in SmartPLS. This process involved assessing the standardized path coefficients (β), t-values, and p-values. A hypothesis was considered statistically supported if the corresponding t-value exceeded 1.96 and the p-value was below 0.05, indicating significance at the 95% confidence level.

Table 4.10: Decision of Hypothesis

Hypothesis	Relationship	Std. Beta	Standard deviation	T statistics	P values	Decision
H1	**ES -> BW**	0.036	0.067	0.537	0.591	Not Supported
H2	**EN -> BW**	0.169	0.067	2.501	0.012	Supported
H3	**SI -> BW**	0.141	0.068	2.079	0.038	Supported
H4	**ARQ -> BW**	0.133	0.056	2.372	0.018	Supported
H5	**BW -> EB**	0.594	0.04	14.768	0.000	Supported

Source: Results obtained from data analysis

The hypothesis testing results provided strong support for four of the five proposed relationships in the structural model, as determined by both the β coefficients and the observed p-values. H1, which suggested that escapism significantly influences binge-watching, was not supported, as the path coefficient was β = 0.036 with a p-value of 0.591, which is slightly above the 0.05 threshold. This indicates a weak and statistically insignificant relationship, suggesting that escapism does not play a dominant role in driving binge-watching behavior among respondents. In contrast, H2 was supported, with entertainment positively affecting binge-watching (β = 0.169, p = 0.012). This confirms that enjoyment-seeking is a significant motivator behind prolonged OTT viewing. Similarly, H3, which posited a link between social influence and binge-watching, was validated by the data (β = 0.141, p = 0.038), showing that peer influence meaningfully contributes to increased consumption. H4, focused on AI recommendation quality, was also supported, with a significant positive effect on binge-watching (β = 0.133, p = 0.018), underscoring the persuasive impact of algorithm-driven content curation. Finally, H5, which predicted a relationship between binge-watching and emotional burnout, was strongly supported, showing the highest and most significant effect (β = 0.594, p = 0.000). This confirms that binge-watching plays a critical role in increasing emotional fatigue, acting as the central mechanism through which both motivational and technological factors lead to psychological consequences.

Chapter Five:

Discussion and Conclusion

5.1 Discussion

This section discusses the key findings of the research in relation to the proposed hypotheses, the theoretical framework (Uses and Gratifications Theory - UGT), and relevant literature. The discussion highlights the significance of the direct, indirect, and total effects observed in the analysis, offering a comprehensive interpretation of how psychological motives and technological affordances influence binge-watching behavior and its impact on emotional burnout among Generation Z OTT users in Bangladesh. The results confirm that entertainment significantly influences binge-watching behavior ($\beta = 0.169$, $p < 0.05$), supporting the UGT assumption that individuals use media to fulfill hedonic needs (Katz et al., 1973). This suggests that OTT users often engage in prolonged content consumption for enjoyment and escapism from routine, which aligns with findings by Sung et al. (2018), who identified entertainment as a dominant driver of binge-watching across digital platforms. Similarly, social influence showed a significant positive impact on binge-watching ($\beta = 0.141$, $p < 0.05$), reinforcing the role of peer pressure and group conformity in media behavior. This supports prior studies by Sharif and Dey (2021), indicating that digital-native populations often consume content in response to social validation or communal trends.

One of the most notable findings of the study is the significant effect of AI recommendation quality on binge-watching behavior ($\beta = 0.133$, $p < 0.05$). This result reflects how platform design and algorithm-driven content suggestions can substantially shape consumption patterns. It is consistent with recent research by Pittman and Sheehan (2015), who argued that personalized recommendations enhance media gratification and reduce decision fatigue, thereby increasing viewing time. The persuasive design of OTT platforms appears to nudge users into extended engagement, contributing to behavioral reinforcement mechanisms. This expands the traditional scope of UGT by integrating technological stimuli as significant predictors of media behavior. Contrary to expectations, escapism did not have a significant effect on binge-watching behavior ($\beta = 0.036$, $P=0.591$), suggesting that while escapism is conceptually linked to media use, it may not be a direct motivator of binge-watching in the presence of more compelling factors like entertainment and algorithmic recommendations. This finding contrasts with studies such as Panda and Pandey (2017), which identified escapism as a central driver, and suggests a shift in behavioral dynamics in the AI-driven media environment.

