MODELING THE EPIDEMICS OF INTERNET GAMING DISORDER WITH SYSTEM DYNAMICS APPROACH

by

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ABSTRACT

MODELING THE EPIDEMICS OF INTERNET GAMING DISORDER WITH SYSTEM DYNAMICS APPROACH

Over the last three decades, video game companies have invested heavily in attracting and retaining gamers in the online world to obtain significant market share. The accessibility of online gaming has contributed to a significant increase in Internet Gaming Disorder defined by the American Psychiatric Association in 2013. Similar to other forms of addiction, it also weakens physical and psychological health, as well as breakdowns in environmental relationships such as family and friends. To explore the global dynamics of Internet Gaming Disorder (IGD), we constructed a population-level system dynamics simulation model covering the COVID-19 pandemic period. Causal relationships among subsectors of gamers, gaming businesses, and streaming with model assumptions, and simplifications are investigated. The model is validated from 2010 to 2022 based on qualitative and quantitative literature. Scenario analyses indicate that the average life of games in the market has a significant impact, affecting the number of addicted gamers within society. The duration of pandemics affects addiction rates differently, with longer durations having diminished effects on addiction proportions. Policy interventions targeting parameters like the "Neutral Gamer Fraction" result in substantial reductions in addicted gamer ratios. A combined policy with multiple parameters is shown to be effective in controlling the addicted gamers. Future research avenues may involve refining model assumptions, exploring alternative mitigation strategies, and developing individual-level system dynamics models to gain deeper insight.

ÖZET

İNTERNET OYUN OYNAMA BOZUKLUĞU YAYILMASININ SİSTEM DİNAMİĞİ YAKLAŞIMI İLE MODELLENMESİ

Son otuz yıldır, video oyun şirketleri pazar payına sahip olabilmek adına büyük yatırımlar yaparak oyuncuları çevrimiçi dünyaya çekmektedir. Çevrimiçi oyunların erişilebilirliği, Amerikan Psikiyatri Birliği tarafından 2013'te tanımlanan İnternet Oyun Oynama Bozukluğu'ndaki önemli artışa katkıda bulunmuştur. Diğer bağımlılık türleri gibi, fiziksel ve psikolojik sağlığı zayıflatırken, aynı zamanda aile ve arkadaşlar gibi çevresel ilişkilerde bozulmalara neden olur. Bu bağımlılığın yayılmasının dinamiklerini anlamak için, COVID-19 pandemi dönemini kapsayan nüfus düzeyinde bir sistem dinamiği simülasyon modeli oluşturulmuştur. Oyuncu, oyun ve video içerik yayıncılığı alt sektörleri arasındaki nedensel ilişkiler, varsayımlar ve basitleştirmeler incelenmiştir. Model, nitel ve nicel literatüre dayanarak 2010'dan 2022'ye kadar doğrulanmıştır. Senaryo analizleri, piyasadaki oyunların ortalama ömürlerinin bağımlı oyuncu sayısını en fazla etkileyen parametre olduğu gözlemlenmektedir. Özellikle, pandemilerin süresi bağımlılık oranlarını farklı şekilde etkilediği ve sürenin uzamasıyla bağımlı oyuncuların diğer oyuncular arasındaki görünürlüğünün azaldığı dikkat çekmiştir. "Nötr Oyuncu Kesiri" gibi parametrelere yönelik politika müdahaleleri, bağımlı oyuncu oranlarında önemli azalmalara yol açmaktadır. Bağımlı oyuncuların kontrol edilmesinde etkili olduğu gösterilen çoklu parametreli bir politika uygulanmaktadır. Gelecek araştırma alanları, model varsayımlarını iyileştirme, alternatif bağımlılığı azaltma stratejilerini keşfetme ve daha derin bir anlayış elde etmek için bireysel düzeyde sistem dinamiği modelleri geliştirme olabilecektir.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS/ABBREVIATIONS

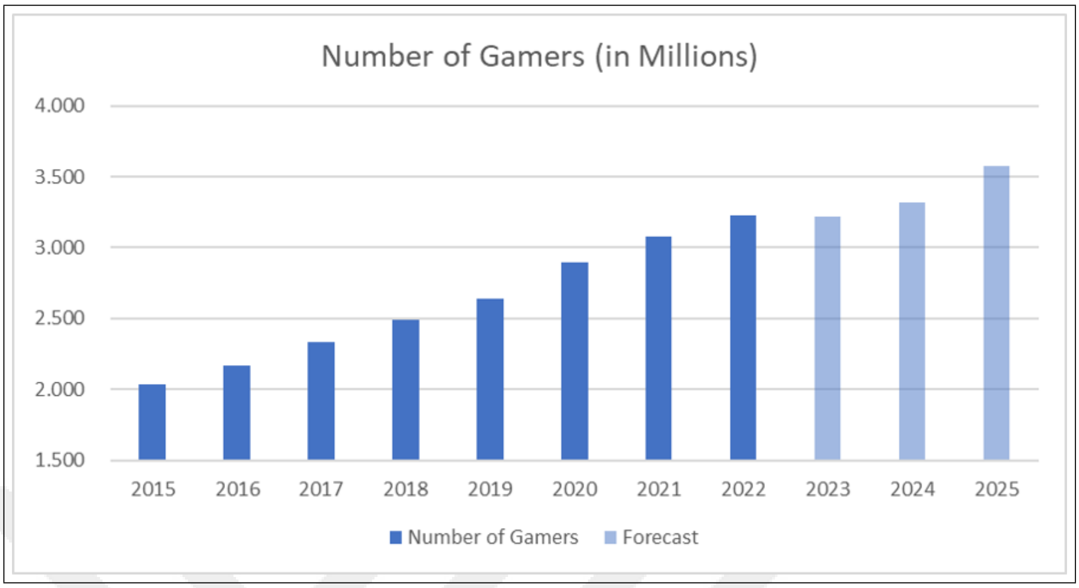
APA	American Psychiatric Association
Bn	Billion
DSM	The Diagnostic and Statistical Manual of Mental Disorders
FPS	First Person Shooter
IGD	Internet Gaming Disorder
I-PACE	Interaction of Person-Affect-Cognition-Execution
MMO	Massive Multiplayer Online
MMOGs	Massive Multiplayer Online Games
MMORPG	Massive Multiplayer Online Role Playing Game
PC	Personal Computer
PEAR	Potential-Engaged-Addicted-Recovers
RPG	Role Playing Game
SEIR	Susceptible-Exposed-Infected-Recovered
SIR	Susceptible-Infected-Recovered
WHO	World Health Organization

1. INTRODUCTION

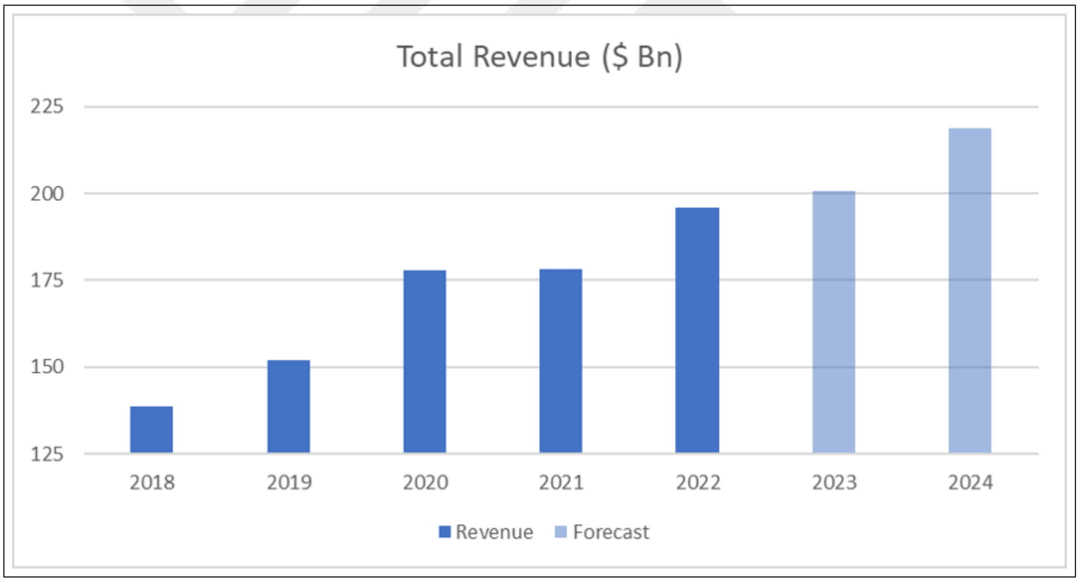
Video gaming has evolved significantly since the coin-operated arcade gaming machines located in gaming centers where people gathered to play and socialize. Over the last decades, digital gaming machines have become more accessible and compact such as home consoles and personal computers. Today, gaming hardware has become a lot more portable and powerful as people can play sophisticated video games anytime on different platforms like mobile phones, tablets, and personal computers (PC). New technologies like virtual reality and augmented reality introduced new experiences that were unimaginable decades ago. This technological accessibility which enables gaming across different platforms contributes to the global increase in the number of gamers.

Newzoo is a prominent provider of market intelligence and data analytics services that focuses on gaming, sports, and mobile industries. Various gaming industry stakeholders, such as game creators, publishers, hardware manufacturers, and investors, are served by this company with reports including insightful information. According to Newzoo Market Reports, even though there were 2.03 billion gamers in 2015, the number of gamers is expected to reach 3.5 billion people by 2025 [1–4] as indicated in Figure 1.1a. In 2022, there were more than 3.2 billion gamers across the world [4] as illustrated in Figure 1.2a. With the increasing number of gamers, the gaming market share has also expanded over the last decades. As Figure 1.1b shows, the global games market generated $184.5 billion in 2022 [4].

Video games are classified into different types based on the platforms for which they are designed. These can be broadly categorized into five main types: smartphone games, console games, downloaded PC games, tablet games, and browser PC games. According to Figure 1.3b, smartphones dominate the video game platform by accounting for 50% of the global market, with a projected revenue of $92 billion [4]. The remaining revenue is distributed between PC games and console games.



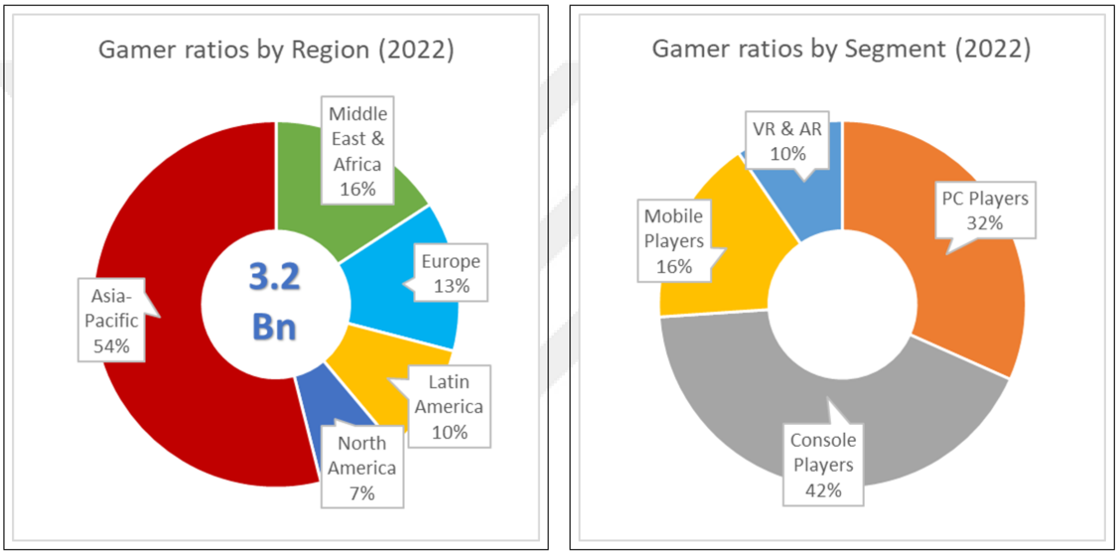
(a) Number of gamers



(b) Revenue

Figure 1.1. Forecasts for gaming industry (data from [1–4]).

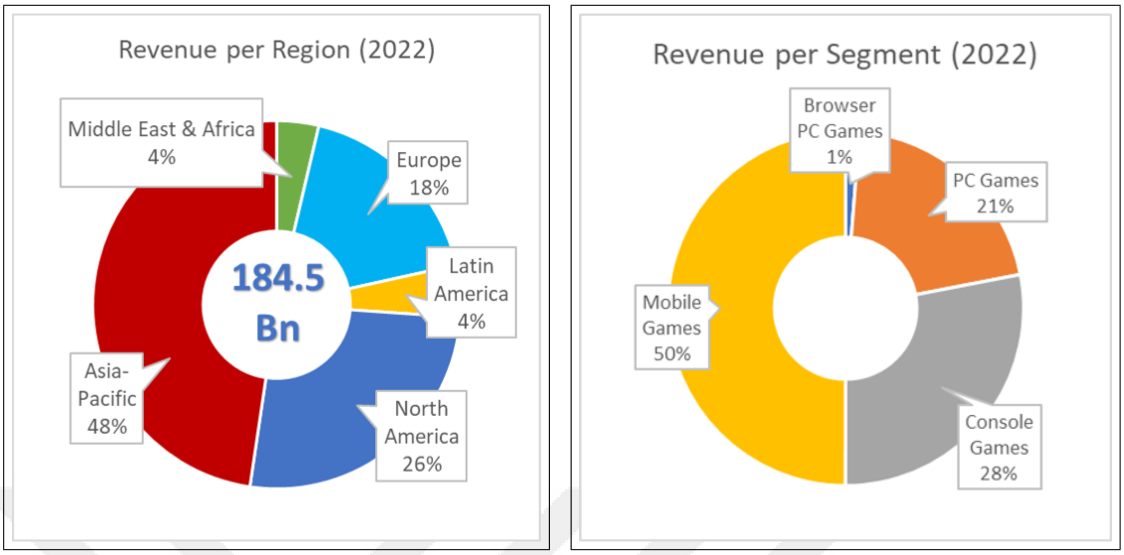
In the rapidly evolving world of digital entertainment, our interactions with virtual worlds and other global players have changed as a result of the popularity of PC games. These games can be classified as single-player or multiplayer. Within the multiplayer category, the connection between players can be either offline or online. Online games surpass geographical boundaries as they combine advanced technology and compelling storytelling to enable players to engage in action-packed missions and brutal fighting. The world of online PC gaming provides an extraordinary opportunity for social interaction and entertainment. It allows lasting bonds between players in online communities. With its attractive visuals and addictive gameplay, it keeps modifying the concept of interactive entertainment as a rapidly growing industry. For these reasons, over the last decade, both the number of PC gamers and the market value of online PC games have consistently increased. In 2022, the market value of online PC gaming reached $42 billion, with nearly 1.8 billion PC gamers [5, 6].



(a) Number of gamers per region (b) Number of gamers per segment

Figure 1.2. Number of gamers worldwide (data from [4]).

The sustained growth in revenue has led to an increase in the prevalence of online gaming. This provides everyone with access to a wide range of game genres, including strategy, adventure, memory, casual, and social games. Moreover, these games have a significant impact on people's lives as they provide opportunities for social interaction, learning, stress relief, exploration, and skill development. Thus, they have transformed into experiences beyond simple games. Adventure games offer a way to confront personal fears, memory games improve cognitive skills, and social games encourage cooperation and communication [7].



(a) Total revenue (b) Revenue by segment

Figure 1.3. Gaming industry revenue (data from [4]).

The most common reasons for playing video games according to global gaming audiences as of the 4th quarter 2020, by PC/laptop are illustrated in Figure 1.4.

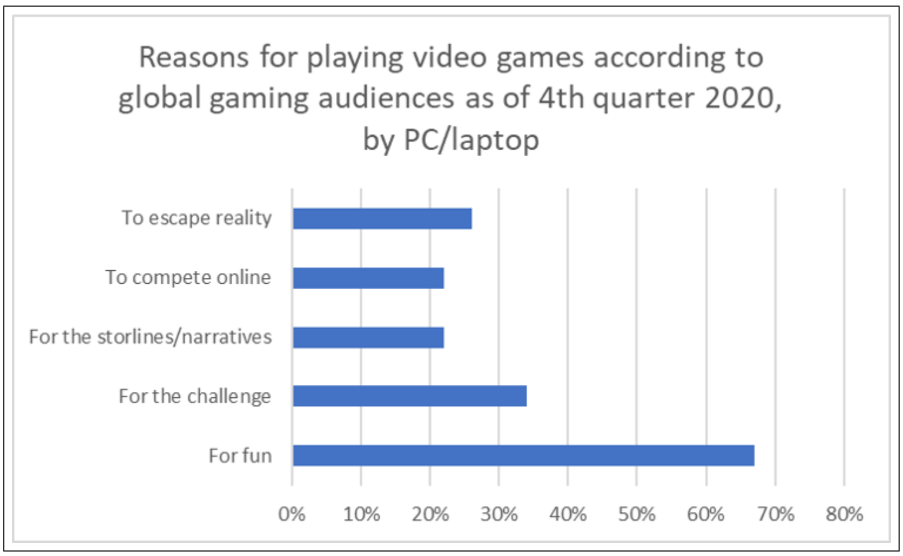


Figure 1.4. Reasons for playing video games (data from [8]).

Numerous video game genres are released on the market, aiming to captivate players with a variety of interests and personalities. The Newzoo Gamer Segmentation report outlines various personas based on gaming, viewing, and social behavior characteristics of gamers, to illustrate the shifts in engagement within the gaming market [9]. These personas are defined as below:

- Ultimate Gamers are individuals who are dedicated to gaming, collecting, networking with others, and watching gaming content.
- All-Round Enthusiasts are passionate about all aspects of gaming, however, their level of enthusiasm is slightly less than that of Ultimate Gamers.
- Time Fillers are those who typically engage in casual gaming during downtime or on social occasions, predominantly using mobile platforms.
- Bargain Buyers are those who choose to play high-quality games for a low price or for free, and they only invest in hardware when it is necessary.
- Community Gamers are those who not only enjoy playing but also actively participate in group discussions, podcasts, forums, news, and videos related to gaming.
- Hardware Enthusiasts constantly strive to improve their gaming experience and stay updated on the latest hardware news and developments.
- Popcorn Gamers are those who play a limited number of games themselves but like watching others play.
- Backseat Viewers are individuals who used to play games a lot but now prefer to watch game content, and 52% of this type of gamers intend to start playing again within the next 6 months.
- Lapsed Gamers are those who once played games frequently but have changed their focus on other interests, and 20% of this type of gamers intend to play again in the next 6 months.

Figure 1.5 demonstrates the distribution of different types of personas. Ultimate Gamers and the all-around enthusiast are the ones who play many hours a week. The ages of the players ranged from 10 to 30, with 28 serving as the median age. In addition, male gamers made up 70% of the players [9]. Understanding the dynamics of age and gender distributions among players has become increasingly important in the field of the gaming sector. Exploring the subtleties of age and gender differences in gaming preferences provides insightful information about the subtle ways that various cohorts engage with virtual environments. The information in Figure 1.6 illustrates the distributions of playing times based on different age groups.

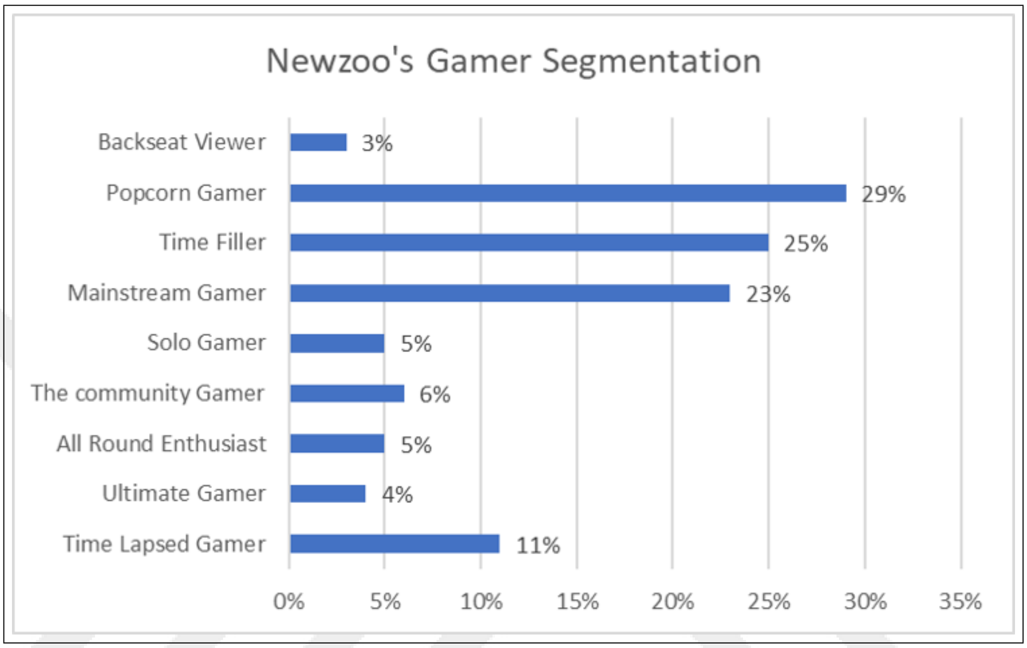


Figure 1.5. Newzoo's gamer segmentation. (data from [9]).

In terms of average duration and weekly frequency of sessions, player types can also be expressed as moderate, tenacious, frequent, and heavy players [10]. The time spent in gaming is an important indicator of internet gaming addiction. Especially among children and teenagers, the fastest-growing form of Internet addiction is Massive Multiplayer Online Role Playing Game (MMORPG) [11]. In the category of social games, massive multiplayer online (MMO) games provide interaction with other players since people can achieve tasks and level up faster by creating a party of a limited number of online friends and in guilds created with an unlimited or limited number of online players. By playing MMORPG, people create a character related to the story of the fantasy world. The popularity of these games has increased over the last decades [12]. Alongside playing multiplayer online games, playing First Person Shooter (FPS) games and time spent on watching video gaming content are also important indicators and contribute to addiction [13].

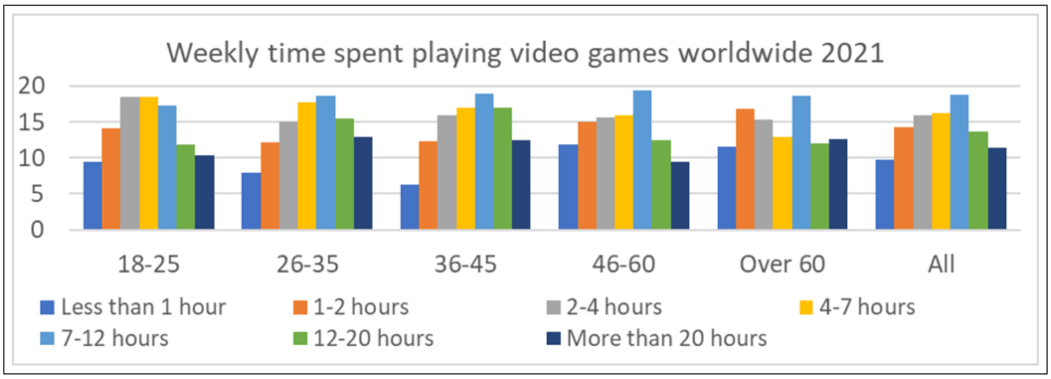


Figure 1.6. Average weekly time spent playing video games worldwide (data from [14]).