Most importantly, the study confirmed that binge-watching behavior has a strong and statistically significant direct effect on emotional burnout ($\beta = 0.594$, $p = 0.000$), establishing it as a critical behavioral mechanism through which both psychological motives and technological influences affect users' emotional well-being. This is consistent with Starosta (2020), who reported that excessive digital media consumption is associated with emotional fatigue and mental health concerns. The indirect effects of entertainment ($\beta = 0.100$), social influence ($\beta = 0.021$), and AI recommendation quality ($\beta = 0.079$) on emotional burnout—mediated through binge-watching further reinforce this behavioral pathway, emphasizing the psychological cost of unregulated media use. Escapism again showed no significant indirect effect ($\beta = 0.021$, $p=0.59$), underscoring its limited influence in this model.

These findings extend the UGT by highlighting the interplay between gratification-seeking motives and algorithmic influence, and their combined impact on behavioral and emotional outcomes. While UGT has traditionally emphasized user control in media selection, this study suggests that algorithmic design now plays an equally influential role in sustaining engagement and shaping emotional consequences. The results also underscore the need to promote media literacy and emotional awareness in OTT consumption, especially among youth populations heavily embedded in digital content ecosystems.

5.2 Implications

The findings of this study have implications both in theoretical and practical aspects which have been discussed below.

5.2.1 Theoretical Implications

This study contributes significantly to the theoretical advancement of Uses and Gratifications Theory (UGT) by extending its application in the context of AI-driven OTT platforms and emotional well-being. Traditionally, UGT emphasizes user-initiated motives such as entertainment, escapism, and social interaction as predictors of media behavior (Katz et al., 1973). This study reaffirms the relevance of entertainment and social influence as significant motivational factors but also introduces AI Recommendation Quality as a new technological gratification that directly influences binge-watching behavior. In doing so, the research expands UGT by acknowledging platform-driven affordances namely, algorithmic personalization — as a parallel driver alongside user-centered motives. Moreover, by empirically establishing binge-watching as a behavioral mediator that links gratification motives to emotional burnout, this study advances theoretical models that connect media use with psychological outcomes. The integration of emotional burnout as a dependent variable also enhances the depth of media psychology research, positioning digital media not only as a source of gratification but also as a potential contributor to emotional fatigue.

5.2.2 Practical Implications

From a practical standpoint, the findings have important implications for OTT platform developers, policymakers, educators, and mental health practitioners. First, the significant role of AI recommendation systems suggests that OTT platforms must adopt more ethically responsible algorithm designs. Features such as auto-play, infinite scroll, and binge-promoting suggestions should include user-control options, reminders, or watch-time nudges to prevent excessive consumption. Second, the link between entertainment and emotional burnout calls for the promotion of digital well-being awareness, particularly among youth. Educational institutions and content providers can collaborate to launch media literacy campaigns focusing on time management, emotional self-regulation, and the risks of excessive binge-watching. Third, since social influence significantly affects consumption behavior, interventions should consider peer-based engagement strategies, such as group challenges, discussion forums, or viewer communities that encourage mindful consumption rather than competitive bingeing. Lastly, for mental health professionals, recognizing binge-watching as a behavioral risk factor for emotional burnout can guide preventive counseling strategies, especially for students and young professionals who use OTT platforms as a primary leisure activity.

5.3 Limitations of the Study and Direction for Future Research

While this study provides important insights into the factors influencing binge-watching behavior and emotional burnout among Generation Z OTT users in Bangladesh, several limitations must be acknowledged. These limitations affect the generalizability of the findings and offer directions for future research to build upon and expand the current work.