With the worldwide popularity, game addiction is causing a serious social problem [15]. Game addiction has classic signs of addiction because game addicts become preoccupied with gaming, unable to control their use, lose interest in activities other than gaming, withdraw from relationships with family and friends, and use games for psychological escape [11, 16, 17]. Hence, online game addiction can cause undesirable consequences since game addicts may play for more than ten or twenty hours and, in the meantime, they intentionally might not sleep, eat, and interact with offline friends to play more [11]. In 2013, the American Psychiatric Association (APA) published Internet Gaming Disorder (IGD) in the 5th edition of The Diagnostic and Statistical Manual of Mental Disorders (DSM-5). IGD is indicated if five or more symptoms of the following criteria set are observed [18]:

- Preoccupation with internet games,
- Withdrawal symptoms when the internet is taken away,
- Tolerance as the need to spend an increasing amount of time engaged,
- Unsuccessful attempt of control the participation in games,
- Loss of interest in other activities,
- Continued excessive use despite knowledge of psychosocial problems,
- Deceiving other people about the amount of Internet gaming,
- Use of Internet games to escape and relieve a negative mood like guilt and anxiety,
- Jeopardizing a significant relationship, job, educational, or career opportunity.

This research aims to construct a population-level model of Internet Gaming Disorder consisting of three sectors (gamer sector, gaming business sector, and streaming sector) to find out the long-term effects of addictive game genres, streamed video gaming content, and treatment. In these terms, the more addictive gaming genres of FPS and MMORPG are chosen. The two main streaming platforms, YouTube Gaming and Twitch, are utilized in our simulation model. For this study, the model is established using data gathered from the Twitch streaming platform which is dominant in the industry. After validating the reference dynamics of the gamer population in the world, scenarios and policies with different characteristics are investigated to observe their effects on the number of addicted gamers. With the help of dynamic simulation models with a systemic approach, future research on successful strategies and preventative policies is likely to benefit from an understanding of the potential links to addiction.

In the second chapter, the literature about IGD is summarized. Next, the objective of the study and research methodology are explained. The compatibility of the system dynamics approach for population-level IGD modeling is emphasized. The fourth chapter provides an overview of the model and the key causalities between different factors. In the fifth chapter, stock-flow diagrams are presented with mathematical equations of parameters based on data acquired and assumptions. The sixth chapter examines, tests, and validates the model. After obtaining the base run, the seventh chapter investigates the model sensitivity to different parameter values and initial conditions. The eighth chapter focuses on the association between various gaming factors and Internet Gaming Disorder (IGD). Subsequently, different scenarios and policy interventions are explored. Finally, a summary of the findings appears in the conclusion chapter.

2. LITERATURE REVIEW AND RESEARCH OBJECTIVE

In the past decades, with the introduction of video games into our lives, the phenomenon of excessive gaming has been called pathological gaming and game addiction. More recently, it is referred to as Internet Gaming Disorder (IGD). While some researchers focus on developing the psychological and conceptual models of IGD, others examine its prevalence in different age groups, societies and regions. Additionally, some researchers attempt to understand the dynamics of IGD by constructing mathematical and system dynamics models. This literature review will investigate these various approaches and the key findings in the existing literature.

2.1. Psychological Models of Internet Gaming Disorder

Since 2001, models of Internet game use and Internet Gaming Disorder (IGD) have been developed and refined. Three main conceptual models have been analyzed: early cognitive-behavioral, neurocognitive, and multidimensional approaches. Davis built a framework for an early cognitive-behavioral model that focuses on the development of pathological Internet game use according to two different types called generalized use, and specific use such as online gaming [19].

According to Davis, the psychopathology of the individual like depression reinforces the maladaptive cognitions, which can be divided into two categories, thoughts about the self and thoughts about the world. Moreover, the maladaptive cognitions directly affected pathological internet use. People behave vulnerably to online shopping to get positive feedback from others and correct their images if thoughts about the self are related to negative self-concepts like self-doubt, low self-efficacy, and negative self-appraisal. As a result, to have positive social feedback for the online self and be better than the real-world self, users are encouraged to spend more time with online activities [19].

Dong & Potenza proposed a conceptual IGD model based on neuroimaging studies on gaming behavior which is developed with the knowledge learned from neurocognitive studies on substance and nonsubstance addictions. The model suggests that the online gaming experience changes brain structure and its functioning, and hence, related cognitive processes. According to Dong & Potenza, three key factors play important roles in addictive gaming: motivating, inhibiting, and weighing. Firstly, reward sensation and stress relief work as motivational factors that reinforce IGD behavior. Secondly, executive control means behavioral control which is an inhibitor factor. Finally, decision-making between short-term pleasure and negative long-term influences works as a factor weighing pros and cons. As a result, these factors result in an individual's behavior [20]. Brand et al. proposed the Interaction of Person-Affect-Cognition-Execution (I-PACE) model to explain Internet use disorders such as IGD. They state that a person's core characteristics such as personality, psychopathology, social cognitions, specific motives, coping style, and biopsychological constitution shape effective and cognitive responses including craving, attentional biases, and urges for mood regulation. Decisions to play games by reducing executive functions and inhibitory control and cognitive responses result in gratification and compensation which also reinforces use. Hence, I-PACE is a multidimensional model compared to other models [21]. According to King & Delfabbro, 'a review of these models reveals that problematic gaming as a condition had been alternately conceptualized as its own distinct disorder, like gambling disorder, as well as a subtype of Internet use disorder' [7].

2.2. Prevalence of Internet Gaming Disorder

Especially before the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) was published, lots of studies about the prevalence of IGD were based on different diagnostic methods with a variety of criteria sets. Considering the rapid expansion of gaming technology over the past two decades, a review of prevalence measurements between 1998 – 2016 reports IGD prevalence range from 0.70% to 15.60% [22]. A systematic review of cross-sectional and longitudinal epidemiological studies of IGD reveals the prevalence range from 0.70% to 27.50% [23]. A systematic review based on studies between 1991 and 2016 suggests IGD prevalence ranges from 0.60% to 50.00% with a median prevalence of 5.5% [24]. Finally, based on criteria set published in DSM-5, a systematic review of 160 studies with 35 different methods to diagnose IGD shows that 'the prevalence of IGD ranged from 0.21% – 57.50% in general populations, 3.20% – 91.00% in clinical populations, and 50.42% – 79.25% in populations undergoing intervention' [25]. The systematic review of Darvesh et. also reveals that the prevalence range of IGD by population type can also differ according to the World Health Organization (WHO) regions such as Eastern Mediterranean (9.20%), European (0.21% – 33.33%), region of the Americas (0.25% – 38.90%), Western Pacific (1.20% – 57.20%), and multiple regions (0.56% – 5.28%); gender as male (0.21% – 57.50%) and female (0.25% – 26.09%); age groups as children (0.26% – 38.00%), adolescent (0.26% – 38.00%), and adults (0.21% – 55.77%) [25].

2.3. The Epidemics of Internet Gaming Disorder

As the number of gamers and internet users increases each year steadily, the number of people suffering from IGD will also increase. Many researchers are interested in discovering how many more people will be addicted to internet gaming. To make predictions and understand the behavior of such systems, epidemiological models can be used such as Susceptible-Infected-Recovered (SIR) models with numerical and system dynamic simulation methodologies.

There are several mathematical models of the population-level dynamics of internet gaming. Li and Guo examine stability and optimal control of online game addiction and simulate with a model constructed by four compartments: susceptible, infective, professional, and quitting [26]. Li and Guo also developed a new model to observe the impact of family education on the spread dynamics of online gaming addiction through numerical simulations [27]. Another study is developed to explore the importance and effects of an education campaign and family understanding by creating a mathematical model based on the transition of potentially addicted, addicted, temporarily quitting addicted, and permanently quitting addicted gamers [28]. Seno explains a mathematical model of population dynamics of IGD with a system of ordinary differential equations with three stages of internet gamers' state: moderate, addictive, and under treatment. The transition between the moderate and the addictive stages is influenced by the social nature of internet gaming so increasing online social interaction leads to addiction [29]. The Potential-Engaged-Addicted-Recovered (PEAR) model is the mathematical modeling of the spread of addiction to electronic games with four stages: potential gamers, engaged gamers, addicted gamers, and recovered gamers [30]. Some studies analyze the online game addiction problem of junior high students and university students with the Susceptible-Exposed-Infected-Recovered (SEIR) model which consists of susceptible, exposed, infected, and recovered a group of students [31]. Another study focuses on analytical models that categorize the Massive Multiplayer Online Games (MMOGs) into simple, competitive, and complimentary to estimate the number of gamers and provide insights into the temporal evolution of games [32].

Early system dynamics studies in the addiction field are primarily focused on topics such as problematic alcohol use, drug misuse, and problematic gambling. With the increasing penetration of the internet, internet-related addictions become a significant form of dependency. Especially, after the American Psychiatric Association (APA) defined IGD in DSM-5, the studies about internet-related addictions have increased. However, there are still limited studies in the system dynamics field. Park and Ahn explore and suggest policy changes for dealing with online game addiction and its societal implications by using a system dynamics methodology [15]. Another internet-related addiction is excessive media usage which has similarities to IGD. By using the system thinking approach, Hwang et al. examine the causal structure of adolescent media addiction analyze and analyze policies such as shutdown policy and deregulation [33]. Another subject that might provide insight is the dynamics of the game market. Brammer and Viehweger looked at the parameters influencing the sharp increase in player numbers in social browser games on websites like Facebook to comprehend how game design, marketing, and support processes affect player motivation and pleasure. Their model explains how well social networks could be used to test intricate dynamic models and create a game prototype for deeper understanding [34].

Wang explores the growth and competition dynamics of the online game market in Taiwan considering the effect of Research and Development capacity [35].

3. PROBLEM DEFINITION AND RESEARCH METHODOLOGY

Since the late 90s, with the development of new technologies, video gaming companies have been investing more money in order to attract potential gamers into their online world and prolong their online engagement. While the primary goal for companies may be to capture a great market share, the effects of increasing the number of gamers and keeping them online are not innocent, as video gaming may become problematic for some individuals. Problematic gaming has been receiving attention since it is classified as a mental disorder called Internet Gaming Disorder (IGD) in The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) by the American Psychiatric Association (APA). Even long before it was classified as a mental disorder, there were studies about dynamics of the problematic gaming in countries that faced the negative consequences of increasing the number of players who suffer from excessive gaming. While long hours spent without sleeping, poor sleep quality, mood changes, depression, anxiety, poor health, and isolation from the world are the negative consequences on the addicted gamer, there are also effects on the addicted gamers' environment as conflicts with family and friends, divorce, loss of workforce and productivity, school absenteeism and dropout, and financial trouble [7].

Researchers utilize epidemiological models such as the Susceptible - Infected - Recovered (SIR) model to predict and comprehend prevalence of addiction. Various mathematical models explore the dynamics of IGD, addressing stability, optimal control, family education impact, and addiction transitions [26–32]. System dynamics studies initially focused on traditional addictions but have expanded to address internet-related dependencies. Insights into the dynamics of the game market and media addiction are explored using system thinking approaches [15, 33–35]. Despite the increasing prevalence of IGD, there is scarce research with the system dynamics methodologies in this field. Therefore, we aimed to conduct a detailed study on the subject of epidemics of IGD, also considering the impact of the pandemic.

This study focuses on simulating the dynamics of worldwide epidemics of IGD to understand the interactions among subsectors of gamers, gaming businesses, and streaming. A long-term quantitative model at population-level is constructed using system dynamics methodology. In the literature, most papers investigate the IGD on adolescents and young adults. Thus, we determine the focus age group as 10 to 30. Following the establishment of a model that exhibits the real gamer population dynamics, validation is performed for the years spanning 2010 to 2022. Subsequently, an analysis of the model is provided, system behavior is evaluated across various scenarios, and the impacts of potential policies are investigated. From a methodological perspective, the constructed model will serve as an extension to the existing epidemiological models of gaming disorder to account for more complex cases and interconnected subsectors. The model can be as a valuable tool for decision-makers, facilitating a more profound understanding of the issue and its underlying relationships. Additionally, it is expected to serve as a testing platform for the evaluation of various policies.

The progression of changes in the addicted gamer population involves numerous subsystems, presenting a significant challenge in predicting the behavior of this intricate system. Given its complex structure with many nonlinear dynamics, the objective is not to make point estimates but to project dynamic patterns. System dynamics methodology emerges as a promising tool for studying internet gaming disorder. It helps analyze many scenarios and policies involving external and/or internal factors. This methodology is based on direct causal relationships, focusing on feedback mechanisms and their resulting dynamics. Once the problem is defined with the appropriate relationships, a stock-flow diagram is constructed using mathematical relationships and available numerical data to simulate the problem. Therefore, it is suitable for large-scale systems with many causal loops, nonlinearities, accumulations, and delays. It facilitates the simulation of interactive feedback loops, providing a holistic representation of complex problems whose behaviors cannot be obtained solely through mathematical analysis. The application of system dynamics allows for testing systems, understanding their structures, and formulating policies. Simulations help researchers and decision-makers anticipate the consequences of their choices and make more informed decisions.

After defining the model boundaries, a causal loop diagram is used to visually represent the parameters and their interrelationships (see Figure 4.1). In the system dynamics methodology, these diagrams capture both negative and positive causal relationships between parameters. When applying this methodology to model the epidemics of IGD, the process involves specifying parameters and relationships through mathematical equations and graphical functions. The stock-flow diagram, a standard tool in system dynamics modeling, enables a quantitative representation of the problem (see Figure 4.1 and 5.4). Within this modeling framework, stocks are the accumulations that characterize the state of the system. Flows, on the other hand, determine the changes in the behavior of stocks over time. Converters influence flows and other converter parameters through equations based on stock variables. These effects are often nonlinear, particularly when addressing complex feedback problems like the population dynamics of IGD.

4. OVERVIEW OF THE MODEL

Thus far, the background and general structure employed for modeling Internet Gaming Disorder (IGD) epidemics have been presented. Moving forward, the model structure will be explained. As gaming became more popular and sophisticated, there has been a notable increase in the number of individuals who dedicated their time to gaming. After 2013, the American Psychiatric Association (APA) defined IGD as a form of addiction in The Diagnostic and Statistical Manual of Mental Disorders (DSM-5), and the focus on this issue amplified.

Figure 4.1 demonstrates a simplified version of the stock-flow diagram. The model is essentially built upon the conventional Susceptible-Exposed-Infected-Recovered-Quitted (SEIRQ) epidemiologic model. Fundamentally, in our model, there are eight stocks within the population:

- Potential Gamers (S): Individuals who do not engage in gaming activities,
- Beginner Gamers (E): Individuals who have been exposed to gaming through word of mouth and advertisements. Infect contacts (Ci) and advertisement effectiveness (a) parameters are calibrated based on the Bass Diffusion Model for innovation [36],
- Neutral Gamers (N): Individuals in this group play games for less than one hour weekly. Their gaming activity can be considered minimal and does not significantly impact their daily routines,
- Moderate Gamers (M): Individuals who display a moderate level of engagement in gaming. They play games for more than one hour and less than sixteen hours per week but do not exhibit addictive tendencies,
- Pre-Addictive Moderate Gamers (PI): Individuals in this group are characterized by their tendency towards gaming addiction. They engage in gaming activities for more than sixteen hours and less than twenty hours per week and may display signs of addictive behavior,

- Addicted Gamers (I): Individuals who have developed a gaming addiction. They play games for more than twenty hours per week, indicating an important impact on their daily lives. According to investigations of King et al., playing video games for thirty hours or more a week usually has negative effects on most users. These effects include upsetting daily obligations and routines, and missing out on opportunities for healthy growth, especially for younger users [7],
- Treated Gamers (R): Individuals who were previously addicted to gaming but have undergone treatment or intervention to address their addiction. They have successfully overcome their addiction and no longer engage in excessive gaming behavior. The initial value is assumed to be zero at the beginning since the significance lies in the accumulated value,
- Non-Gamers (Q): Individuals who do not have an interest in gaming and abstain from playing.

Considering the purpose of our model, we have determined the key variables that have been at the center of IGD. The causal structure of the proposed model presents 6 main reinforcing and 4 main balancing loops.

Exposure to Gaming (R1): Potential Gamers (S) commence their gaming journey through word-of-mouth (WoM), and flow into Beginner Gamers (E). Beginner Gamers (E) are then divided into three stocks based on their gaming durations. Individuals who participate in online gaming sessions for less than 1 hour per week flow from Beginner Gamers (E) to Neutral Gamers (N). Over time, Neutral Gamers (N) discontinue playing, with some of the population preferring to quit and others reverting to the Potential Gamers (S).

Moderate Gamers Induced Exposure (R2) & Pre-addicted Moderate Gamers Induced Exposure (R3): An increase in Adoption based on WoM corresponds to a rise in the conversion of Potential Gamers into Beginner Gamers (E). As the Beginner Gamers (E) population grows, there is a subsequent increase in both Moderate and Pre-addicted Moderate Gamers, fostering a feedback loop that further amplifies the

Adoption of WoM. This interconnected dynamic highlights the reciprocal relationship between the adoption process and the prevalence of different gaming states.

Treatment Phase (B1): A rise in the number of Addicted Gamers (I) triggers an increase in the visibility of the disorder. This necessitates an expansion in the capacity dedicated to patients with IGD. Consequently, this expanded capacity contributes to an elevated recovery rate, leading to a reduction in the overall number of Addicted Gamers (I). This phenomenon establishes a balancing loop, where the increased capacity and the subsequent improvement in recovery rates act as a balancing factor.

Adoption From Advertisement (R4): Potential Gamers (S) exposed to advertisements may initiate gaming. Some fraction of these individuals move through Neutral Gamers (N), Moderate Gamers (M), and Pre-addicted Moderate Gamers (PI) to eventually become Addicted Gamers (I). Notably, Moderate, Pre-Addicted, and Addicted Gamers all exhibit spending behavior while gaming, however, the most financial contribution comes from Addicted Gamers (I). Increases in Monthly Advertising Expenses and Advertising Effectiveness is directly correlated with a rise in Monthly Revenue. This positive feedback loop resulting from this interconnected dynamic promotes a continuous increase in the Adoption from Advertisements.

Addictive Genres and New Game Production (R5 & B2): The revenue generated from all of the gamers' spending contributes to increased investments in the Production of New Games, therefore leading to a rise in the Number of New Games in Production. Over time, these new games are released into the market. The impact of more addictive game genres like first-person shooter (FPS) and massively multiplayer online role-playing games (MMORPG) in the market is especially noteworthy, as it leads to a higher percentage of Beginner Gamers (E) moving to the Pre-addicted Moderate Gamers (PI) stock instead of the Moderate Gamers (M) stock. This shift creates a reinforcing loop, amplifying the numbers of Pre-addicted (PI) and Addicted Gamers(I). However, it also creates a balancing loop with the decline in Moderate Gamers(M).

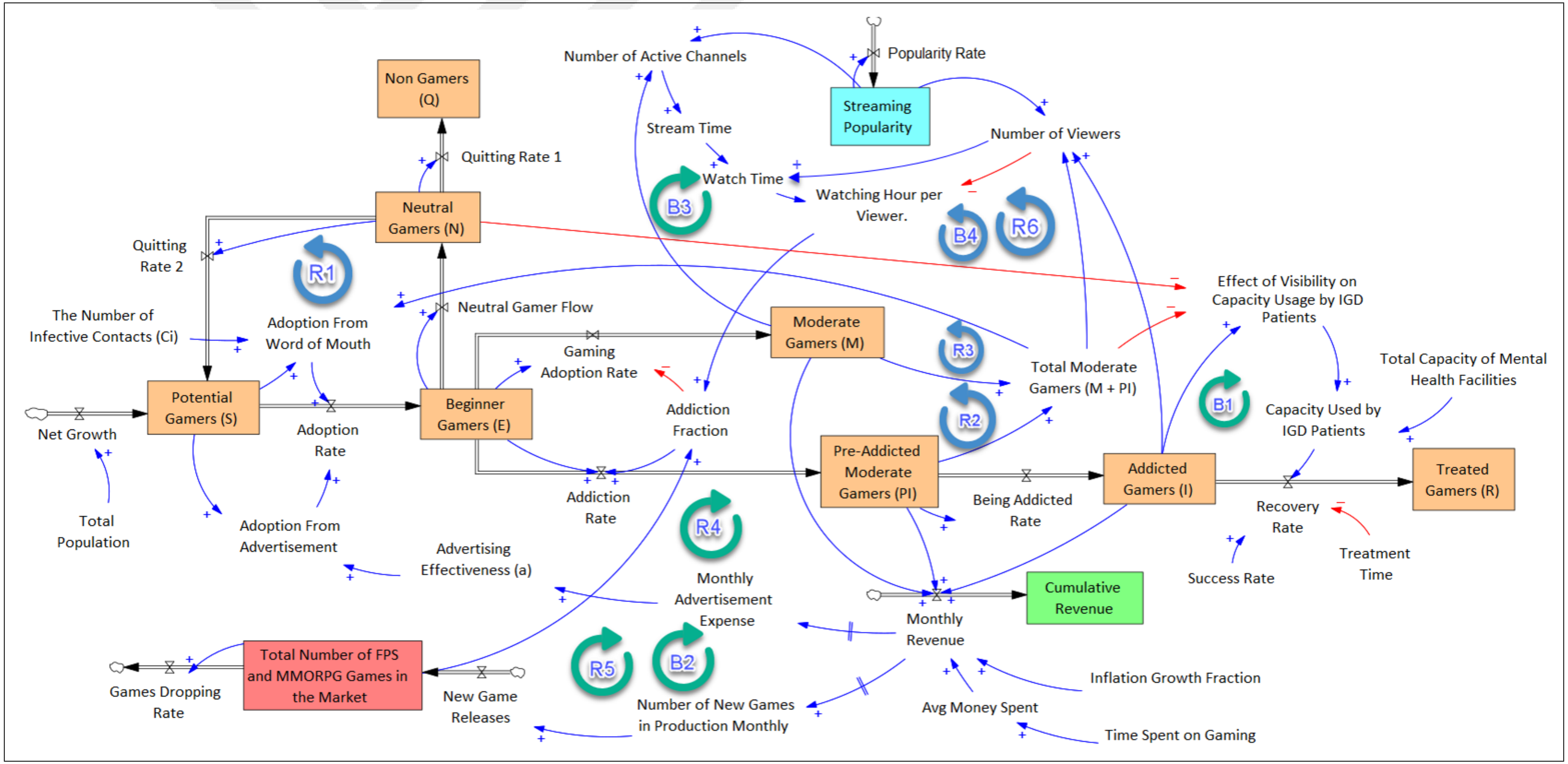


Figure 4.1. The simplified structure of the S-F diagram and causal loops.

Streaming of Video Gaming Content (B3): Moderate Gamers (M) are differentiated by their ability to maintain channels and produce video gaming content through streaming platforms like Twitch and YouTube Gaming. Thus, they contribute significantly to the gaming community. An increase in the population of Moderate Gamers (M) leads to a rise in the total amount of time spent streaming. This heightened streaming activity, in turn, results in an increase in stream-watching hours. One important indicator of a higher addiction fraction among the viewers is the increase in watching hours per viewer. This amplified addiction fraction results in a distinctive pattern. Instead of flowing into Moderate Gamers (M) stock, Beginner Gamers (E) directly flow into the Pre-addicted Moderate Gamers (PI) stock.

Viewership of Video Gaming Content (R6 & B4): In the gaming community, Moderate, Pre-addicted, and Addicted Gamers all share an interest in video gaming content. However, Addicted Gamers (I) notably dedicate more time to this activity. The growth in Addicted Gamers (I) increases the overall watch time of video gaming content which leads to a rise in watch time per viewer which is an important indicator of Internet Gaming Disorder. The increasing watch time leads to an increase in addiction fraction. As the addictive atmosphere intensifies, the reinforcing loop comes into effect and fosters continuous growth in the number of Addicted Gamers (I) instead of Moderate Gamers (M). However, watch time per viewer declines with the increase in the number of viewers which serves as a balancing loop.

5. MODEL DESCRIPTION

The model consists of three sectors: (1) Gamer Sector, (2) Gaming Business Sector, and (3) Streaming Sector. In this section, mathematical equations, and effect functions of each sector are discussed. In addition, the background information and assumptions behind the model are summarized to explain the quantitative representation of variables. Our study aims to examine the long-term dynamics of Internet Gaming Disorder (IGD), thus, the time unit is chosen as a month. The global gamer population, aged between 10 and 30 years old, is simulated within a time horizon of 15 years. After validating our model using time series data from 2010 to 2017, different scenarios are simulated to gain insights into the potential relationships among gamers, gaming business, and streaming, including COVID-19 pandemic effects.

5.1. Gamer Sector

5.1.1. Background Information

Advances in computer technology, especially the widespread use of gaming consoles and personal computers, led to a dramatic increase in the number of gamers. The video game business expanded in the 70s and 80s and became a key component of the entertainment industry together with the development of personal computers. Graphics technology developments added to the interactivity of the gaming experience and supported the industry's ongoing expansion.

The world's interaction has been transformed by the internet's universal integration, which makes it simple for people to interact across borders and cultures. A more linked world has been made possible by the widespread use of online communication tools, which have been essential in promoting digital connections, allowing people to connect. The internet has also changed the video game industry. With the development of online multiplayer games and related online genres, players can interact with one another from anywhere in the world. This connectivity has increased the number of people who play video games as well as making it a more sociable and communal activity. With the increasing popularity of online gaming, the number of online PC gamers reached nearly 1.8 billion in 2022, as shown in Figure 5.1 [5].

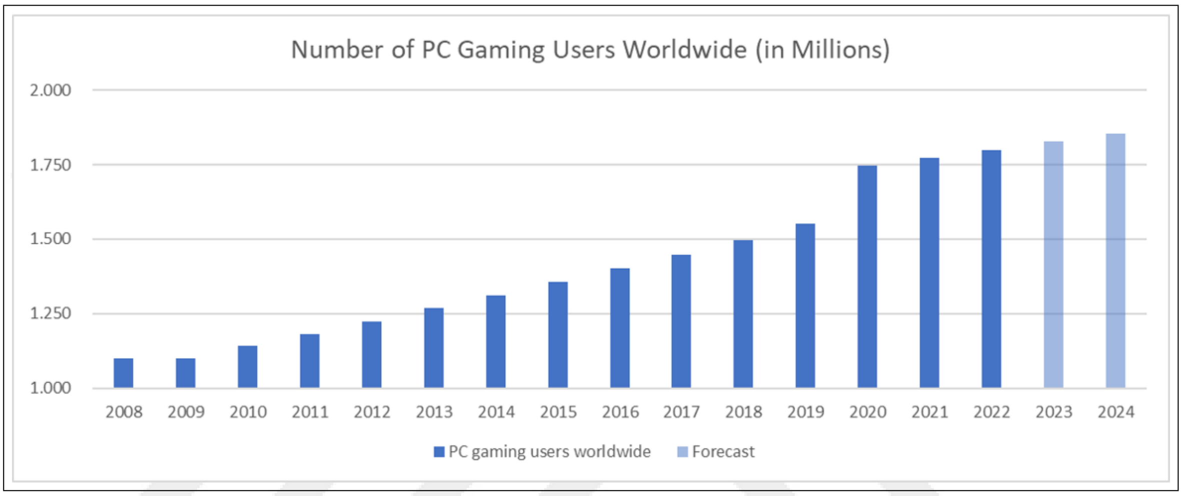


Figure 5.1. Actual and expected numbers of PC gaming users (data from [5]).

Young people in particular are becoming more interested in gaming because of technological advancements. This has increased the accessibility of gaming material which resulted in rising exposure to gaming interactions. Almost 60% of gamers are under the age of 30 [37].

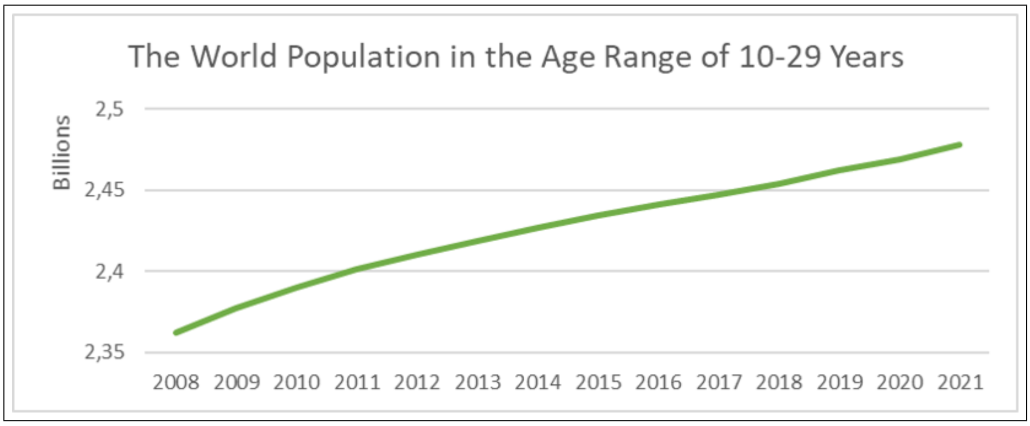


Figure 5.2. The global population categorized by age (data from [38]).

The number of people in this age group has grown from 2,37 billion people in 2008 to almost 2,5 billion people in 2021 [38]. Consequently, this pattern indicates a potential increase in gamers who will be exposed to the expanding diversity of the gaming industry.

Table 5.1. Level of engagement with the online gaming experience (data from [39]).

It is important to find the right fit of players when playing games online	84%
Online gaming has become a larger part of my gaming experience over the past year	76%
COVID-19 has caused more of my social interactions to be conducted via gaming	74%
I expect online gaming to become a larger part of my gaming experience in the future	73%
I have been more involved in gaming communities in the past year	68%

Due to the worldwide catastrophe of the COVID-19 pandemic, many individuals were obliged to stay indoors and find comfort and entertainment. As a result, the gaming industry experienced a boom during this period because more people began to use online games for social interaction and entertainment. Gamers have become more engaged with the online gaming experience in particular because of the rise in social interactions through gaming.

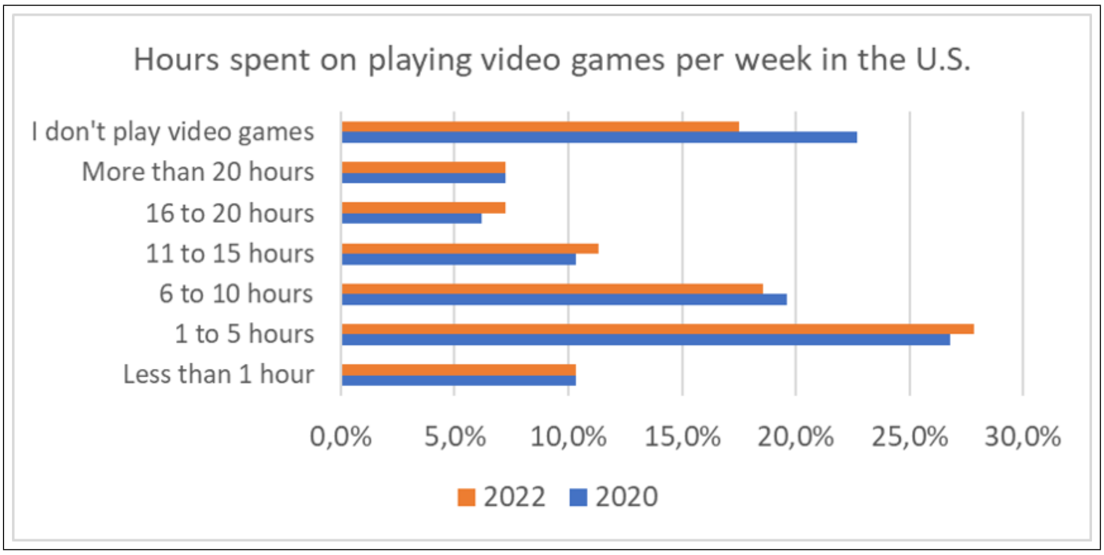


Figure 5.3. Hours spent playing video games per week in the U.S. (data from [40, 41]).

The growth in the level of engagement is concluded by increasing time spent in gaming. Figure 5.3 compares the distribution of hours spent playing video games weekly in the United States between 2020 and 2022 [40, 41].

There are consistent patterns in play times under an hour in the weekly data on video game engagement following the COVID-19 pandemic. On the other hand, there have been modest increases in the 1-5 hour playing time group and a slight decrease in the 6-10 hour playing time group. Interestingly, the 11–20 hour playing time group is expanding. Between 2020 and 2022, the percentage of non-players dropped dramatically from 22.7% to 17.5%. This data also demonstrates that after the pandemic, there was an increase in the number of people suffering from IGD. Excessive internet usage over a year is an important indicator and one of the symptoms of IGD along with tolerance, withdrawal, loss of control, relapse, unfavorable outcomes, and continued use despite awareness of the problem [42].

Passionate gamers usually dedicate 20 to 30 hours a week to playing games without meeting any IGD requirements. Gaming more than 30 hours a week, however, has detrimental effects on the majority of users. Some gamers invest almost 8-12 hours daily in gaming. Excessive video game playing results in missed opportunities, disturbances to and displacement from routine and functioning, including primary responsibilities like work and school, in-person social interaction, and basic activities like eating, sleeping, and taking care of personally. [7].

It is crucial to recognize that excessive gaming can lead to addiction. Specialized centers are implementing various treatment options in response to this developing concern. These therapies demonstrate a broad range of approaches, recognizing the multidimensional nature of gaming addiction. Variations in success are indicated by reports, highlighting the need for customized interventions based on the needs and circumstances of each individual. In 2020, there were 14.5 beds in mental health facilities for every 100,000 people worldwide [43]. For the entire world's population, this means a total of 1,130,245 beds. The utilization of capacity in the U.S. mental health treatment facilities varied for different age groups in 2020. While 56.9% of the capacity served children aged 6 to 12, 64.9% served adolescents between the ages of 13 and 17, and 87.8% served young adults between the ages of 18 and 25 [44].

5.1.2. Sector Structure

In this section, the Gamer Sector in the model is discussed. Figure 5.4 demonstrates the stock flow structure for population stocks of various gamer types and associated mathematical equations. The number of *Potential Gamers (S)* (people) who are susceptible to experience the act of playing a game due to the growing number of the *Total Population* (people). *Net Growth* (people/Month) of population is computed as

$$Net\,Growth = \frac{Total\ Population}{Net\,Growth\ Delay} \times Net\,Growth\,Fraction \tag{5.1}$$

by using *Net Growth Fraction* (unitless) and *Net Growth Delay* (Month). The *Total Population* in the equation above is calculated as

$$\begin{aligned} Total\ Population &= Potential\,Gamers(S) + Beginner\ Gamers(E) \\ &+ Neutral\,Gamers(N) + Total\ Moderate\,Gamers(M+PI) \\ &+ Addicted\,Gamers(I) + Treated\,Gamers(R) + Non\,Gamers(Q) \end{aligned} \tag{5.2}$$

with the use of *Total Moderate Gamers (M+PI)* (people) as a summation of different types of moderate gamers. *Total Moderate Gamers (M+PI)* is calculated as

$$\begin{aligned} &Total\,Moderate\,Gamers\,(M+PI) = \\ &\qquad Moderate\,Gamers(M) + Pre\ Addicted\,Moderate\,Gamers(PI). \end{aligned} \tag{5.3}$$

Adoption from Advertising (A) and *Adoption from Word-of-Mouth (WoM)* are the two ways that people can be exposed to gaming. The *Adoption Rate* is expressed as

$$Adoption\ Rate = Adoption\,from\,Advertising + Adoption\,from\,WoM. \tag{5.4}$$

Within the gaming community, interactions occur at a specific pace that is referred to as the *Contact Rate (C)*. The number of people contacted per person over a given period is called the Contact Rate. The term *Infectivity (i)* describes how likely

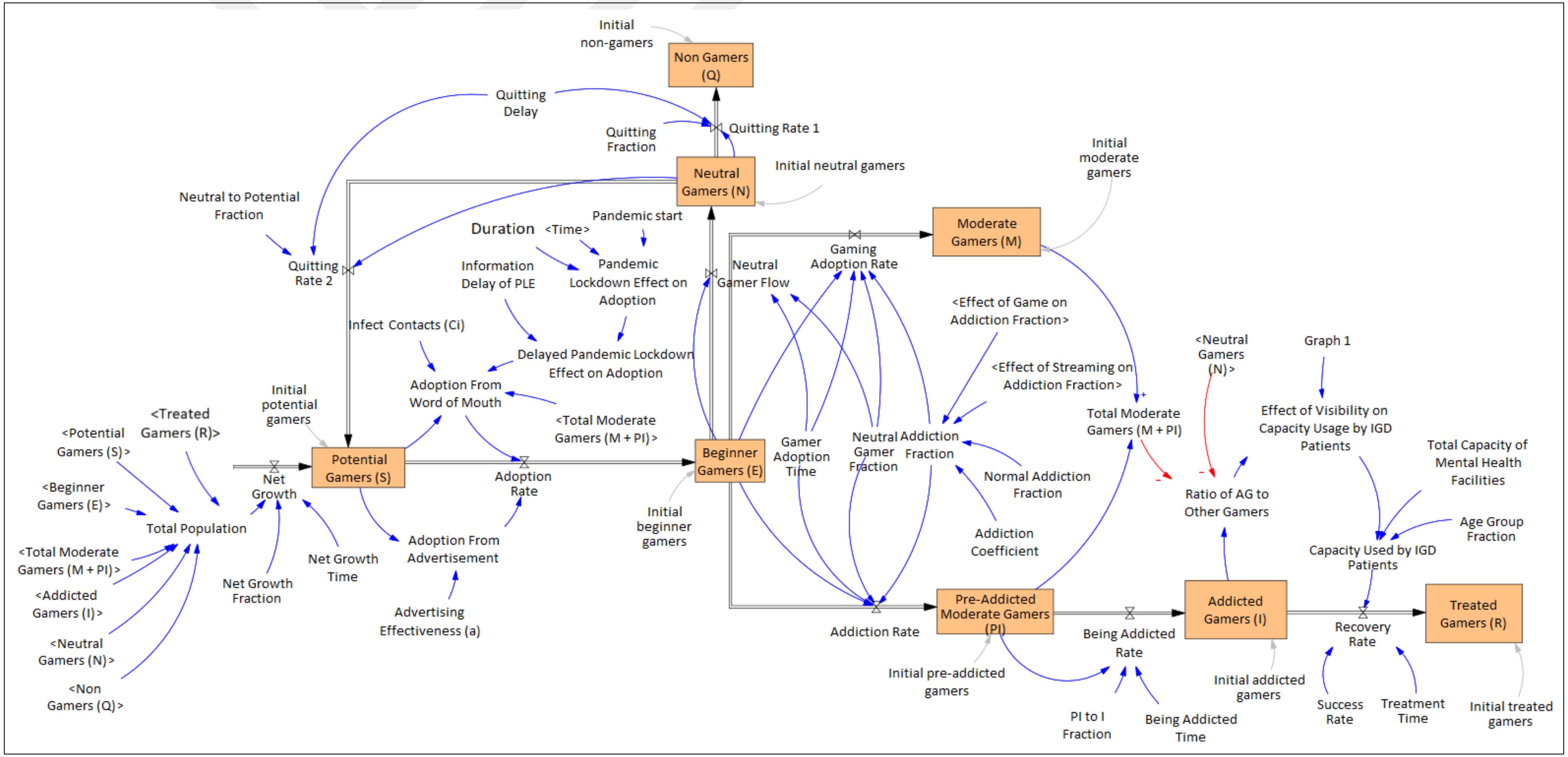


Figure 5.4. Gamer sector and population stocks.

it is for an individual to get a disease after coming into contact with an infectious person [36].

The first way to adopt gaming is through advertisements as the Bass Diffusion Model when innovation is introduced and adopted for the first time. When innovation is first introduced and there is no initial population of adopters, external factors especially advertising, will be the only catalyst for adoption. The impact of advertising will be most pronounced at the onset of the diffusion process and then progressively diminish as the reservoir of potential adopters is depleted [36]. The *Adoption from Advertisement (A)* is represented as

$$A = Potential\,Gamers(S) \times Advertising\,Effectiveness\,(a) \tag{5.5}$$

where *Advertising Effectiveness* (1/month) is the fractional adoption rate from advertising [36].

The second way to adopt gaming for *Potential Gamers (S)* is to contact other moderate gamers with the *Contact Rate (C)*. *Addicted Gamers (I)* do not establish contact with Potential Gamers (S) as they are more engaged in building relationships with fellow gamers. Thus, they are not included in the *Adoption from WoM* equation. Instead of calculating *Contact Rate (C)* and *Infectivity (i)*, we calibrated the *Infect Contacts (Ci)* (People/People/Month) with real data acquired from Newzoo's reports [1–4]. The resulting equation for the *Adoption from WoM* is

$$\begin{aligned} Adoption\,from\,WoM &= Potential\,Gamers(S) \times Infect\,Cont(Ci) \\ &\times \frac{Total\,Moderate\,Gamers(M+PI)}{Potential\,Gamers(S)\,+\,Total\,Moderate\,Gamers(M+PI)} \\ &\times Delayed\,Pandemic\,Lockdown\,Effect\,on\,Adoption \end{aligned} \tag{5.6}$$

by using *Delayed Pandemic Lockdown Effect on Adoption* (unitless) as a third-order delayed version of *Pandemic Lockdown Effect on Adoption* (unitless) which is only valid for the Pandemic period to show the effects on Word-of-Mouth (for detailed explanation see Section 5.4). Moreover, the Equation (5.6) is analogous to traditional Susceptible-Infected-Recovered (SIR) models with "Infected" people including a summation of *Moderate Gamers (M)* and *Pre-addicted Moderate Gamers (PI)* (people).

A constant fraction called *Neutral Gamer Fraction* (unitless) of *Beginner Gamers (E)* only plays less than 1 hour in a week after the first exposure whereas the remaining is split between *Moderate Gamers (M)* (people) and *Pre-addicted Moderate Gamers (PI)* (people) stocks. The distribution is calculated using the *Neutral Gamer Rate* (People/Month). *Gaming Adoption Rate* (People/Month) and *Addiction Rate* (People/Month) flows are modeled as typical fractions and delay equations using average times (Month) as delays.

The *Beginner Gamers (E)* who start playing less than 1-hour weekly flow into Neutral Gamers (N) via *Neutral Gamer Rate* (People/Month) which is calculated as

$$Neutral\ Gamer\ Rate = \frac{Beginner\ Gamer(E)}{Gaming\ Adoption\ Time} \times Neutral\ Gamer\ Fraction. \tag{5.7}$$

There are two outflows from the *Neutral Gamer (N)* (people) stock. Some *Neutral Gamers (N)* flow into the *Non-Gamer (Q)* (people) with the *Quitting Rate 1* (People/Month), while some of them flow into the *Potential Gamer (S)* with the *Quitting Rate 2* (People/Month). These flows are calculated as

$$Quitting\ Rate\ 1 = \frac{Neutral\ Gamer(N)}{Quitting\ Delay} \times Quitting\ Fraction \tag{5.8}$$

and

$$Quitting\ Rate\ 2 = \frac{Neutral\ Gamer(N)}{Quitting\ Delay} \times Neutral\ to\ Potential\ Fraction. \tag{5.9}$$

The ones who start playing more than 1 hour and less than 16 hours weekly flow into *Moderate Gamers (M)* via *Gaming Adoption Rate* (People/Month) is derived as

$$\begin{aligned} Gaming\ Adoption\ Rate = & \frac{Beginner\ Gamer(E)}{Gaming\ Adoption\ Time} \\ & \times (1 - Neutral\ Gamer\ Fraction) \\ & \times (1 - Addiction\ Fraction). \end{aligned} \tag{5.10}$$

The ones who start playing more than 16 hours weekly flow into *Pre-addicted Moderate Gamers (PI)* stock via *Addiction Rate* (People/Month) is quantified as

$$\begin{aligned} Addiction\ Rate =& \frac{Beginner\ Gamer(E)}{Gaming\ Adoption\ Time} \\ & \times (1 - Neutral\ Gamer\ Fraction) \\ & \times Addiction\ Fraction. \end{aligned} \tag{5.11}$$

The value of *Addiction Fraction* (unitless) depends on two parameters: *Normal Addiction Fraction* (unitless) and *Addiction Coefficient* (unitless). The *Normal Addiction Fraction* parameter represents the impact of addictive aspects excluding the effects of FPS and MMORPG games in the market, as well as Streaming. On the other hand, the Addiction Coefficient is a multiplier for the effects of FPS and MMORPG games in the market, as well as Streaming. The *Addiction Fraction* is computed as

$$\begin{aligned} Addiction\ Fraction =& Normal\ Addiction\ Fraction + Addiction\ Coefficient \\ & \times (Effect\ of\ Game\ on\ Addiction\ Fraction \\ & + Effect\ of\ Streaming\ on\ Addiction\ Fraction) \end{aligned} \tag{5.12}$$

utilizing the *Effect of Game on Addiction Fraction* (unitless) which expresses the impact of FPS and MMORPG genre games on the addiction fraction. Similarly, the *Effect of Streaming on Addiction Fraction* (unitless) indicates the influence of Watching Hours per Viewer (Hour/People) on the addiction fraction.