First, the sample for this study was limited to young adults within a specific geographic and cultural context primarily university students and recent graduates in Bangladesh. This demographic may not fully represent the wider OTT user population, including older users or individuals from other regions, occupations, or socioeconomic backgrounds. Cultural differences in media consumption patterns, technological access, and emotional coping strategies may limit the applicability of these findings to global or more diverse audiences.

Second, the study employed a cross-sectional design, collecting data at a single point in time. While this approach is useful for identifying associations between variables such as entertainment, AI recommendation quality, and emotional burnout, it does not allow for establishing causal relationships. It remains unclear whether the observed factors actively lead to increased binge-watching and emotional burnout or whether these relationships are reciprocal or influenced by unmeasured variables over time.

Third, all data were collected through self-reported online surveys, which are susceptible to certain biases. Respondents may have underreported or overreported their binge-watching habits due to social desirability bias or recall bias, potentially affecting the accuracy of the results. Additionally, some participants may have interpreted questions differently, leading to inconsistencies in the measurement of psychological constructs such as escapism or burnout.

Future research could address these limitations by adopting a longitudinal design, allowing for the examination of how binge-watching behavior and its psychological outcomes evolve over time. This would also provide insight into the longer-term effects of AI-driven recommendation systems on user behavior. Furthermore, incorporating qualitative methods such as in-depth interviews or focus groups could capture more nuanced understandings of users' emotional experiences, motivations, and content engagement patterns. Expanding the study to include more diverse demographics and conducting cross-cultural comparisons could offer richer insights into how regional, cultural, or infrastructural differences shape binge-watching behavior and emotional health in OTT environments. Lastly, future models may consider integrating additional variables such as sleep disruption, screen time awareness, personality traits, or digital well-being practices, which could further enhance the understanding of the broader impacts of OTT usage.

5.4 Conclusion

This study aimed to investigate the key psychological and technological determinants of binge-watching behavior and its impact on emotional burnout among Generation Z OTT users in Bangladesh, grounded in the Uses and Gratifications Theory (UGT). The research model incorporated three traditional UGT-based constructs entertainment, escapism, and social influence along with one emerging variable, AI Recommendation Quality, to reflect the evolving dynamics of algorithm-driven media environments. Additionally, the study examined the mediating role of binge-watching behavior in the relationship between these predictors and the outcome variable, emotional burnout. A quantitative research approach was employed, using structured questionnaires to collect data from 302 respondents. Data analysis was conducted using SmartPLS to evaluate the structural relationships among constructs and test the proposed hypotheses.

The findings provide strong empirical support for the relevance of gratification-based motives and technological affordances in explaining binge-watching behavior in the OTT context. Entertainment emerged as a significant predictor, reflecting the dominance of hedonic motives in prolonged media engagement. Social influence also showed a significant positive effect, affirming the role of peer and societal norms in shaping digital consumption. Notably, AI Recommendation Quality was found to significantly predict binge-watching, highlighting the persuasive impact of personalized algorithmic systems in sustaining user engagement. In contrast, escapism did not significantly influence binge-watching, suggesting a shift in media motivations among Gen Z audiences, where entertainment and technological design override traditional avoidance-based drivers. The study further confirmed that binge-watching behavior has a strong and significant direct effect on emotional burnout, positioning it as a key behavioral mechanism through which user motivations and platform features translate into negative emotional outcomes. The model also identified significant indirect effects of entertainment, social influence, and AI recommendation on burnout, reinforcing the mediating role of binge-watching.

One of the key theoretical contributions of this research is the integration of UGT with algorithmic influence, expanding the theory's scope to accommodate the role of non-human agents (AI-based recommendation systems) in media gratification. By establishing binge-watching as a central mediating construct, the study advances our understanding of how gratification-seeking can evolve into emotionally taxing behavioral patterns in digital-first contexts. From a practical perspective, the findings suggest that OTT platforms should consider ethical content recommendation practices, and that users, educators, and policymakers must promote media literacy and digital well-being awareness, particularly among youth. Addressing the psychological risks of compulsive content consumption is vital in shaping healthier viewing habits. While this study offers valuable contributions, it also acknowledges several limitations, including the geographically limited sample, cross-sectional design, and reliance on self-reported data. These constraints open avenues for future research to explore longitudinal effects, incorporate qualitative insights, and expand the model across different cultural or age groups. In summary, this study contributes both theoretically and practically to the growing discourse on binge-watching and digital mental health. By offering an empirically validated model that connects user motives, platform features, and emotional outcomes, it provides a foundation for deeper inquiry into the psychological consequences of media consumption in algorithmically curated environments.