Pre-addicted Moderate Gamers (PI) are the ones who are prone to IGD. Moreover, in time, they might start playing more than 16 hours weekly and become *Addicted Gamers (I)*. *Being Addicted Rate* is derived from

$$\begin{aligned} Being\ Addicted\ Rate =& Pre\ addicted\ Moderate\ Gamers\ (PI) \\ & \times \frac{PI\ to\ I\ Fraction}{Being\ Addicted\ Time}. \end{aligned} \tag{5.13}$$

When a habit of gaming begins to turn into an addiction, whether it is at the request of the addicted people, for health reasons, or due to societal pressure, addicts may need treatment to overcome the problematic gaming. Therefore, various treatment centers worldwide provide interventions to restore their health. The visibility of the addiction plays an important role, especially on the societal pressure. When the proportion of *Addicted Gamers (I)* to other gamers increases, the addiction becomes more visible and turns into a priority. Therefore, the allocated capacity for patients who suffer from Internet Gaming Disorder (IGD) increases. *Recovery Rate* and *Capacity Used by IGD Patients* are determined by

$$Recovery\ Rate = \frac{Capacity\ Used\ by\ IGD\ Patients \times Success\ Rate}{Treament\ Time}, \tag{5.14}$$

and

$$\begin{aligned} Cap.\ Used\ by\ IGD\ Patients =& Age\ Group\ Fraction \\ & \times Eff.\ of\ Visibility\ on\ Capacity\ Usage \\ & by\ IGD\ Patients \times Total\ Capacity\ of \\ & Mental\ Health\ Facilities, \end{aligned} \tag{5.15}$$

where the *Effects of Visibility on Capacity Usage by IGD Patients* (unitless), *Total Capacity of Mental Health Facilities* (People), and *Age Group Fraction* (unitless) are utilized. *Effects of Visibility on Capacity Usage by IGD Patients* is derived from a graphical function of *Ratio of AG to Other Gamers* which is computed as

$$\begin{aligned} & Ratio\ of\ AG\ to\ Other\ Gamers = \\ & \frac{Addicted\ Gamer\ (I)}{Total\ Moderate\ Gamers\ (M+PI) + Neutral\ Gamers\ (N)} \end{aligned} \tag{5.16}$$

by utilizing *Total Moderate Gamers (M+PI)* (people) as summation of *Moderate Gamers (M)* (people) and *Pre-addicted Moderate Gamers (M+PI)* (people).

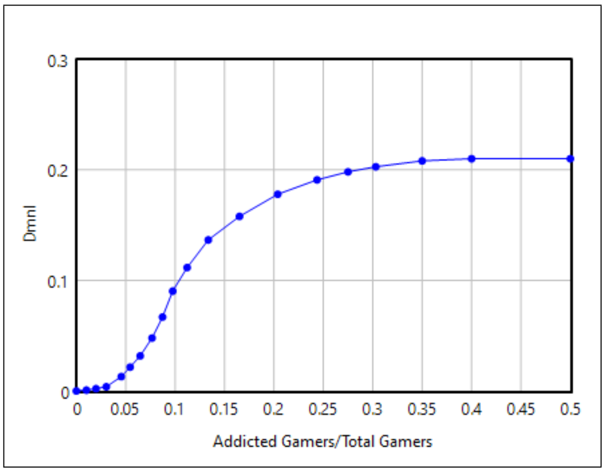


Figure 5.5. Graphical function of effects of visibility on capacity usage.

The S-shape graphical function demonstrated in Figure 5.5 is increasing since the increasing appearance of addiction creates a need to use more capacity. If the proportion of *Addicted Gamers (I)* to other gamers is less than 10%, society might not perceive the addictions as important, however, the climb in proportion forces medical centers to treat IGD patients. Capacity usage is limited to around 20% as it will also be used for other kinds of addictions and psychological diseases.

5.2. Gaming Business Sector

5.2.1. Background Information

Starting from the year 2000, there has been a linear increase in the number of computer games until 2015. The growth rate then accelerated until 2021 and later experienced a decrease in the rate of increase as data presented in Figure 5.6. This indicates the dynamically evolving gaming business with unique stages development stages across time [45].

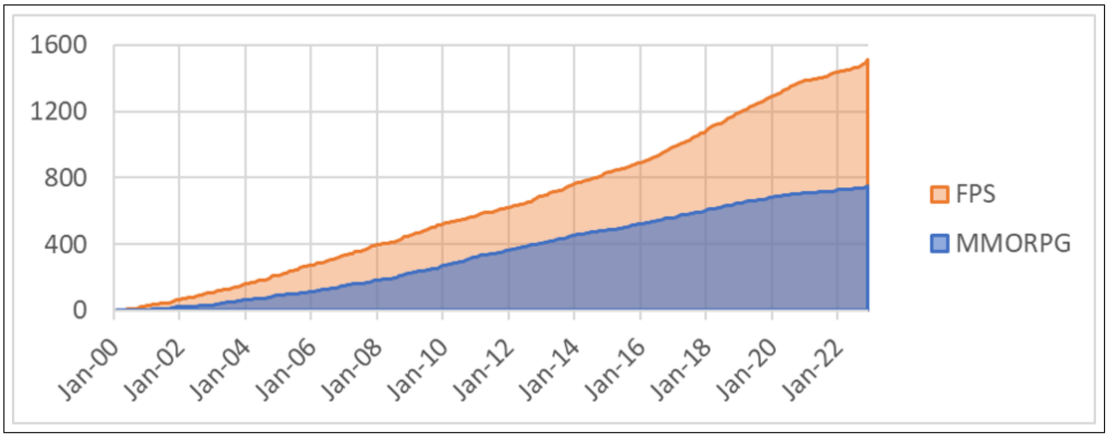


Figure 5.6. The cumulative number of released PC games (data from [45]).

The market value of online PC gaming increased and reached $42 billion in 2022, as indicated by Figure 5.7, due to the rising number of online games and inflation rate [6, 46]. Some of the revenue is allocated to marketing expenses to attract more people into the gaming world.

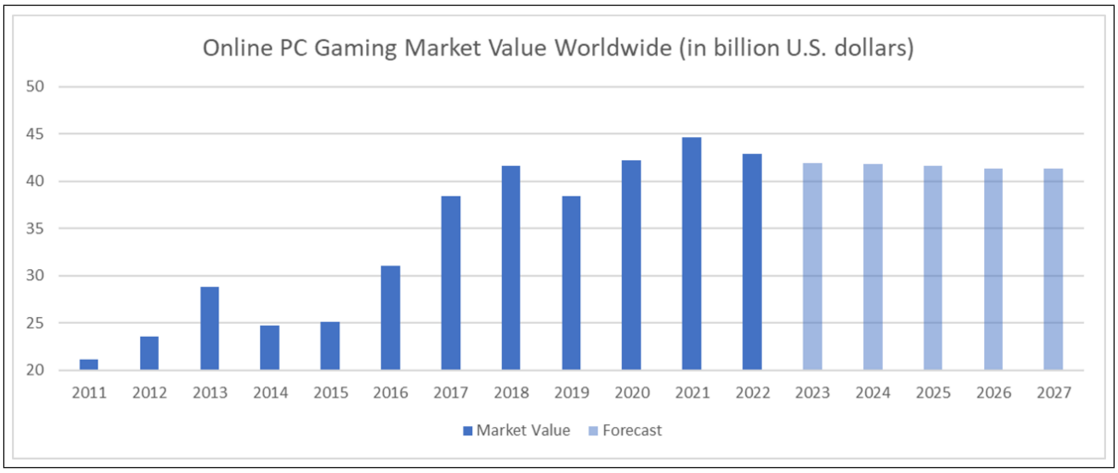


Figure 5.7. Online PC gaming market value (data from [6]).

Every genre has a different share of units sold as the action, shooter and role-playing genres have respectively 27%, 21%, and 11% share of revenue [47]. Among all genres, FPS and MMORPG genres are especially significant as they have been related to IGD [13]. As indicated in Table 5.2, other genres such as RPG, MOBA, adventure, and simulation have less probability of being addictive compared to FPS and MMORPG. These odds ratios in Table 5.2 provide insights into the relationship between gaming genres and IGD status.

Table 5.2. Odd ratios of internet gaming disorder for different genres (data from [13]).

Game Genre	Crude OR (95% CI)
FPS	2,104 (1,194-3,705)
MMORPG	2,435 (1,456-4,073)
RPG	1,166 (0,698-1,974)
MOBA	1,212 (0,729-2,014)
Adventure	0,792 (0,391-1,605)
Simulation	0,727 (0,407-1,297)

As Figure 5.6 demonstrates, the number of FPS and MMORPG genre games has consistently increased over the years so it is more likely to engage and interact with addictive games. Even if there has been a deceleration in the rate of increase in the number of FPS and MMORPG games after 2021, it is interesting that the research shows that the level of engagement with the online gaming experience has increased according to gamers worldwide in 2021 [39, 45].

5.2.2. Sector Structure

The Gaming Business Sector is discussed for revenue and games in the market along with related mathematical equations. Figure 5.8 illustrates the stock flow structure. Gamers contribute to the expansion of the gaming industry revenue by purchasing and playing games. However, the expenditures of gamers vary based on their habits, with *Addicted Gamers* (people) notably spending considerably more time and money than *Total Moderate Gamers* (people). The *Monthly Revenue* ($/Month) is

$$\begin{aligned} &Monthly\ Revenue = \\ &Avg\ Money\ Spent \times (1 + Inflation\ Growth\ Fraction)^{Time/Time\ Coefficient} \\ &\times [Money\ Spent\ Coeff.\ for\ AG \times Addicted\ Gamers\ (I) \\ &+ Total\ Moderate\ Gamers\ (PI + M)] \end{aligned} \tag{5.17}$$

given that *Money Spent Coeff. for AG* (unitless) represents that *Addicted Gamers (I)* spend twice as much time as other gamers [13]. Moreover, *Inflation Growth Fraction* (unitless) is to incorporate the annual change in the Average Money Spent ($/People/Month) which represents the average money spent by a gamer. A *Time Coefficient* (Month) with a value of 1 is added to the equation in order to maintain unit consistency.

Avg Money Spent in Equation (5.17) is consists of the product of *Normal Ave Money Spent* ($/Month) and *Delayed Pandemic Lockdown Effect on Playing Time and Money Spent* (unitless) as a third-order delayed version of *Pandemic Lockdown Effect on Playing Time and Money Spent* (unitless) which is only activated in the Pandemic period to demonstrate the effects on the money spent due to increasing playing video games (for detailed explanation see Section 5.4).

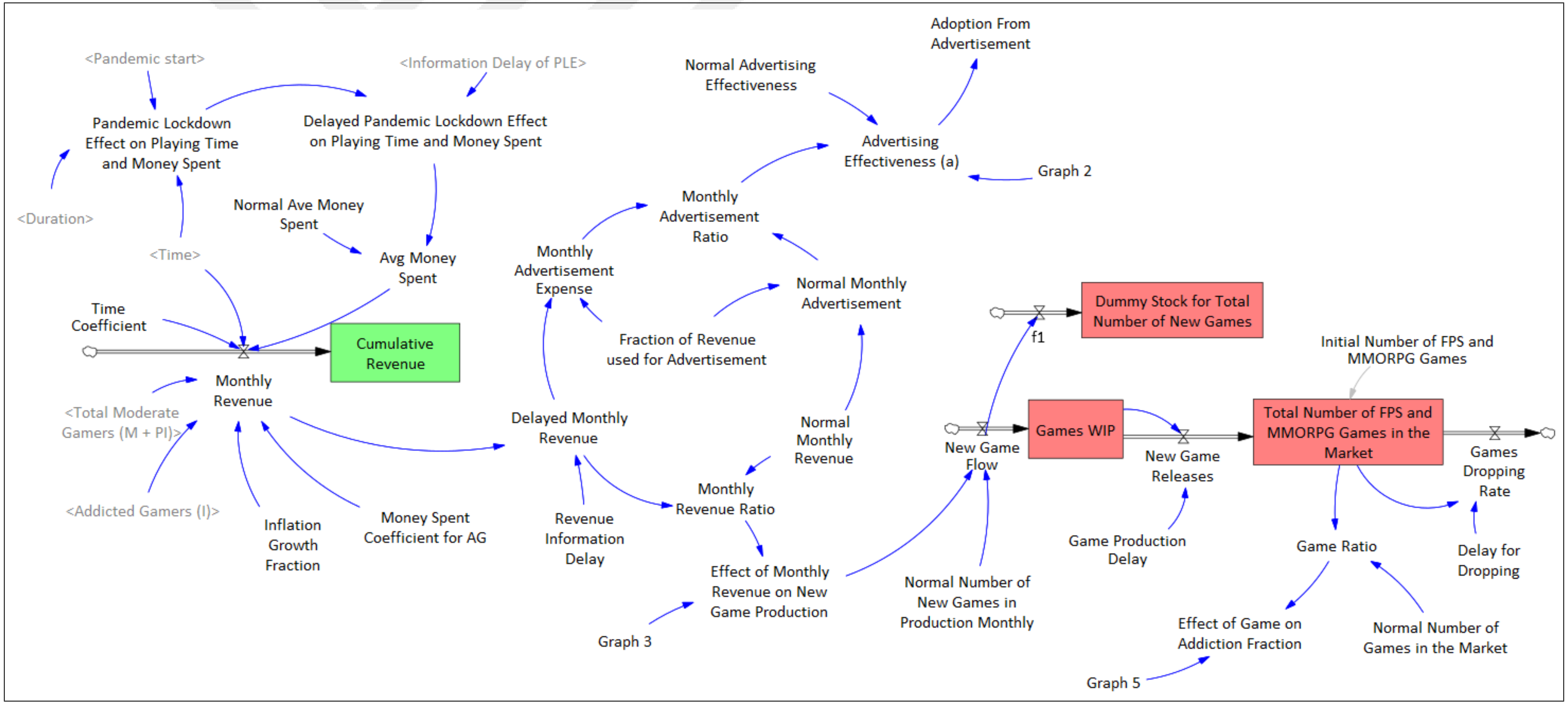


Figure 5.8. Gaming business sector.

Gaming firms, after earning revenue, allocate a portion of *Delayed Monthly Revenue* ($/Month) for advertising purposes over time. The effectiveness of an advertisement is directly influenced by the *Monthly Advertisement Ratio* (unitless) which is calculated as

$$Monthly\ Advertisement\ Ratio = \frac{Monthly\ Advertisement\ Expense}{Normal\ Monthly\ Advertisement} \tag{5.18}$$

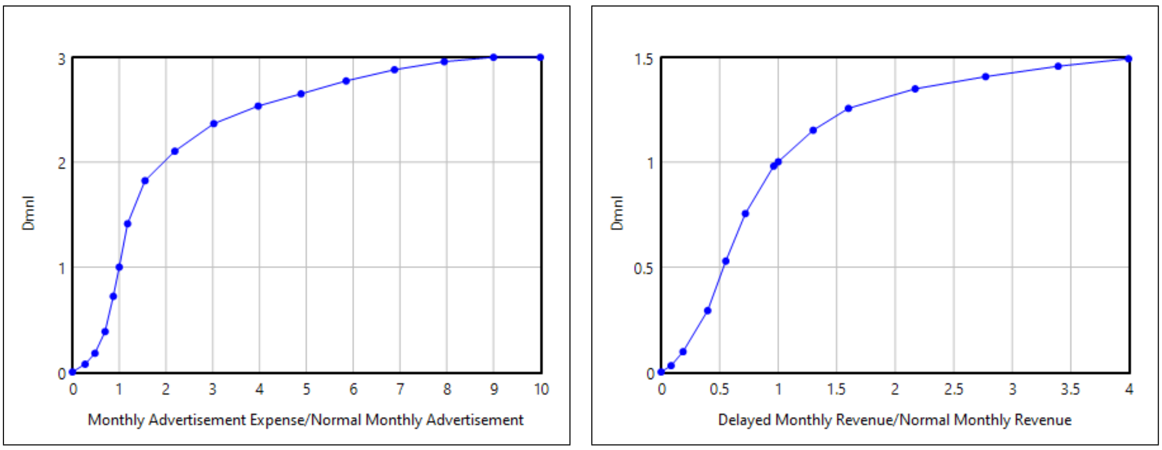
where

$$\begin{aligned} &Monthly\ Advertisement\ Expense = \\ &Delayed\ Monthly\ Revenue \times Fraction\ of\ Revenue\ used\ for\ Advertisement \end{aligned} \tag{5.19}$$

and *Advertisement Effectiveness (a)* (1/Month) is derived from a graphical function illustrated on Figure 5.9a as

$$\begin{aligned} Monthly\ Advertisement\ Ratio = &f(Monthly\ Advertisement\ Ratio) \\ &\times Normal\ Advertisement\ Effectiveness \end{aligned} \tag{5.20}$$

using *Normal Advertisement Effectiveness* (1/Month) as the average of the initial five years.



(a) Effect of monthly advertisement expenses on advertisement effectiveness

(b) Effect of monthly revenue on new game production

Figure 5.9. Graphical functions in gaming business sector.

As the gaming industry generates more revenue and expands, it further increases its investments in producing new games. Consequently, a greater number of games are released into the market. Figure 5.9b demonstrates the effects of the change in monthly revenue divided by its normal value on the new game production utilizing normal values as the average of the initial five years. *New Game Flow* is calculated as

$$\begin{aligned} New\,Game\,Flow =& Normal\,Number\,of\,New\,Games\,in\,Prod.\,Monthly \\ & \times Eff.\,of\,Monthly\,Revenue\,on\,New\,Game\,Production \end{aligned} \tag{5.21}$$

where *Normal Number of New Games in Production* (Games/Month) as the normal number of new games in the production derived from reference data, and *Effect of Monthly Revenue on New Game Production* (unitless) is derived from a graphical function of *Monthly Revenue Ratio* (unitless) which is calculated as

$$Monthly\,Revenue\,Ratio = \frac{Delayed\,Monthly\,Revenue}{Normal\,Monthly\,Revenue} \tag{5.22}$$

utilizing *Normal Monthly Revenue* (\$/Month) as the average of the initial five years. Following investments in new games, there is a time delay before the actual production of the games takes place. FPS and MMORPG genres in the market were examined as they are considered to be more addictive [13].

The *Effect of Games on Addiction Fraction* (unitless) is derived from a graphical function of *Game Ratio* (unitless) that is computed as

$$\begin{aligned} & Game\,Ratio = \\ & \frac{Total\,Number\,of\,FPS\,and\,MMORPG\,Games\,in\,the\,Market}{Normal\,Number\,of\,Games\,in\,the\,Market} \end{aligned} \tag{5.23}$$

using *Normal Number of Games in the Market* (Games) as the average of the number of FPS and MMORPG genre games in the market for the initial five years and using an S-shape function as shown in the Figure 5.10.

From the graphical function, it is discernible that it increases slowly up to half of the normal value while accelerating up to 1.6 times the normal value. Afterwards, it decelerates, reaching maximum impact.

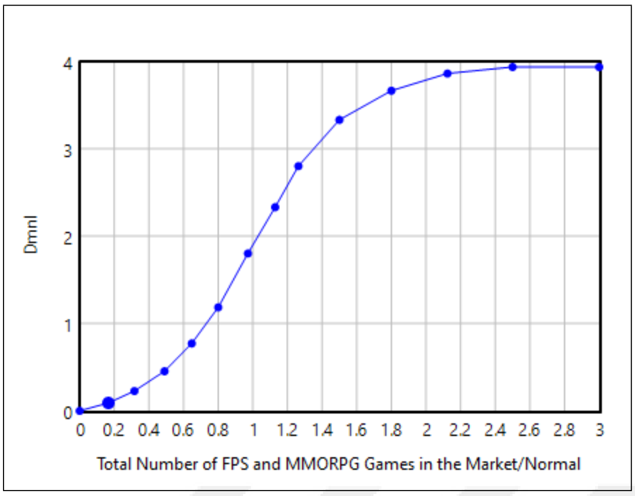


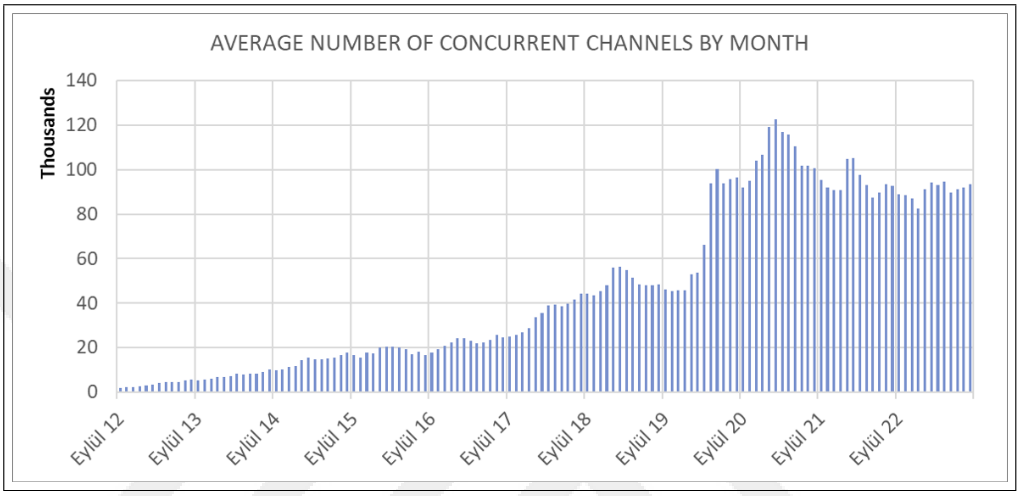
Figure 5.10. Graphical function of effects of games on addiction fraction.

5.3. Streaming Sector

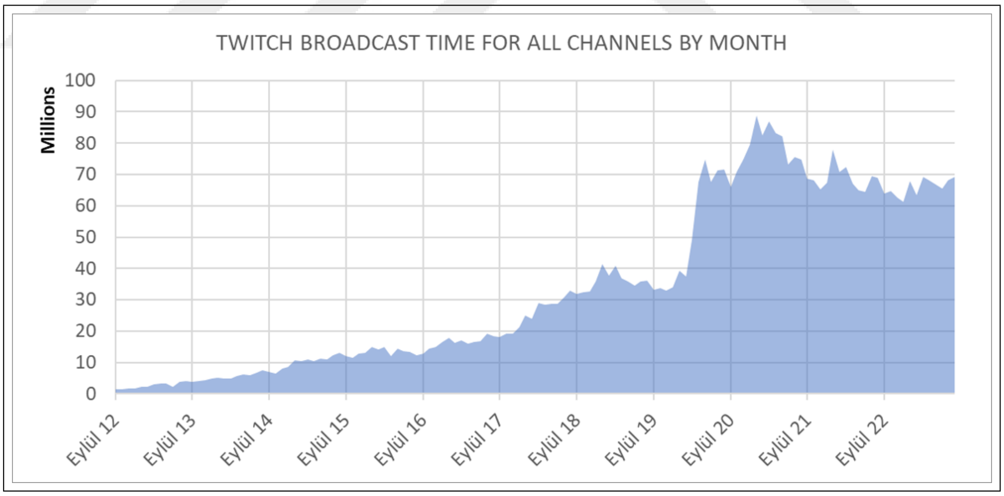
5.3.1. Background Information

The popularity and influence of video game content and live streaming have risen significantly, rendering them essential elements of online entertainment. With their exciting spaces for gaming enthusiasts and popcorn gamers to interact, share experiences, and create communities, platforms like Twitch and YouTube Gaming have been essential in this cultural transformation. The rise in viewers is evidence of the increased interest in video game content. In addition to the gameplay itself, streamers' captivating personas and insightful commentary also keep audiences watching. By enabling spectators to actively engage in the game experience, live chat capabilities during streams promote a sense of community and provide an interactive element.

In the beginning, video gaming broadcasts were being made on the YouTube Gaming. In 2011, Twitch streaming was introduced and gradually gained popularity, eventually surpassing YouTube Gaming and becoming dominant in the sector. Within the scope of this study, we were able to access data from Twitch streaming. As shown in Figure 5.11a, the average number of concurrent channels has been increasing over the years. Particularly during the pandemic, when many broadcasters were in lockdown, they spent most of their time broadcasting. In parallel with the increasing number of broadcasting channels, the broadcast time has also demonstrated an upward trend as illustrated in Figure 5.11b.



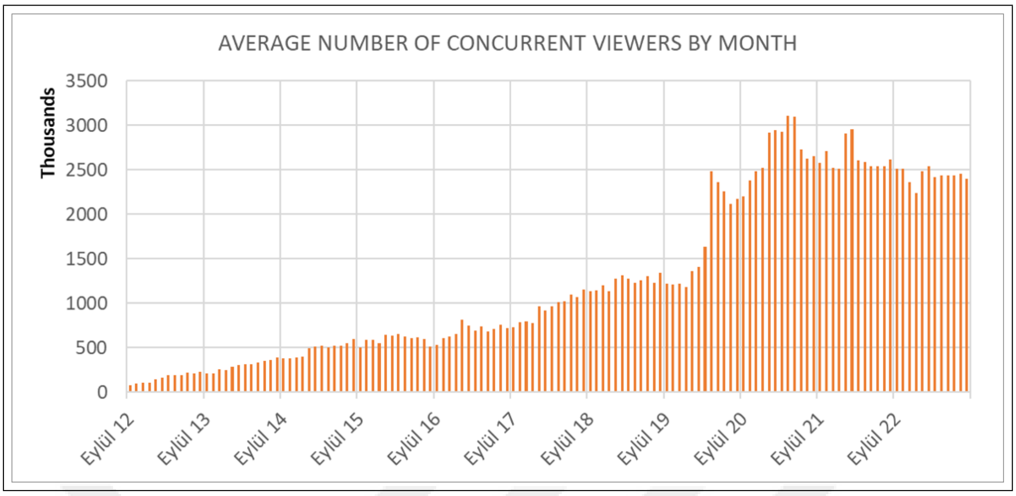
(a) Average number of concurrent channels by month



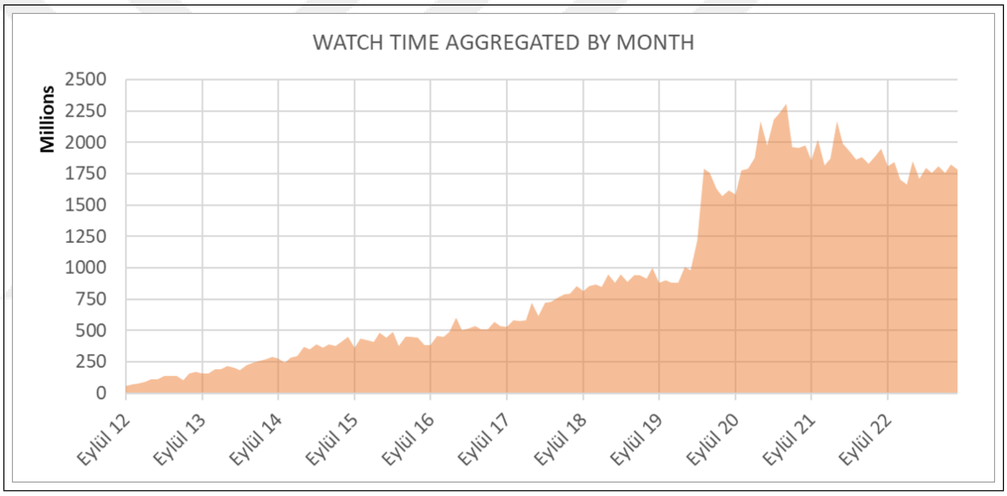
(b) Twitch broadcast time for all channels by month

Figure 5.11. Twitch channel and broadcast time statistics (data from [48]).

As indicated in Figure 5.12a, the average number of concurrent viewers has shown an increase over time, similar to the number of channels, reaching its peak rapidly during the lockdowns. The watch time along with broadcast time has exhibited a parallel growth as shown in Figure 5.12b.



(a) Average number of concurrent viewers by month



(b) Watch time aggregated by month

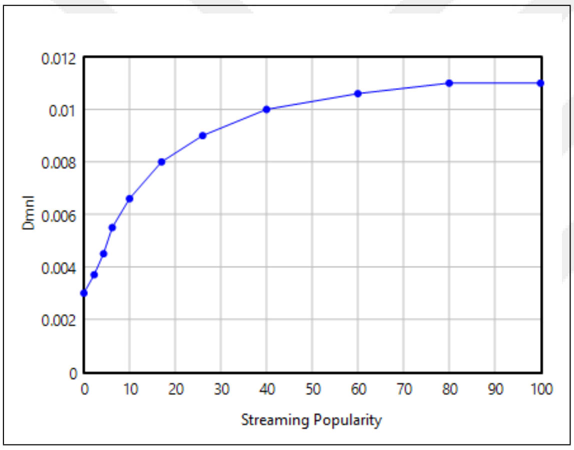
Figure 5.12. Twitch viewer and watch time statistics (data from [48]).

5.3.2. Sector Structure

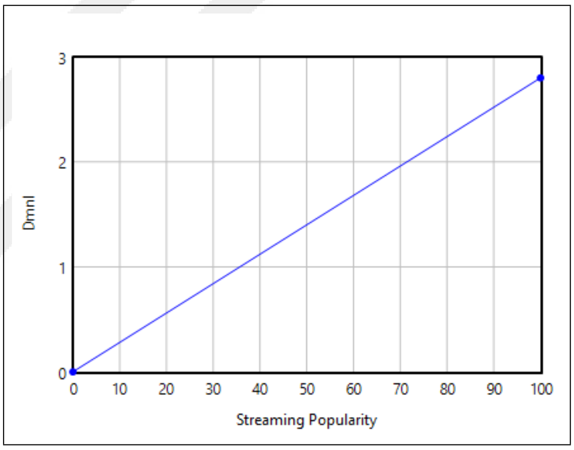
In this section, the Streaming Sector in the model is discussed. Figure 5.14 portrays the stock flow structure for the channels, broadcast time, viewers, and watch time of the video gaming content considering the popularity increase of Twitch streaming along with related effect equations.

In the year 2010, video gaming content was being broadcast on the YouTube Gaming platform, while Twitch streaming had not yet started its broadcasts. Our model begins in the year 2010, and within the initial eighteen months, only YouTube

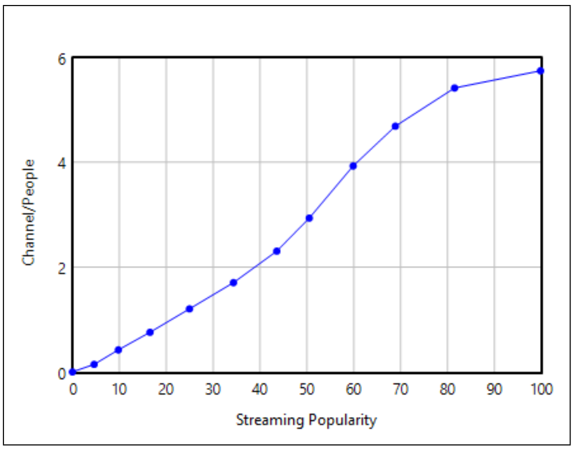
Gaming is present. Considering that YouTube Gaming is an established platform with a history of broadcasting various genres besides video gaming content, it is assumed to have a certain level of popularity. However, Twitch streaming gradually gained its popularity starting from June 2011 onwards and eventually became dominant in the industry. Therefore, a stock named Streaming Popularity is added to the model. Figure 5.13 shows the graphs of effect functions in Streaming Sector. As streaming popularity increases, it provides a faster spread among gamers. Therefore, the value of *Streaming Popularity Fraction* (unitless) demonstrates an upward trend.



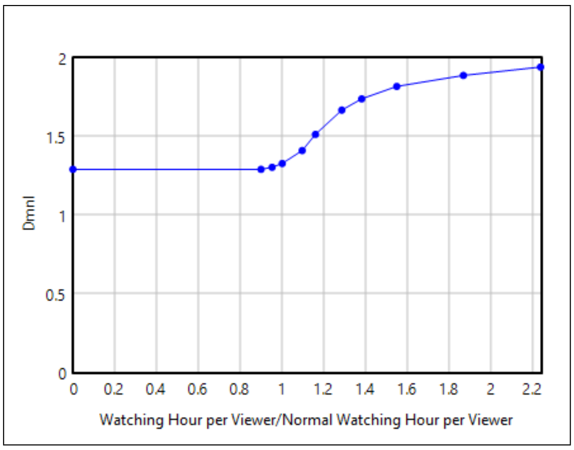
(a) Effect of streaming popularity on streaming popularity fraction



(b) Effect of streaming popularity on viewer co-effiecient



(c) Effect of streaming popularity on channel per moderate gamers



(d) Effect of streaming on addiction fraction

Figure 5.13. Graphical functions in streaming sector.

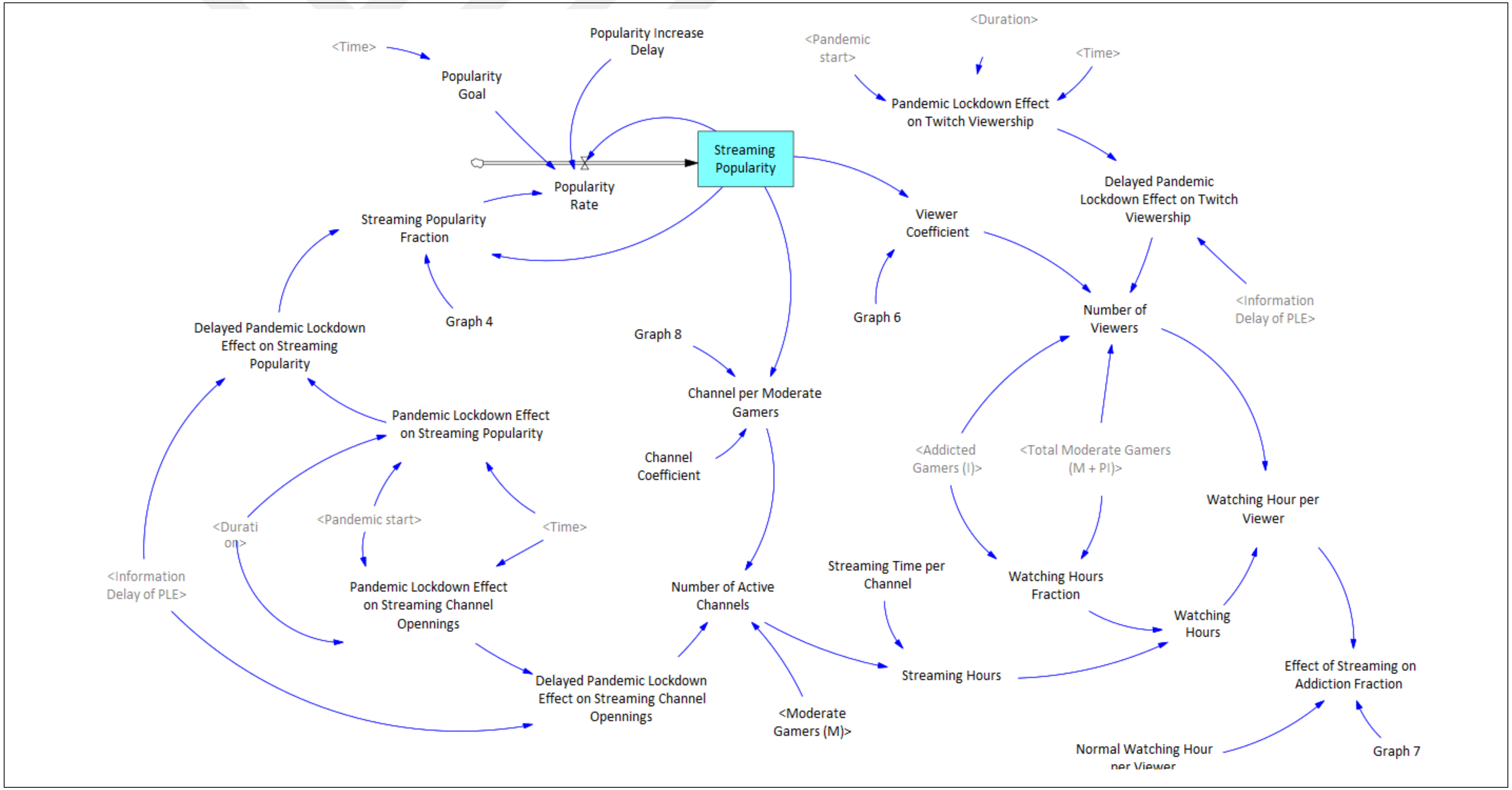


Figure 5.14. Streaming sector.

Figure 5.13a elucidates the relationship between *Streaming Popularity* (unitless) and *Streaming Popularity Fraction.* Since there was YouTube Gaming platform before the fraction for Twitch streaming does not start from zero. *Popularity Rate* is calculated with a goal function as

$$\begin{aligned} Popularity\,Rate =& (Popularity\,Goal - Streaming\,Popularity) \\ & \times \frac{Streaming\,Popularity\,Fraction}{Popularity\,Increase\,Delay} \end{aligned} \tag{5.24}$$

utilizing *Popularity Goal* (unitless) as a hundred starting from the 18th month. *Streaming Popularity Fraction* is derived from the graphical function of *Streaming Popularity* (unitless) demonstrated in Figure 5.13a.

Figure 5.13b and 5.13c visualize the impact of streaming popularity on *Viewer Coefficient* (unitless) and *Channel per Moderate Gamers* (Channel/People), respectively. Thus, we can observe the effects of popularity eventually on *Number of Active Channels* (Channel), which represents the variation in the number of channels opened by moderate gamers, and on *Number of Viewers* (people), which determines the change in the number of viewers as popularity increases by using *Viewer Coefficient* (unitless). Thus, utilized equations are as follows:

$$\begin{aligned} & Number\,of\,Active\,Channels = Channel\,per\,Moderate\,Gamers \\ & \times Moderate\,Gamers\,(M) \times (Delayed\,Pandemic\,Lockdown\,Effect\,on \\ & Streaming\,Channel\,Opennings) \end{aligned} \tag{5.25}$$

and

$$\begin{aligned} & Number\,of\,Viewers = (Addicted\,Gamers + Total\,Mod.\,Gamers) \\ & \times Viewer\,Coeff \times (Delayed\,Pandemic\,Lockdown\,Effect\,on\,Twitch \\ & Viewership) \end{aligned} \tag{5.26}$$

by using *Delayed Pandemic Lockdown Effect on Streaming Channel Opennings* (unitless) and *Delayed Pandemic Lockdown Effect on Twitch Viewership* (unitless) as a third-order delayed version of *Pandemic Lockdown Effect on Streaming Channel Opennings* (unitless) and *Pandemic Lockdown Effect on Twitch Viewership* (unitless), respectively (for detailed explanation see Section 5.4). *Streaming Hours* (Hour) are directly influenced by the *Number of Active Channels* (Channel) and *Streaming Time per Channel* (Hour/Channel). The computation of *Watching Hours* (Hour) involves *Watching Hours Fraction* (unitless), serving as the viewing coefficient for each *Streaming Hour*(Hour). Equations can be derived from

$$\begin{aligned} Streaming\,Hours =& Number\ of\ Active\,Channels \\ & \times Streaming\,Time\,per\,Channel \end{aligned} \tag{5.27}$$

and

$$Watching\,Hours = Streaming\,Hours \times Watching\,Hours\,Fraction \tag{5.28}$$

where

$$\begin{aligned} & Watching\,Hours\,Fraction = \\ & 25 \times (\frac{2 \times Addicted\,Gamers\,(I) + Total\,Moderate\,Gamers\,(PI+M)}{Addicted\,Gamers\,(I) + Total\,Moderate\,Gamers\,(PI+M)}) \end{aligned} \tag{5.29}$$

given that a standard rate of twenty-five times is applied to each hour that is streamed, and the rate can vary depending on the number of Addicted Gamers (I) (people) since they spend twice as much time as other gamers [13]. The time spent watching online video game video per viewer is a significant indicator of addiction [13]. Therefore, *Watching Hour per Viewer* (Hour/people) is calculated as

$$Watching\,Hour\,per\,Viewer = \frac{Watching\,Hours}{Number\ of\ Viewers} \tag{5.30}$$

so as to evaluate *Effect of Streaming on Addiction Fraction* (unitless). Figure 5.13d shows the changes in the effect function according to the proportion of *Watching Hours per Viewer* (Hour/People) to its normal value. Therefore, the *Fffect of Streaming on Addiction Fraction* is a graphical function of a value consisting of the *Watching Hour per Viewer* (Hour) divided by the *Normal Watching Hour per Viewer* (Hour) as a mean of the initial five years.

5.4. The Pandemic Lockdown Effect

The Covid-19 outbreak forced countries to enact strict safeguards all across the world, including lockdowns, social distancing, and remote working, in an attempt to slow down the spread of the virus. In the context of gaming, the lockdowns imposed during the pandemic have led to an increase in online connections and verbal recommendations called word of mouth, prompting *Potential Gamers (S)* to explore new games and participate in gaming activities. During times of isolation, dedicating more hours to gaming led to an increase in the money spent on gaming activities. Additionally, the lockdowns have motivated people to create and consume video gaming content. While *Moderate Gamers (M)* opened new channels to generate income, the rest of the gamers spent their spare time on their hands to watch. In this exploration, we include the effect of the pandemic lockdowns on gaming behavior in our model. In general, utilized equations are as follows:

$$Pandemic\,Lockdown\,Effect\,on\,... = IF\,THEN\,ELSE(Time >= Pandemic\,start : AND : Time < Pandemic\,start + Duration, X, 1) \tag{5.31}$$

utilizing X as an amplifier depending on the parameter, *Duration* (Month) as twelve months representing the pandemic lockdown duration, and

$$Delayed\,Pandemic\,Lockdown\,Effect\,on\,... = DELAY3(Pandemic\,Lockdown\,Effect\,on\,..., Information\,Delay\,of\,PLE) \tag{5.32}$$

using DELAY3 as a 3rd-order exponential delay of the input and information delay of PLE as an average constant delay time.

6. PARAMETER ESTIMATION AND VALIDITY OF THE MODEL

Diverse studies from the existing literature are employed to infer the model parameters. The initial parameters, formulated through literature reviews and assumptions, are calibrated and validated using data spanning 12 years from 2010 to 2022. Following the completion of validation of the model, a simulation with a time span of 20 years (2010 to 2030) was conducted and analyzed. Moreover, the pandemic period between 2020 and 2022 is taken into account in validation.

6.1. Parameter Estimation

Utilizing data on the number of PC gamers from 2008 to 2022, the total number of gamers amounts to approximately 1.1 billion at the end of 2009, with 60% of this demographic falling within the age range of 10 to 29 [5, 37]. We computed the number of Potential Gamers (S) by extracting the PC gamer population from the overall population aged from 10 to 29 [38]. The allocation of initial values for gamer stocks is calibrated based on gaming habits and the time spent by individuals in gaming activities [40,41]. Fundamentally, in our model, there are eight stocks within the population with the initial values presented in Table 6.1:

- Susceptible stock is Potential Gamers,
- Exposed stock is Beginner Gamers,
- Infected stocks are separated as Neutral Gamers, Moderate Gamers, and Pre-Addicted Gamers based on the playing time of individuals. Following the incubation period, Pre-Addicted Gamers flows into Addicted Gamers stock,
- Recovered stock is Treated Gamers,
- Quitted stock is Non-Gamers.

Table 6.1. Initial values.

Initials Values of Stocks	Unit	Value
Potential Gamers (S)	People	1.561.036.876
Beginner Gamers (E)	People	14.550.000
Neutral Gamers (N)	People	84.441.160
Moderate Gamers (M)	People	478.458.000
Pre-addicted Moderate Gamers (PI)	People	44.000.000
Addicted Gamers (I)	People	52.800.000
Treated Gamers (R)	People	0
Non-Gamers (Q)	People	139.936.364
Initial Value of Cumulative Revenue	Bn $	10,68
Initial Number of FPS and MMORPG Games	Games	785
Initial Number of Games WIP	Games	260
Initial Number of Streaming Popularity	-	0

Worldwide mental health facility capacity is estimated at 14.5 beds per 100,000 people [43]. Additionally, a significant proportion of this capacity caters to various age groups, with 56.9% serving children (6-12 years old), 64.9% serving adolescents (13-17 years old), and 87.8% serving young adults (18-25 years old) [44].

The total number of FPS and MMORPG games is 785 which is also the initial value in our model [45]. Time spent for game production is assumed an average of 24 months so games that are Work in Progress are calculated as 260 games.

The revenue generated by the online PC gaming market is 21.1 Billion dollars in 2011. Therefore, the examination of the increase by years allows us to derive the revenue at the end of 2009 (t=0) [6].

The data utilized for the number of active channels, streaming time, the number of viewers, and watch times pertains to the Twitch platform [48]. As Twitch started broadcasting in June 2011, the initial values are considered as zero. Information regarding other platforms has not been taken into account as it is deemed less significant compared to Twitch.

Our simulation spans the twenty-year interval with time unit as months. Hence, certain data in this investigation lacks the necessary detail for the calibration of model parameters. Therefore, we used the annual data from [5, 6] and monthly data from [45, 48] for numerical calibration. The remaining parameters of the three main sectors are calibrated based on the behavior of the dynamic model. Parameters formulated through literature reviews and assumptions defining the Base Run in Table 6.2.

Table 6.2. Parameter values of gamer sector.