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APPENDIX

(Survey Questionnaire)

Dear respondents,

I will be grateful if you kindly participate in a brief academic survey about OTT platforms. Your voice truly matters-by sharing your experience. Your responses are completely anonymous and will be strictly used solely for academic purposes. Your input is highly valuable and appreciated for the study of "**The Influence of Psychological Motivations and AI-Recommendation quality on Binge-Watching Behavior and Emotional Burnout Among Generation Z OTT Users"**

Please read carefully and **tick (√)** the appropriate column for each statement as promptly as possible. All information gathered shall be used purely for research purpose and shall be treated with confidentiality.

Thank you so much for kind cooperation

Sincerely

Mimma Akter

Department of Marketing

Comilla University

Demographic Questions

Gender: 1. Male 2. Female

Were you born between 1995 and 2010? ☐ Yes ☐ No

Age: ☐ Under 18 ☐ 18-20 ☐ 21-23 ☐ 24-26

Proffered OTT platform: ☐ Netflix ☐ Amazon prime video ☐ Chorki ☐ Bongo ☐ Hoichoi

Q: How Many episodes of a program you usually watched in one setting?

☐ 1 episode at a time ☐ 2 or 3 episode ☐ 4 or 5 episode ☐ over six episode

Q: The amount of time you usually binge watch OTT content?

☐ Less than one hour ☐ 1 to 3 hours ☐ 3 to 5 hours ☐ over five hours

	Escapism: ব্যক্তিগত সমস্যা থেকে মুক্তি পেতে মিডিয়া ব্যবহারের প্রবণতা]					
ES1	I use OTT platform (Netflix, Amazon, prime video, disney plus, Youtube) to escape from my personal problem *(আমি সমস্যার কথা ভুলে যেতে OTT দেখি)*	1	2	3	4	5
ES2	Binge – watching (watching 2/3 episodes in one setting) content on OTT platforms helps me forget about my worries, even temporarily (OTT প্ল্যাটফর্মে ২/৩টি এপিসোড একসাথে দেখা আমাকে সাময়িকভাবে হলেও দুশ্চিন্তা ভুলে থাকতে সাহায্য করে)	1	2	3	4	5
ES3	I Binge - watch OTT content when i feel overwhelmed or stressed (যখন আমি স্ট্রেসড বা চাপে থাকি, তখন OTT কনটেন্ট একসাথে অনেকটা দেখি।)	1	2	3	4	5
	Social Influence (পরিবেশ বা আশেপাশের মানুষ দ্বারা প্রভাবিত হওয়া)					
SI1	People around me have influenced me to use OTT platforms for watching shows. (আশেপাশের মানুষ আমাকে OTT প্ল্যাটফর্মে শো দেখতে উৎসাহিত করেছে)	1	2	3	4	5
SI2	People around me think watching OTT shows help us stay connected (আশেপাশের মানুষ মনে করে OTT শো দেখা আমাদের মধ্যে যোগাযোগ বজায় রাখে)	1	2	3	4	5