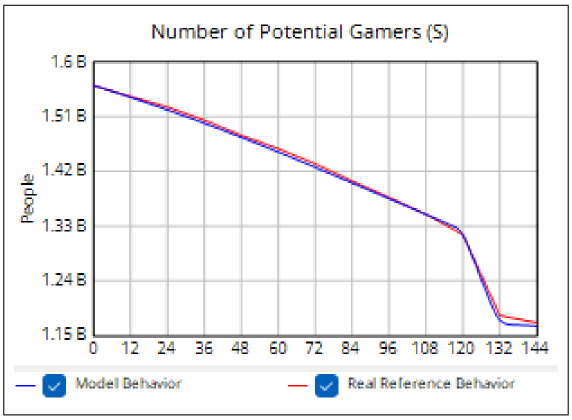
Parameter Name	Unit	Value
Infect Contacts (Ci)	People/(Person*Month)	0,01
Normal Advertising Effectiveness	1/Month	0,01/12
Neutral Gamer Fraction	Unitless	0,69
Normal Addiction Fraction	Unitless	0,1
Addiction Coefficient	Unitless	0,05
Gamer Adoption Time	Month	3
PI to I Fraction	Unitless	0,05
Being Addicted Time	Month	12
Neutral to Potential Fraction	Unitless	0,1
Quitting Fraction	Unitless	0,016
Quitting Delay	Month	3
Total Capacity of Mental Health Facilities	People	1.130.200
Age Group Fraction	Unitless	0,649
Success Rate	Unitless	0,1
Treatment Time	Month	3
Normal Average Money Spent	$/(People*Month)	1,3
Money Spent Coefficient for AG	Unitless	5
Inflation Growth Fraction	Unitless	0,69

Table 6.2: Parameter values of gamer sector (cont.).

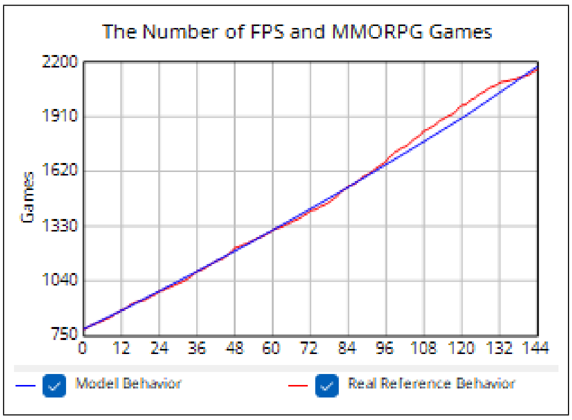
Parameter Name	Unit	Value
Revenue Information Delay	Month	3
Normal Monthly Revenue	Bn $/Month	1,125
Fraction of Revenue used for Advertisement	Unitless	0,05
Normal Number of New Games in Production	Games/Month	8,7
Normal Number of Games in the Market	Games	920
Game Production Delay	Month	24
Delay for Dropping	Month	120
Popularity Goal	Unitless	100
Popularity Increase Delay	Month	1
Channel Coefficient	Unitless	1/44000
Streaming Time per Channel	Hour/Channel	700
Normal Watching Hour per Viewer	Hour/People	500
Duration	Month	12
Pandemic Start	Month	117
Information Delay of PLE	Month	3

6.2. Model Credibility

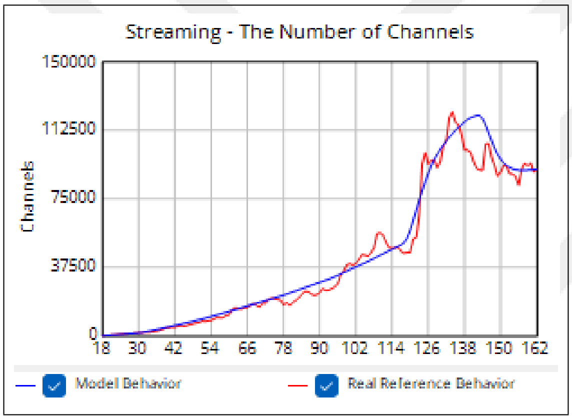
Barlas expresses that the intention of creating a causal descriptive model is to formulate a theory about the real system that not only predicts its behavior but also explains the generation of the behavior. Hence, the first step is to test the model for internal consistency by verifying if the simulation accurately represents the conceptual model and fulfills the modeler's intentions. With the verification, the modeler aims to eliminate inconsistencies between the model and the dynamic hypothesis by checking equations and functions for potential errors [49]. In this context, the model structure is constructed based on the current qualitative and quantitative information within the literature. The robustness of the mathematical equations is checked, ensuring unit consistency of parameters throughout the model-building process.



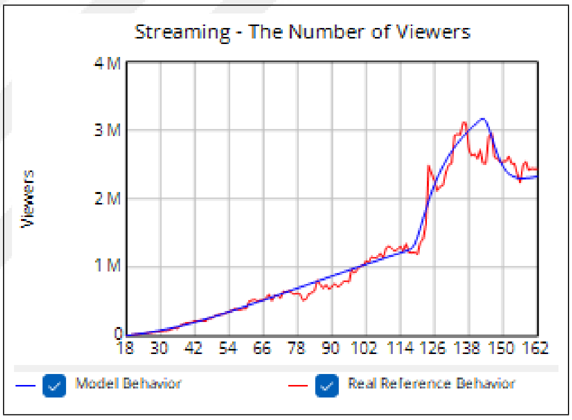
(a) Number of potential gamers (data from [5, 37, 38, 40, 41])



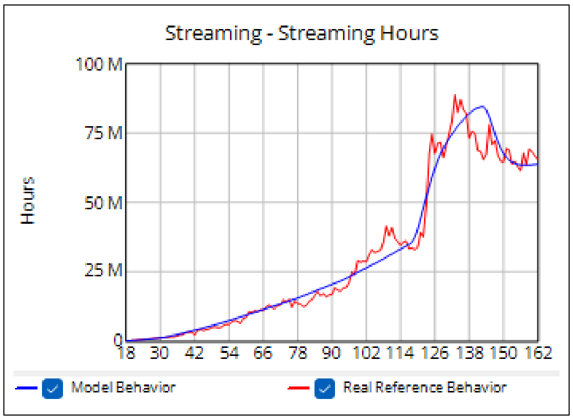
(b) The number of FPS and MMORPG games (data from [45])



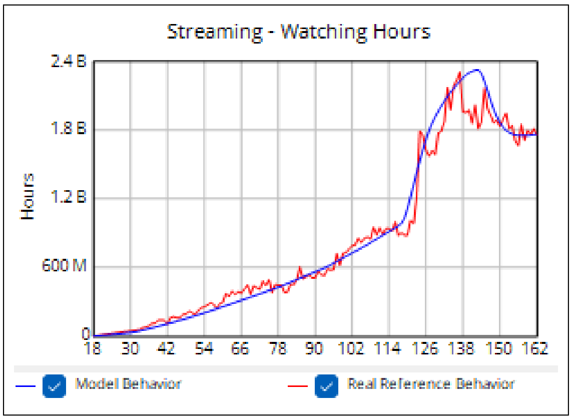
(c) The average number of channels (data from [48])



(d) The average number of viewers (data from [48])



(e) Streaming hours per month (data from [48])



(f) Watching hours per month (data from [48])

Figure 6.1. Behavior validity of the model.

All model parameters have meaningful real-world equivalents, and assumptions or simplifications are explicitly explained in the Model Description and Parameter

Estimation sections. For acceptable numerical accuracy, the time step (dt) of the simulation is chosen to be 0,0625. Unit consistency and model verification are conducted using the Vensim tools.

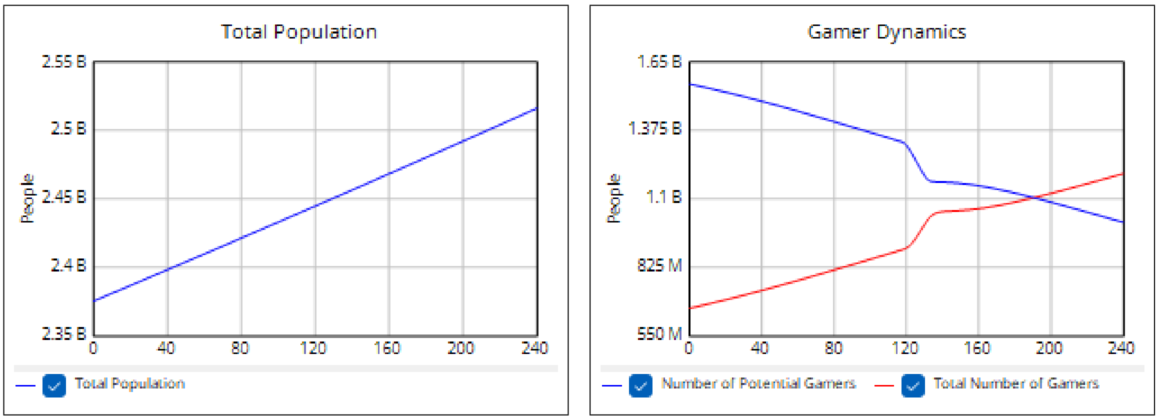
After the verification of structural validity, the assessment of behavioral validity is undertaken in system dynamics modeling. Output behavior tests are devised to compare the primary pattern components in the model behavior with those observed in the actual behavior. In our model, it has been observed that the model exhibits valid behavior. The initial parametrization is calibrated to align with real data spanning from 2010 to 2022. It is evident from Figure 6.1a that the decline in the number of Potential Gamers (S) parallels the real data. Even the sharp decline during the pandemic period behaves similarly. As depicted in Figure 6.1b, the number of FPS and MMORPG games are changing similarly to the cumulative game counts in real data with differences so small that they are negligible. Figure 6.1c-f demonstrates the data within the streaming sector. Even though there are fluctuations in monthly streaming data due to the inclusion of average values, the behavior of the simulated data is generally similar.

7. BASE RUN AND SENSITIVITY ANALYSIS

The simulation of the model has been conducted for 20 year period from 2010 to 2030, referred to as the Base Run. In this model prepared for the examination of the epidemic of Addicted Gamers (I), outcomes of interest related to Addicted Gamers (I) have been selected. Additionally, a sensitivity analysis has been implemented to examine the effects of changes in parameters on the model.

7.1. Base Run

For the base run, the calibrated parameters that are validated with real data are used. Population-level dynamics of the base run are illustrated in Figure 7.1. According to the base run, the total population aged between 10 and 29 will surpass the 2.5 billion people within 20 years. While the number of Potential Gamers (S) decreases to almost 1 billion people, the total number of gamers will reach 1.2 billion people in 2030.

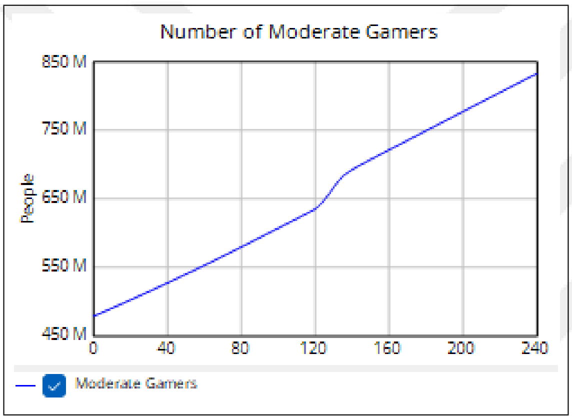


(a) The total population aged from 10 to 29 (b) Population level dynamics of gamers

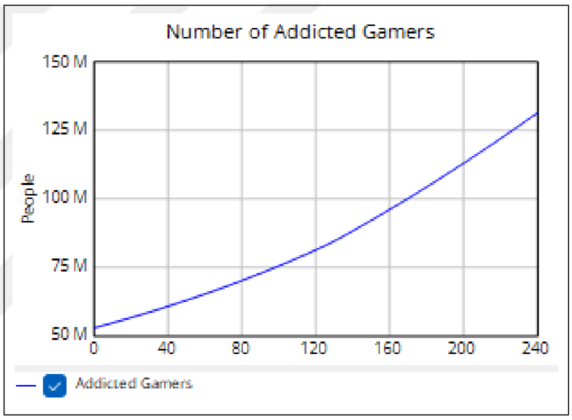
Figure 7.1. Population-level dynamics.

According to our model, an increase is observed in all of the gamer stocks. As shown in Figure 7.2a-b, the number of Neutral Gamers (N) who play less than 1 hour shows a gradual increase over time, especially experiencing a significant increase during the pandemic period, indicating a substantial rise in the number of Potential Gamers

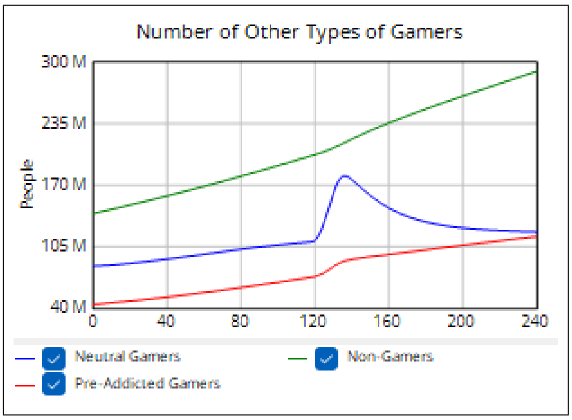
(S) entering the gaming scene. However, in the post-pandemic period, as the lockdown ended, the number of Neutral Gamers (N) exhibits a downward trend after reaching 170 million in the 136th month (the year 2023) of simulation. The number of Moderate Gamers (M) reaches 830 million, while the number of Pre-addictive Moderate Gamers (PI) reaches 115 million. Inspection of Figure 7.2c shows that the focus of our model, Addicted Gamers (I), demonstrates a rapid increase at an accelerated pace and reaches 130 million people by the end of the year 2030.



(a) Moderate gamers



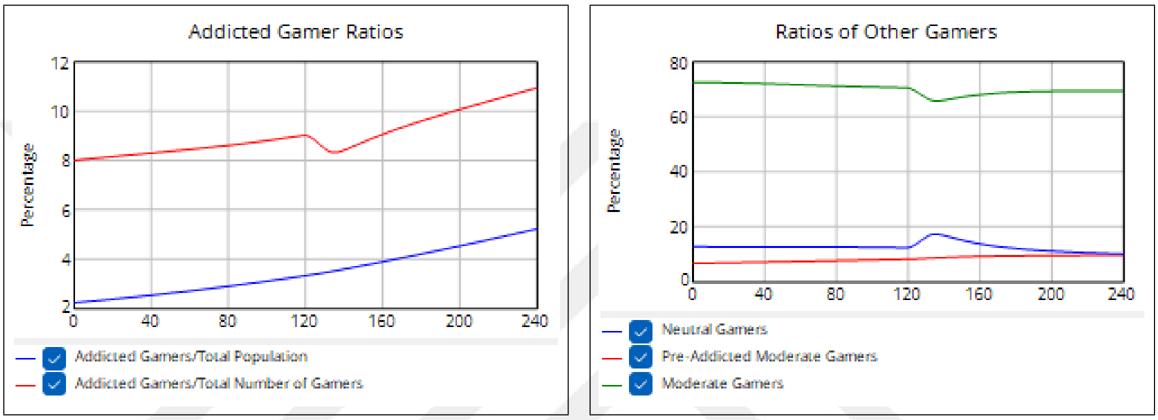
(b) Addicted gamers



(c) Various gamers

Figure 7.2. Population-level dynamics of gamers.

As the focus of our model is gamers with Internet Gaming Disorder (IGD), two outcomes of interest are determined as the ratios of Addicted Gamers (I) to the overall gamer population and the total population. The data in Figure 7.3a points to the fact that both of the ratios are increasing in time. However, during the pandemic period, a decline is observed in the ratio of Addicted Gamers (I) to the overall gamer population since many people have experienced gaming due to time spent in lockdowns, leading to a rapid increase in the number of overall gamers. In other words, the visibility of Addicted Gamers (I) has diminished during the pandemic. Figure 7.3b demonstrates the changes in the ratios of other types of gamers to overall gamer population.



(a) Addicted gamers (b) Other gamers per overall gamers

Figure 7.3. Ratios of gamers.

7.2. Sensitivity of Model Behavior to Changes in the Model Parameters

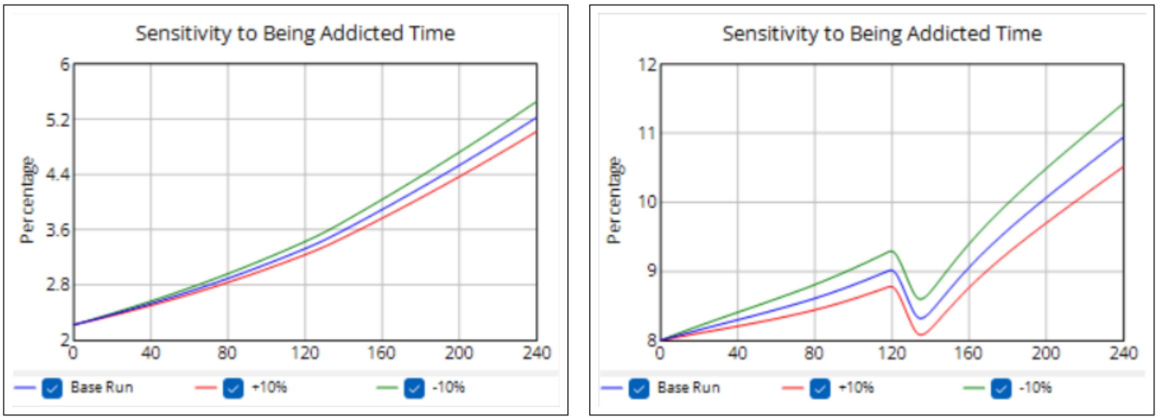
Sensitivity analysis is implemented to assess how the model responds to variations in its parameters. This analysis is done by modifying one parameter at a time to prevent complexity caused by combinations. For our model, the Sensitivity2all tool in Vensim is employed. This tool rapidly identifies the most sensitive constants by computing Mean Absolute Deviation in the model and provides an overview of how each constant influences specific parameters by systematically increasing or decreasing each constant by 10%. This allows for quick insights into the parameters that influence the model's behavior.

As depicted in Table 7.1, based on the results obtained when using the Sensitivity2All tool of Vensim, the parameters that most significantly influence the ratios of addicted gamers to total population and total number of gamers are as follows:

Table 7.1. Selected parameters by sensitivity analysis, units, and values.

Parameter Name	Unit	Value
Infect Contacts (Ci)	People/(Person*Month)	0,01
Neutral Gamer Fraction	-	0,69
Neutral to Potential Fraction	-	0,1
Addiction Coefficient	-	0,05
Being Addicted Time	Month	12
Quitting Delay	Month	3
Normal Average Money Spent	$/(People*Month)	1,3
Money Spent Coefficient for AG	-	5

Complete outcomes of the sensitivity analysis are provided in Appendix B, while significant runs are discussed in this section. In general, the model exhibits consistent behavior concerning both model assumptions and real-world expectations.

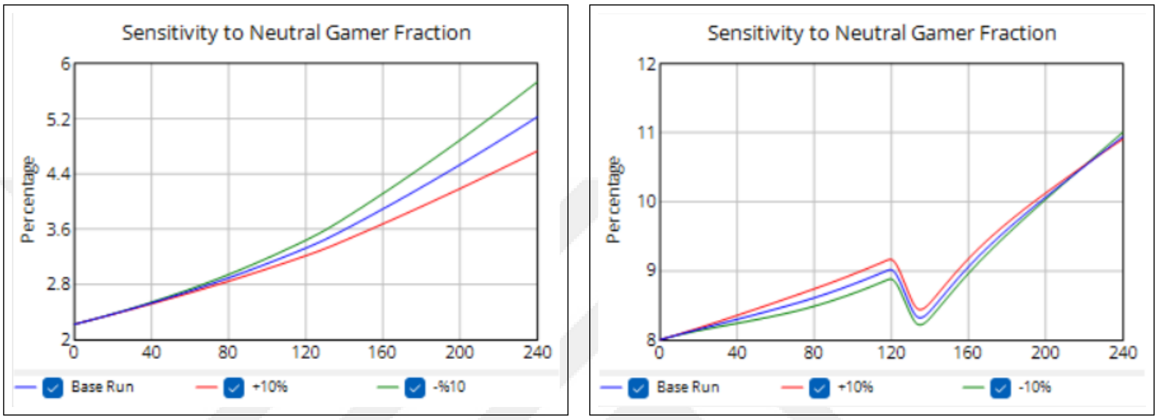


(a) The ratio of addicted to total population (b) The ratio of addicted to tot. number of gamers

Figure 7.4. Sensitivity tests of being addicted time.

We obtained different behaviors and results for both outcomes of interest. Figure 7.4 demonstrates the most impactful parameter which is Being Addicted Time in terms of influencing changes. Since a 10% increase or decrease in this parameter influences both the gamers ratio to the total population and the total number of gamers.

The parameter Neutral Gamer Fraction also holds considerable influence, primarily affecting the ratio of addicted gamers to the total population, despite its minor impact on the other one. Particularly, following the pandemic lockdowns, the influence of this parameter on the ratio to the total number of gamers diminishes.



(a) The ratio of addicted to total population (b) The ratio of addicted to tot. number of gamers

Figure 7.5. Sensitivity tests of neutral gamer fraction.

The changes in infect contacts (Ci) result in the expected impact on the ratio of addicted individuals to the total population. However, its effect on the other outcomes of interest is noteworthy. While the influence of a 10% increase or decrease in this parameter is significant until the pandemic period, its effect has started to decline afterward. This decline can be attributed to the increase in the number of players during the pandemic period. The amplified manifestation of this behavior can also be observed in the sensitivity test of Normal Average Money Spent. The influences of the parameters named Quitting Delay and Neutral to Potential Fraction on the ratio of addicted gamers to the total population are negligible; however, they do impact the proportion of addicted gamers to overall gamers. The Money Spent Coefficient for AG exhibits minimal changes in comparison to the sensitivity tests of other parameters.

Table 7.2 indicates the outcomes of interest that we will focus on in simulation experiments in the following chapters.

Table 7.2. Resulting outcomes of interest for the base run.

No	Outcome of Interest	Unit
1	Addicted Gamers/Total Population	Percentage
2	Addicted Gamers	People
3	Moderate Gamers	People
4	Non Gamers	People

8. SCENARIO ANALYSIS

The model structure and its credibility are demonstrated in previous chapters. With the calibrated and validated parameters, a simulation is conducted to obtain the base run which shows the basic behavior of our model. In this section, our objective is to analyze different hypothetical yet possible scenarios and examine changes in the four outcomes of interest. The chosen parameters for the scenario analysis are presented in Table 8.1:

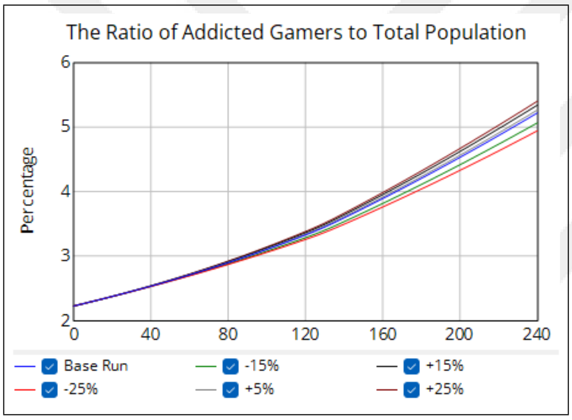
Table 8.1. Selected parameters for scenario analysis and alterations.

No	Parameters	Alterations based on Base Run					
1	Normal Average Money Spent	-25	-15	+5	+15	+25	%
2	Delay for Dropping	-50	-30	+30	+50	+Inf.	%
3	Duration	-50	+100	+150	+200		%

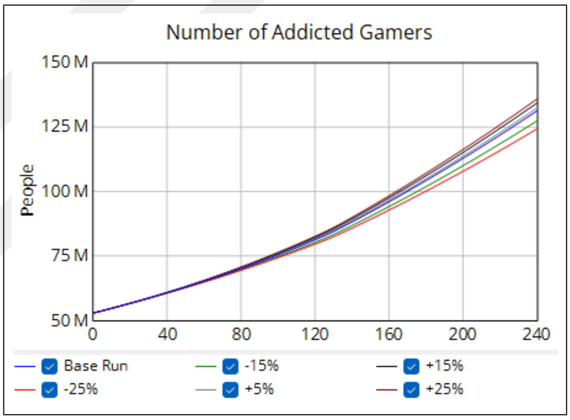
In Table 8.1, Normal Average Money Spent corresponds to the average money spent on gaming by gamers depending on the duration of gameplay. Additionally, Delay for Dropping parameter represents the time it takes for games to lose their popularity or exit the market. Finally, Duration refers to time spent during the pandemic lockdown period.

8.1. The Average Amount of Money Expended on Gaming

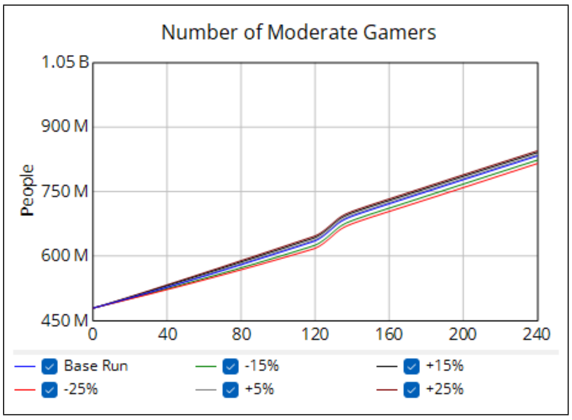
Over the last decades, the gaming industry has experienced significant expansion, which has resulted in changes to revenue generation models. Some games enter the market as free-to-play, generating income through in-game item sales and the sale of premium user products, while other games earn revenue directly from the sale of the game itself. Due to the increasing revenue, it has evolved into a more attractive sector for investors. Consequently, with new investments, game firms seeking to attract new gamers have invested in enhancing narrative elements, and visual aesthetics. Gamers tend to engage with games when they experience a sense of relatedness, autonomy, and competence within the framework of the Self-Determination Theory, driven by factors such as engaging narratives and in-game sociability. Therefore, they are inclined to spend more time, leading to increased money spent on gaming. Within the context of this section, an examination will be conducted on the variation in the Normal Average Money Spent. Changes in the range of -25% to +25% have been applied to the value of the Normal Average Money Spent, and the effects on the outcomes have been derived.



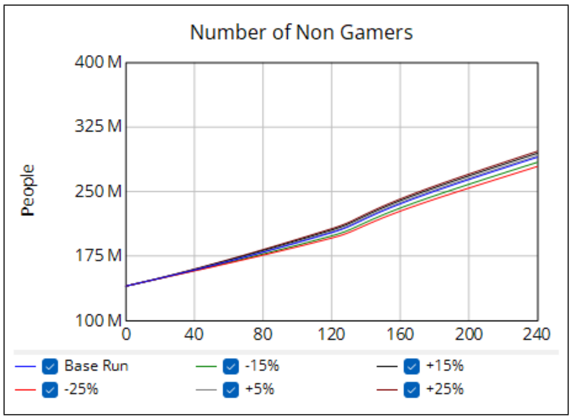
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

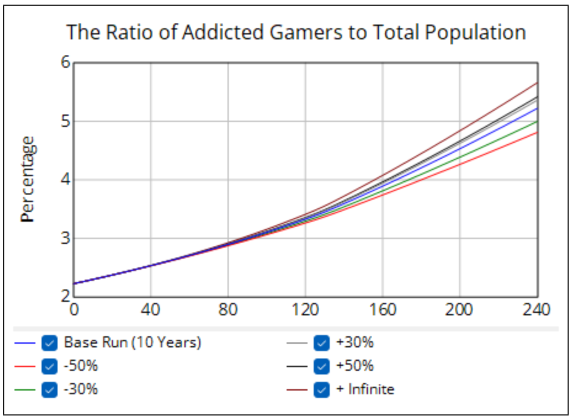
Figure 8.1. Scenario analysis using the normal average money spent.

In Figure 8.1a, as expected, an increase in the parameter is observed to lead to an increase in the ratio of addicted to the total population. However, interestingly, Figure 8.1b-d reveals an unexpected behavior as the Addicted Gamers (I) is affected much more compared to other types of gamers. When the time allocated to gaming is kept low, that is, when the money spent on gaming stands low, the visibility of Addicted Gamer (I) among other gamers remains higher. During the pandemic lockdown period, there is such an important increase in the total number of gamers in the market that, regardless of the value of the examined parameter, the visibility of addicted gamers among other gamers decreases considerably. For example, in the scenario where the parameter is 25% lower, visibility among other gamers is higher compared to the Base Run. However, interestingly, in the post-pandemic period, this situation reverses, and it exhibits lower visibility compared to the Base Run.

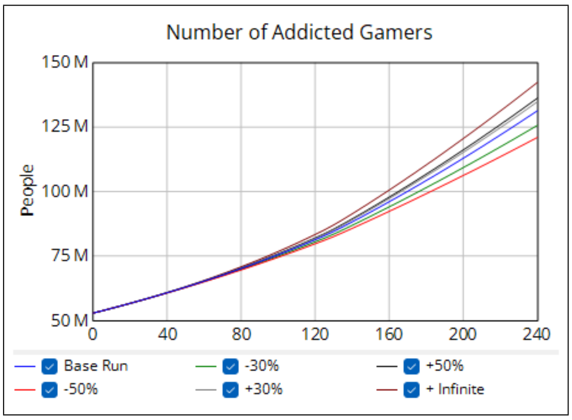
8.2. The Average Life of Games in the Market

Each year, games with larger maps and higher resolutions are released. Even though new games entering the market rapidly, many gamers persist in playing old games that have become a routine and enabled them to establish social connections in-game. However, notably, online games, particularly in genres such as MMORPGs and FPS, tend to lose their popularity and eventually withdraw from the market after a certain period. The question of what would have happened if games withdrew from the market either sooner or later holds significance.

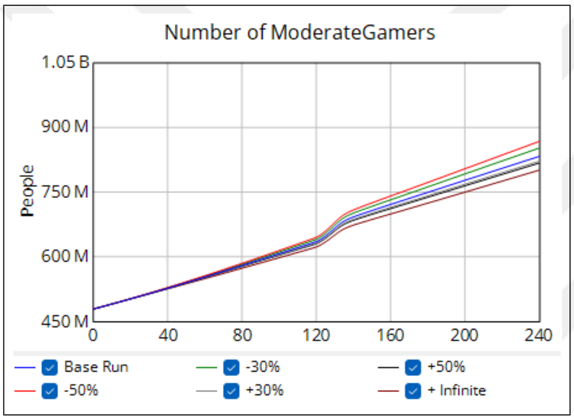
In this section, a scenario analysis has been conducted based on the parameter Delay for Dropping. Figure 8.2 indicates that the parameter particularly influences the behavior of both outcomes of interest. In these scenarios, the time has been reduced by 5 years and 3 years, while in other scenarios, it has been extended by 3 years and 5 years. Besides, the scenario where games are never withdrawn from the market has also been considered. As seen in Figure 8.2, shortening the delay time has a much greater impact compared to extending it. When considering the absolute deviations from the Base Run outcomes, the results obtained from the scenario where the delay time is shortened by 5 years are similar to the scenario where games are never withdrawn.



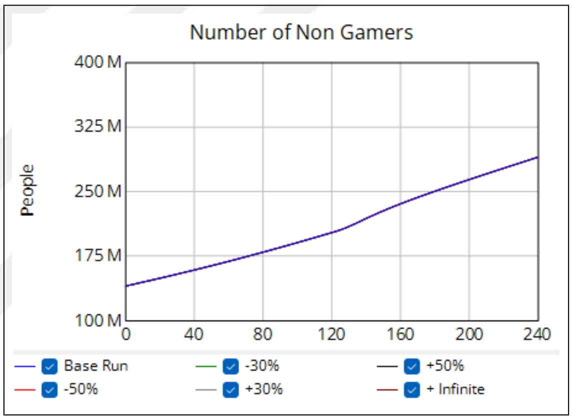
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



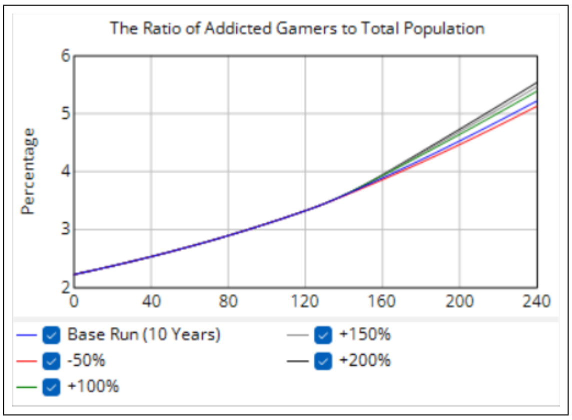
(d) The number of non gamers

Figure 8.2. Scenario analysis using delay time for dropping a game.

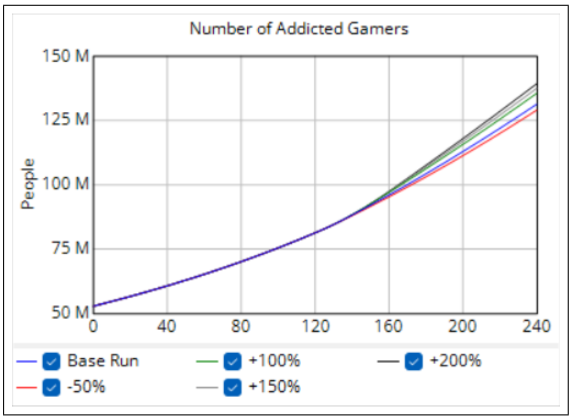
8.3. The Duration of Pandemic Lockdowns

The pandemic period represented a unique time of great uncertainties for each person. Upon reconsideration, the lockdowns due to the pandemic appear quite a surprising phase since spending the entire day at home required the exploration of activities to spend the time. Hence, activities conducted over the internet at home gained importance, particularly online gaming, as they facilitated remote social connections with family and friends.

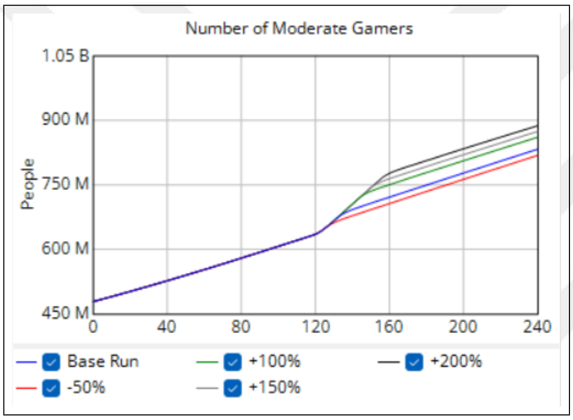
In this section, scenario analyses are conducted on how the ratio and the number of Addicted Gamers (I) would be influenced if the pandemic had occurred for a shorter or longer duration.



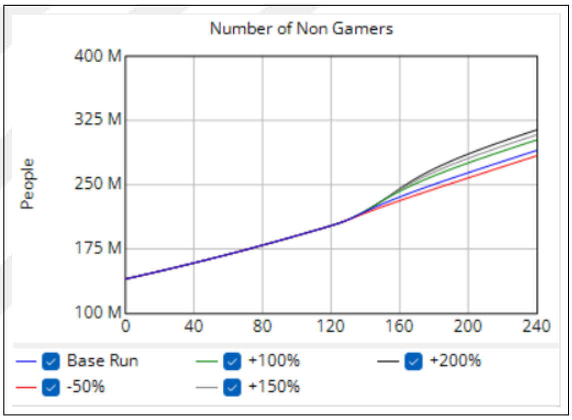
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

Figure 8.3. Scenario analysis using the pandemic duration.

The effects of changes in the duration of pandemic lockdowns are illustrated in Figure 8.3. Adjusting Duration parameter creates a rapid increase in the numbers of different types of gamers. As seen in Figures 8.3b-c, during the pandemic period, the number of Moderate Gamers (M) is rapidly increasing, while the number of Addicted Gamers (I) is increasing slowly compared to others but at an increasing rate. Particularly in Figure 8.3d, even though there is a slight effect on the number of Non-Gamers (Q) in the base run, the number of people leaving gaming is rapidly increases as the duration increases. Therefore, while the visibility of Addicted Gamers (I) in society increases, the visibility among other gamers has decreased especially in the pandemic period.

9. POLICY INTERVENTIONS

Policy interventions were implemented to assess their impact on the epidemics of gaming addiction. Thus, an analysis was conducted to understand the model's reactions and behaviors in response to these interventions. This provided insights into potential actions that could be taken. As seen in Table 9.1, alterations have been applied to parameters related to gamers.

Table 9.1. Selected parameters and alterations for policy interventions.

No	Parameters	Alterations based on Base Run		
1	Neutral Gamer Fraction	+10	+25	%
2	Infect contacts (Ci)	-10	-25	%
3	Addiction Coefficient	-10	-25	%
4	IsolFract	-10	-25	%

The simulations have been run for a total of 360 months with the new policy values changing from the 144th month when reference period ends. The constant value in the equation of the relevant parameter has been replaced with the following equation;

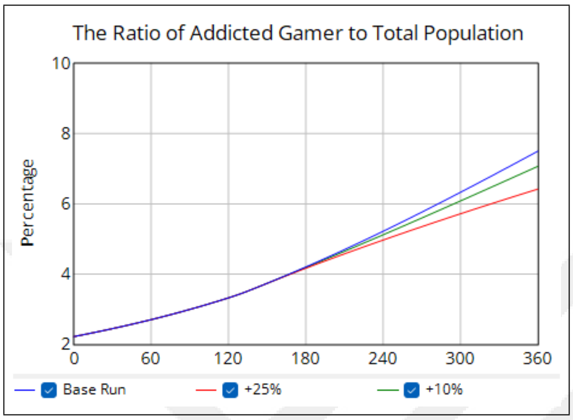
$$New\,Value\,of\,the\,Parameter = \\ IF\,THEN\,ELSE(Time > 144, Initial\,Value \times (1 + C), Initial\,Value) \tag{9.1}$$

utilizing C as the percentage change on *Initial Value* of the parameter.

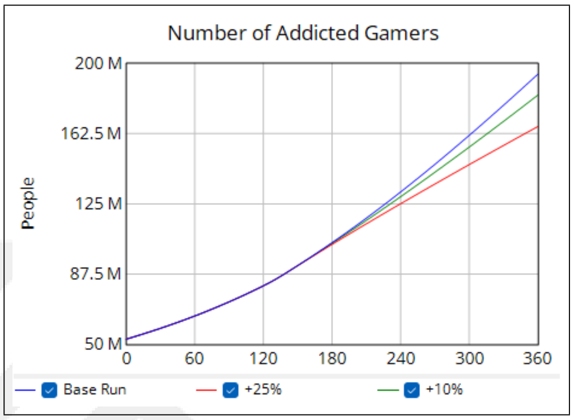
9.1. The Neutral Gamer Fraction

Each year, various games are released, and an increasing number of Potential Gamers (S) are becoming Beginner Gamers (E) by being exposed to online gaming. There are three different outflows from Beginner Gamers (E) and some of these gamers flow into the stock of Neutral Gamers with a constant fraction called Neutral Gamer Fraction. This policy investigates how player dynamics will change if Beginner Gamers

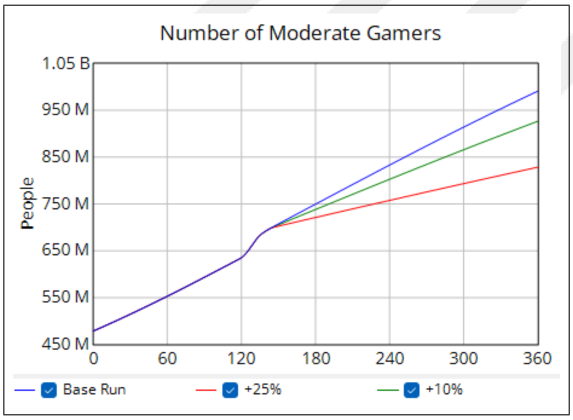
(E) are encouraged to play for less than 1 hour per week. Therefore, this section explores the potential outcomes of increasing the Neutral Gamer Fraction by 10% and 25%.



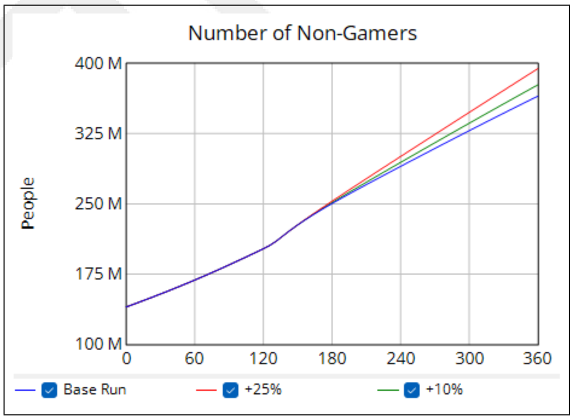
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



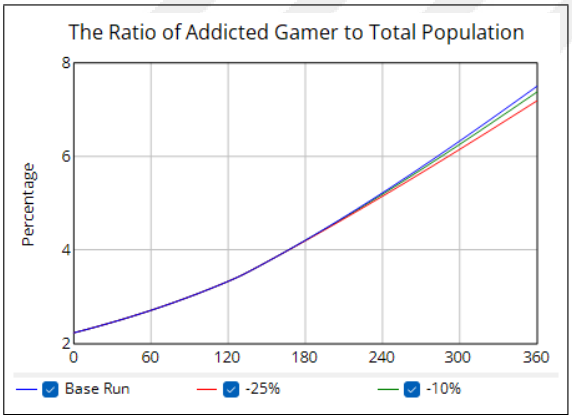
(d) The number of non gamers

Figure 9.1. Policy intervention using the neutral gamer fraction.

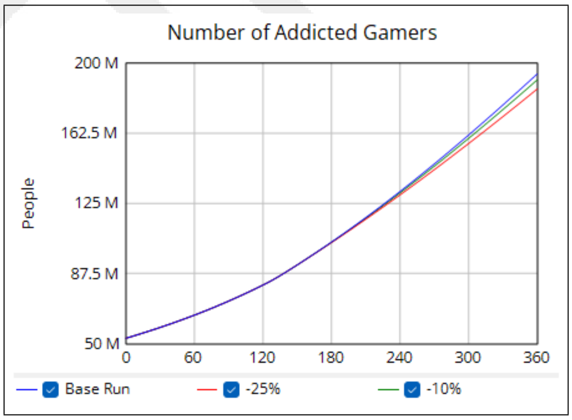
When the Neutral Gamer Fraction increases, there is a rise in the flow from Beginner Gamers (E) to Neutral Gamers (N). This also increases the number of people joining the Non-Gamer (Q) stock as some people try online gaming but do not engage with these games. Consequently, the number of people returning to the system as Potential Gamers (S) decreases over time. As depicted in Figure 9.1, the outcomes indicate a decrease in the numbers of Addicted Gamers (I) and Moderate Gamers (M) due to the increase in the Neutral Gamer Fraction. Particularly, the population of Moderate Gamers (M) is significantly affected. Consequently, there is a decrease in the ratio of addicted gamers to the total population, leading to a reduced visibility of addicted gamers in society. Comparing the outcomes resulting from changes in subsequent policies reveals that the impact of this parameter appears to be relatively significant.

9.2. The Number of Infective Contacts

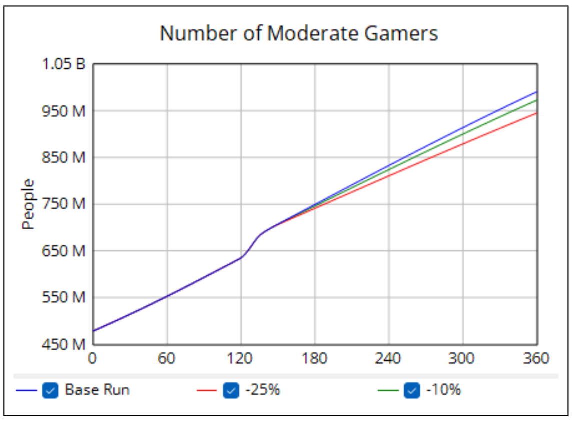
People start playing games for different reasons which include escaping reality, seeking engaging stories, pursuing entertainment, and fostering social interactions [7,8]. Social interaction is a significant motivator for initiating gaming activities, as some people play games to spend time with their families and friends, while others aim to make new acquaintances in the online environment due to social isolation.



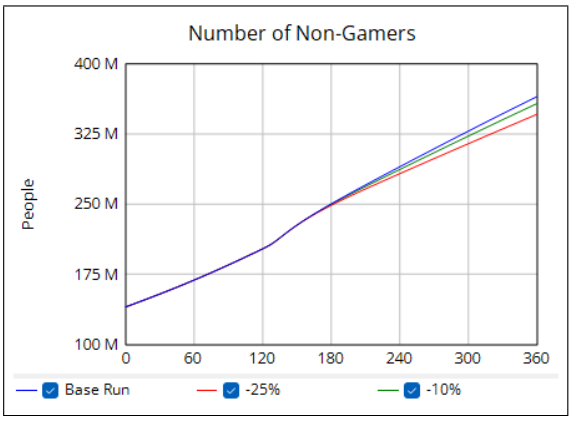
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

Figure 9.2. Policy intervention using infect contacts (Ci).

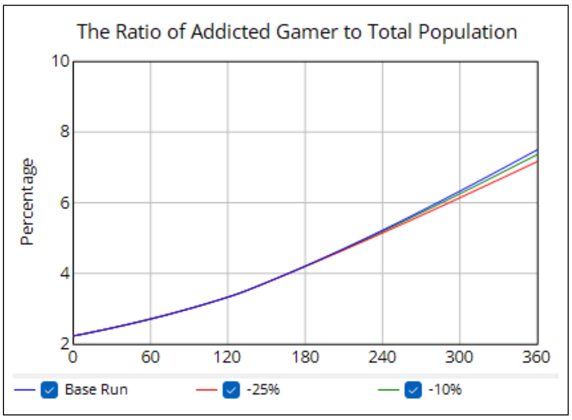
When people engage socially, they listen to stories about their friends' gaming preferences and observe gameplay. When they are sufficiently influenced, they begin playing games to spend time online with their peers. The parameter named infect contacts (Ci) is a critical factor indicating Potential Gamers' inclination to start gaming through word of mouth.