SI3	People around me feel it’s important that i stay updated with trending OTT series (ট্রেন্ডিং সিরিজ না দেখলে সামাজিকভাবে পিছিয়ে পড়ি বলে অনেকে মনে করে)	1	2	3	4	5
Entertainment মজাদার এবং আগ্রহী করে তোলা কনটেন্ট উপভোগ করা						
EN1	I find OTT content exciting and engaging to watch OTT কনটেন্ট আমি উপভোগ করি কারণ এগুলো উত্তেজনাপূর্ণ ও আকর্ষণীয়।	1	2	3	4	5
EN2	I am drawn to OTT platform because they provide entertaining content *(OTT-তে মজার কনটেন্ট পাই)*	1	2	3	4	5
EN3	OTT platforms left me watch what i want , when i want OTT প্ল্যাটফর্ম আমাকে যখন খুশি, যেটা খুশি দেখার সুযোগ দেয়।	1	2	3	4	5
	AI Recommendation Quality [পছন্দ অনুযায়ী কনটেন্ট সাজেশন পাওয়া এবং তাতে সন্তুষ্ট হওয়া]					
ARQ1	The recommendation i receive on OTT platforms are highly relevant to my interest OTT প্ল্যাটফর্মে আমি যে সাজেশনগুলো পাই, সেগুলো আমার আগ্রহের সাথে ভালোভাবে মেলে।	1	2	3	4	5
ARQ2	The OTT platforms recommend shows and movies that match my taste OTT প্ল্যাটফর্মে আমাকে যেসব সিনেমা ও শো সাজেস্ট করে, সেগুলো সাধারণত আমার পছন্দ অনুযায়ী হয়।	1	2	3	4	5
ARQ3	I usually enjoy watching the content recommended to me by OTT platforms OTT প্ল্যাটফর্মের সাজেস্ট করা কনটেন্ট আমি সাধারণত উপভোগ করি।	1	2	3	4	5

Binge -Watching						
BW1	I usually spend more time watching shows on OTT platforms that i originally planned (আমি সাধারণত OTT প্ল্যাটফর্মে যতটা সময় দেখা পরিকল্পনা করি, তার চেয়ে বেশি সময় কনটেন্ট দেখি।)	1	2	3	4	5
BW2	I sacrifice my sleep because I spend too much time watching content on OTT platforms (আমি OTT কনটেন্ট দেখার জন্য প্রায়ই ঘুমের সময় ত্যাগ করি।)	1	2	3	4	5
BW3	I frequently feel like watching OTT shows all the time and find it hard to stop (আমি প্রায়ই অনুভব করি যে আমি সারাক্ষণ OTT শো দেখতে চাই এবং শুরু করলে থামাতে কষ্ট হয়)	1	2	3	4	5
BW4	when an episode ends on an OTT platform, I feel a strong urge to continue watching to find out what happens next (OTT প্ল্যাটফর্মে একটি এপিসোড শেষ হলে, পরেরটা কী হবে তা জানার জন্য আমি তাড়িত অনুভব করি আরও দেখতে)					
	Emotional Burnout [দীর্ঘ সময় OTT কনটেন্ট দেখার ফলে মানসিক অবসাদ, বিরক্তি ও সংযোগ বিচ্ছিন্নতা]					
EB1	I feel emotionally exhausted after prolonged OTT content দীর্ঘ সময় ধরে OTT কনটেন্ট দেখার পর আমি মানসিকভাবে ক্লান্ত অনুভব করি।	1	2	3	4	5
EB2	After watching OTT content prolonged, I sometimes feel emotionally numb or detached (অনেকক্ষণ OTT কনটেন্ট দেখার পর আমি মাঝে মাঝে অনুভব করি যে আমি মানসিকভাবে *শূন্য লাগে* বা সংযোগহীন হয়ে পড়েছি)	1	2	3	4	5

EB3	My communication with people around me has weakened due to prolong watching OTT contents OTT কনটেন্ট দীর্ঘ সময় দেখার ফলে আশেপাশের মানুষের সাথে আমার যোগাযোগ দুর্বল হয়ে গেছে।	1	2	3	4	5
EB4	Binge-watching OTT content has made me more impatient in real life situations আমি দীর্ঘ সময় OTT শো দেখার পর সহজেই রেগে যাই।	1	2	3	4	5
EB5	I get irritated easily after spending long hours watching OTT shows: OTT কনটেন্ট একসাথে অনেকক্ষণ ধরে দেখার ফলে বাস্তব জীবনের পরিস্থিতিতে আমার ধৈর্য কমে গেছে।					