Figure 9.2 illustrates the impact of varying infect contacts (Ci) on the selected outcomes of interest. A 25% fall in infect contacts (Ci) results in a noticeable change in the outcomes. As presented in Figure 9.2, the order of the decrease from the greatest to the least is as follows: Non-gamer (Q), Moderate Gamer (M), Addicted Gamer (I). The fall in Addicted Gamers (I) results in a decrease in the ratio within the total population. However, as the number of other types of gamers in the system decreases rapidly, Addicted Gamers (I) become more visible and noticeable among other gamers.

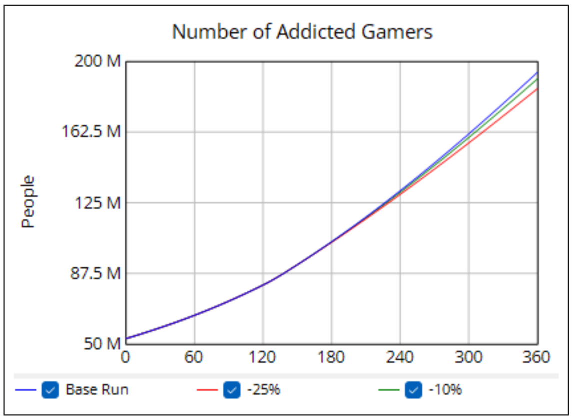
9.3. The Addiction Coefficient

A crucial component of the Addiction Fraction is the Addiction Coefficient which represents the proportion responsible for addiction. This fraction is influenced by addictive games and streaming within the Addiction Fraction. In this policy analysis, adjustments ranging from -25% to -10% in Addiction Coefficient will be explored.

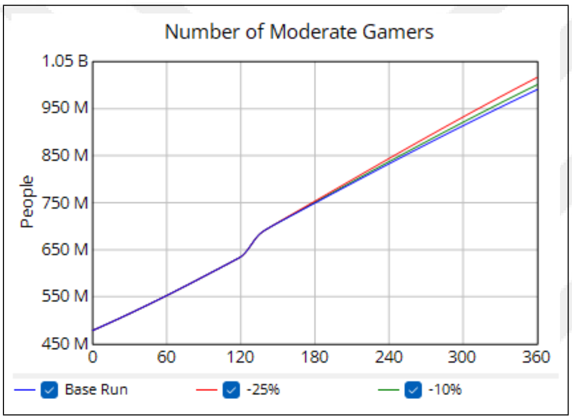
When the influence of addictive factors in the environment is reduced, people are more likely to become Moderate Gamers (M) who play games for shorter durations instead of becoming Addicted Gamers (I) according to Figure 9.3. Thus, there is a reduction in the proportion of addicted gamers within society. In contrast, Non-Gamers (Q) stock has been minimally affected and this change can be considered negligible.



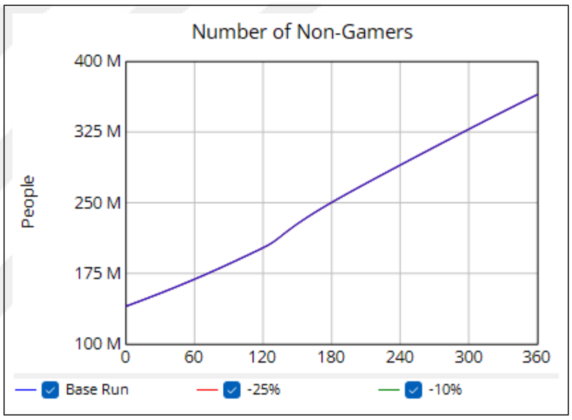
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

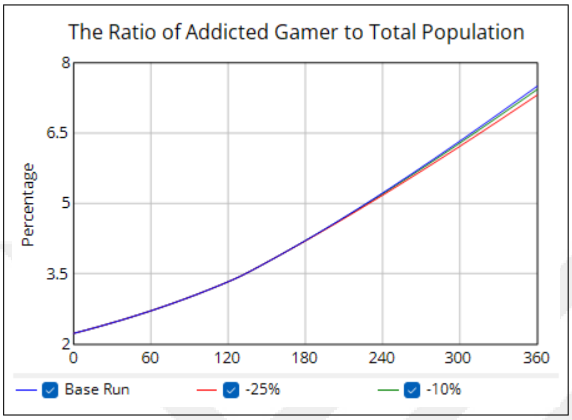
Figure 9.3. Policy intervention using the addiction coefficient.

9.4. The Isolated Gamers

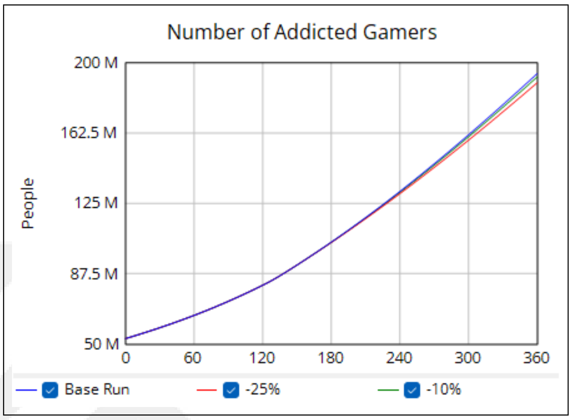
One of the factors contributing to Internet Gaming Disorder (IGD) is the adoption through word of mouth induced by Moderate Gamers (M) and Pre-Addicted Moderate Gamers (PI). Isolating a fraction of Total Moderate Gamers (M+PI) has been considered as a policy intervention, and *Adoption from WoM* in Equation (5.6) has been modified as follows;

$$\begin{aligned} &Adoption\ from\ WoM = Potential\ Gamers(S) \times Number\ of\ Inf\ Cont(Ci) \\ &\times \frac{Total\ Moderate\ Gamers(M+PI) \times IsolFract}{Potential\ Gamers(S)\ +\ Total\ Moderate\ Gamers(M+PI) \times IsolFract} \\ &\times Delayed\ Pandemic\ Lockdown\ Effect\ on\ Adoption \end{aligned} \tag{9.2}$$

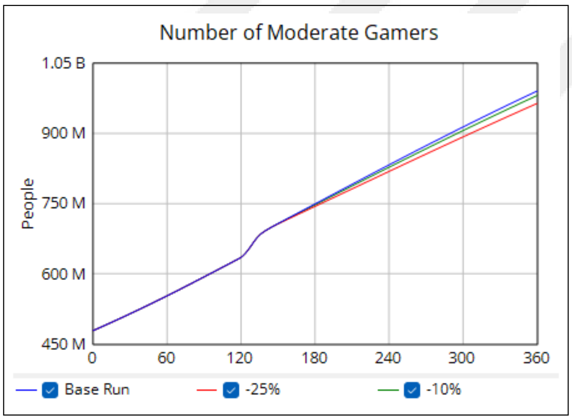
utilizing *IsolFract* (Unitless) as the isolated fraction of *Total Moderate Gamers (M+PI)*. This section will focus on examining the effects of the *IsolFract* on outcomes of interest in our model.



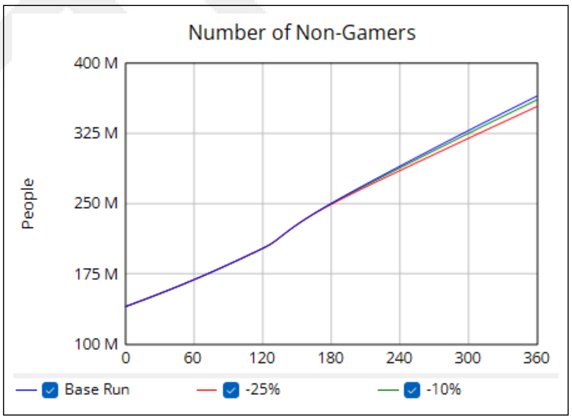
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

Figure 9.4. Policy intervention using the isolated fraction.

When isolating 25% and 10% of the Total Moderate Gamers (M+PI) from word of mouth decreases, all outcomes of interest, particularly the number of Addicted Gamers (I), decrease. This leads to a reduction in the ratio of addicted gamers to the total population. Isolating 25% of them results in a decrease more than twice as significant as isolating 10% of them. As presented in Figure 9.4, the order of the decrease from the greatest to the least is as follows: Non-gamer (Q), Moderate Gamer (M), Addicted Gamer (I). However, when comparing the outcomes resulting from changes in other parameters in policy interventions, it is observed that the impact of isolating a fraction seems to be relatively minor compared to other policy parameters above.

9.5. Combined Policy Intervention

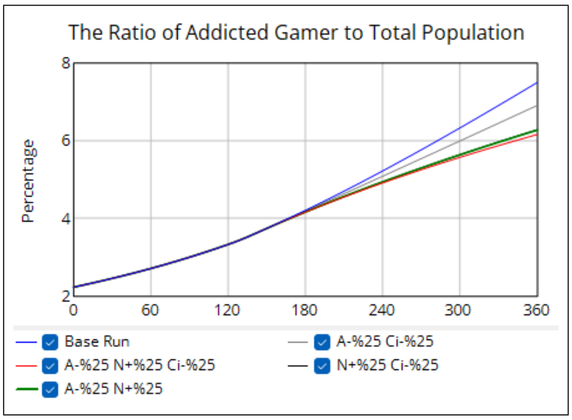
Upon examining Figure 9.1, 9.2, and 9.3, it becomes evident that alterations in each policy parameter yield varying degrees of impact. Considering both triple and double combinations of the prior policy interventions, four experiments were conducted as illustrated in Table 9.2.

Table 9.2. Selected parameters for combined policy intervention.

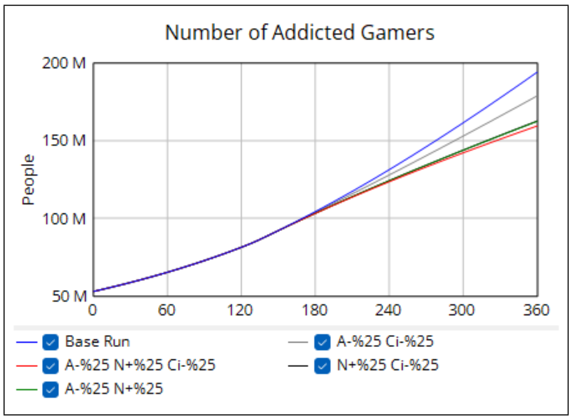
			Experiments				
No	Parameters		1	2	3	4	
1	Neutral Gamer Fraction	N	+25	-	+25	+25	%
2	Infect Contacts	Ci	-	-25	-25	-25	%
3	Addiction Coefficient	A	-25	-25	-	-25	%

As seen in Table 9.2, the Addiction Coefficient parameter is denoted by the letter A, the Neutral Gamer Fraction parameter by the letter N, and the Infect Contacts parameter by the Ci for ease of reference in figures. Figure 9.5 shows that interventions have yielded effective results in reducing the ratio of addicted gamers in the total population. However, when considering all experiments, the most effective intervention involves changes in the Neutral Gamer Fraction.

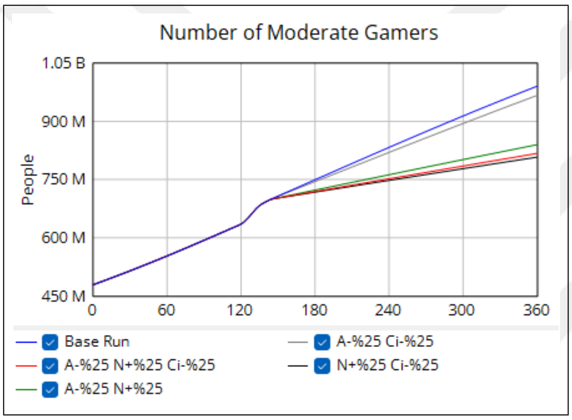
Figure 9.5c shows that Experiment 2 did not effectively alter the number of Moderate Gamers (M). While the results of the remaining experiments are considered similar, Experiment 3, unlike Addicted Gamers (I), resulted in the most significant decrease in the number of Moderate Gamers (M).



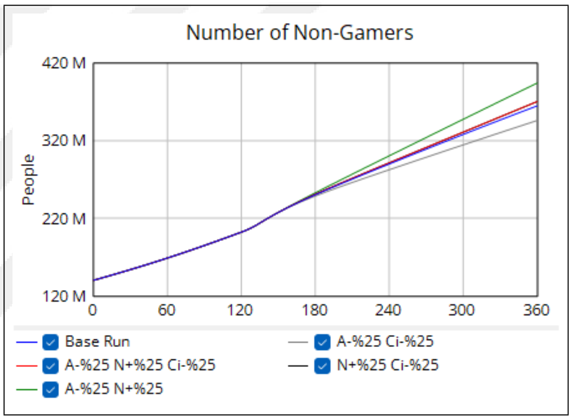
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

Figure 9.5. Combined policy intervention.

Looking at Figure 9.5d, it is concluded that the experiments resulted in both increases and decreases in the Non-Gamers (Q) stock. While Experiment 3 and Experiment 4 created almost the same amount of increase, Experiment 1 resulted in the highest increase in the Non-Gamers (Q), hence more gamers quit gaming. Different from the others, Experiment 2 led to a decrease in those quitting gaming and a decrease in the number of Non-Gamers (Q).

Upon examining the outcome named the number of Addicted Gamers (I) in Figure 9.5b, it is observed that the most effective result was achieved in Experiment 4, where all three parameters were modified. Similar outcomes were observed in Experiments 1, 3, and 4, all of which involved changes in the Neutral Gamer Fraction.

10. CONCLUSION

The widespread popularity and accessibility of online gaming has led to a significant increase in game addiction. To understand the dynamics of worldwide epidemics of Internet Gaming Disorder (IGD), we constructed a system dynamics simulation model at population-level. In the literature, most papers investigate IGD for adolescents and young adults, thus, we determine the focus age group as 10 to 30. Causal relationships among subsectors of gamers, gaming businesses, and streaming with model assumptions, and simplifications are explored. The model is developed by including information from both quantitative and qualitative literature, and its validation is carried out using actual data spanning 12 years. Subsequently, an analysis of the model is provided, system behavior is evaluated across various scenarios such as changes in Normal Average Money Spent, Delay for Dropping, and Duration. Policy interventions are tested for the changes in the Neutral Gamer Fraction, Infect Contacts (Ci), Addiction Coefficient, and Isolated Fraction (IsolFract). Ultimately, the findings from scenario analyses and policy interventions are discussed.

The scenario analysis indicates that the average life of games in the market ("Delay for Dropping") has the most substantial impact, increasing both the ratio of addicted gamers to the total population and the total number of gamers which also leads to be noticeable. The scenario involving the Normal Average Money Spent is less effective compared to other scenarios. However, it has a unique impact considering pre and post-pandemic periods as it affects the number of Addicted Gamers more than the numbers of other types of gamers. Therefore, before the pandemic, a decrease in spending leads to a higher proportion of addicted gamers to overall gamers, while in the post-pandemic period, the effect is reversed due to a sudden rise in the total number of gamers. An experiment is also conducted for the COVID-19 pandemic effect, including its duration. As anticipated, an increase in the duration of pandemic results in a higher ratio of addicted gamers to the total population. Surprisingly, an increase in the duration causes a decrease in the proportion of addicted gamers to overall gamers as the number of gamers inclines. However, with an extended duration of over 1 year, this effect diminishes.

For policy analysis, the simulation time horizon is 360 months and interventions start from the 144th month when the reference period ends. The results obtained from the policy analysis highlight that adjusting the Neutral Gamer Fraction has the most significant impact on the outcomes of interest. Increasing this parameter leads to the highest decrease in the ratio of addicted gamers to the total population among policies. Addiction Coefficient has the second substantial impact on the outcomes of interest. Hence, the results demonstrate that the effects of First Person Shooter (FPS) and Massive Multiplayer Online Role Playing Games (MMORPG) genre games and streaming of video gaming content are more influential, and decreasing their influence people are more likely to become Moderate Gamers. The policy intervention with the Infect Contacts is the third influential. Decreasing its value leads to a decrease in the proportion of addicted gamers to the total population. Its effects on the number of other types of gamers are higher than its effect on the number of Addicted Gamers. Hence, Addicted Gamers become more noticeable among other gamers. With the information collected from policy interventions, we decided to make experiments including Neutral Gamer Fraction, Infect Contacts, and Addiction Coefficient. The results demonstrate that Neutral Gamer Fraction has a dominant influence on the outcomes of interest and combining it with other parameters creates the largest decrease in the number of Addicted Gamers.

In summary, our model is analyzed and the results indicate that increasing the Neutral Gamer Fraction, or in other words, encouraging or forcing people to play games for shorter durations, creates the largest decrease in the number of Addicted Gamers.

Future research studies might focus on examining the model assumptions, outputs, and the resilience of insights by employing more extensive cross-sectional and dynamic data considering different age groups. Moreover, the exploration of alternative mitigation strategies within the model, and assessment of their effectiveness in diverse scenarios, might be taken into account. Another direction for future research studies might be developing an individual-level system dynamics modeling for the dynamics of addiction in an individual, examining the dynamics of becoming an addicted gamer. With the outcomes from this individual-level model and the insights obtained from the literature, agent-based modeling for population-level addiction dynamics can be created to examine the interpersonal dynamics of Internet Gaming Disorder.

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APPENDIX A: MODEL EQUATIONS

(001) “Addicted Gamers (I)”= INTEG (Being Addicted Rate-Recovery Rate, Initial addicted gamers)
Units: People

(002) Addiction Coefficient= 0.05
Units: Dmnl

(003) Addiction Fraction= Normal Addiction Fraction+Addiction Coefficient* (Effect of Game on Addiction Fraction + Effect of Streaming on Addiction Fraction)
Units: Dmnl

(004) Addiction Rate= (1-Neutral Gamer Fraction)*Addiction Fraction*“Beginner Gamers (E)”/Gamer Adoption Time
Units: People/Month

(005) Adoption From Advertisement= “Advertising Effectiveness (a)”*“Potential Gamers (S)”
Units: People/Month

(006) Adoption From Word of Mouth= Delayed Pandemic Lockdown Effect on Adoption*“Infect Contact (Ci)” *“Potential Gamers (S)”*(“Total Moderate Gamers (M + PI)”)/(“Potential Gamers (S)” +“Total Moderate Gamers (M + PI)”)
Units: People/Month

(007) Adoption Rate= Adoption From Advertisement+Adoption From Word of Mouth
Units: People/Month

(008) “Advertising Effectiveness (a)”= Graph 2(Monthly Advertisement Ratio)* Normal Advertising Effectiveness
Units: 1/Month

(009) Age Group Fraction= 0.649
Units: Dmnl

(010) Avg Money Spent= Normal Ave Money Spent*Delayed Pandemic Lockdown Effect on Playing Time and Money Spent
Units: Dollar/Month/People

(011) “Beginner Gamers (E)”= INTEG (Adoption Rate-Addiction Rate-Gaming Adoption Rate-Neutral Gamer Flow, Initial beginner gamers)
Units: People

(012) Being Addicted Rate= “Pre-Addicted Moderate Gamers (PI)”*PI to I Fraction/Being Addicted Time
Units: People/Month

(013) Being Addicted Time= 12
Units: Month

(014) Capacity Used by IGD Patients= Effect of Visibility on Capacity Usage by IGD Patients*Total Capacity of Mental Health Facilities *Age Group Fraction
Units: People

(015) Channel Coefficient= 1/44000
Units: Dmnl

(016) Channel per Moderate Gamers= Channel Coefficient*Graph 8(Streaming Popularity)

Units: Channel/People

(017) Cumulative Revenue= INTEG (Monthly Revenue, 1.068e+10)
Units: Dollar

(018) Delay for Dropping= 120
Units: Month

(019) Delayed Monthly Revenue= DELAY3(Monthly Revenue,Revenue Information Delay)
Units: Dollar/Month

(020) Delayed Pandemic Lockdown Effect on Adoption= DELAY3(Pandemic Lockdown Effect on Adoption,Information Delay of PLE)
Units: Dmnl

(021) Delayed Pandemic Lockdown Effect on Playing Time and Money Spent= DELAY3(Pandemic Lockdown Effect on Playing Time and Money Spent,Information Delay of PLE)
Units: Dmnl

(022) Delayed Pandemic Lockdown Effect on Streaming Channel Opennings= DELAY3 (Pandemic Lockdown Effect on Streaming Channel Opennings,Information Delay of PLE *2)
Units: Dmnl

(023) Delayed Pandemic Lockdown Effect on Streaming Popularity= DELAY3 (Pandemic Lockdown Effect on Streaming Popularity,Information Delay of PLE)
Units: Dmnl

(024) Delayed Pandemic Lockdown Effect on Twitch Viewership= DELAY3 (Pan-

demic Lockdown Effect on Twitch Viewership,Information Delay of PLE *2)
Units: Dmnl

(025) Dummy Stock for Total Number of New Games= INTEG (f1, 785)
Units: Games

(026) Duration= 12
Units: Month

(027) Effect of Game on Addiction Fraction= Graph 5(Game Ratio)
Units: Dmnl

(028) Effect of Monthly Revenue on New Game Production= Graph 3(Monthly Revenue Ratio)
Units: Dmnl

(029) Effect of Streaming on Addiction Fraction= Graph 7(Watching Hour per Viewer/Normal Watching Hour per Viewer)
Units: Dmnl

(030) Effect of Visibility on Capacity Usage by IGD Patients= LOOKUP EXTRAPOLATE(Graph 1,Ratio of AG to Other Gamers)
Units: Dmnl

(031) f1= New Game Flow
Units: Games/Month

(032) FINAL TIME = 240
Units: Month The final time for the simulation.

(033) Fraction of Revenue used for Advertisement= 0.05

Units: Dmnl

(034) Game Production Delay= 24
Units: Month

(035) Game Ratio= Total Number of FPS and MMORPG Games in the Market/Normal Number of Games in the Market
Units: Dmnl

(036) Gamer Adoption Time= 3
Units: Month

(037) Games Dropping Rate= Total Number of FPS and MMORPG Games in the Market/Delay for Dropping
Units: Games/Month

(038) Games WIP= INTEG (New Game Flow-New Game Releases, 260)
Units: Games

(039) Gaming Adoption Rate= (1-Neutral Gamer Fraction)*(1-Addiction Fraction)*"Beginner Gamers (E)"/Gamer Adoption Time
Units: People/Month

(040) Graph 1([(0,0)-(0.35,0.22)],(0,0), (0.0101514, 0.000783034), (0.0198708, 0.00208809), (0.0302382, 0.00378467), (0.0454319, 0.0129952), (0.0544261, 0.0215531), (0.0645733 , 0.0316957), (0.0765655, 0.0478605), (0.087174, 0.066878), (0.0975518, 0.0903328), (0.112081, 0.111569), (0.133528, 0.136609), (0.165123,0.157845), (0.203778, 0.17784), (0.243569, 0.190871), (0.27492, 0.198153), (0.303055, 0.202753), (0.35, 0.208), (0.4, 0.21), (0.5, 0.21))
Units: Dmnl

(041) Graph 2([(0,0)-(10,10)],(0,0), (0.271003, 0.0741351), (0.48103, 0.177924), (0.697832, 0.385502), (0.873984, 0.721582), (1,1), (1.17886, 1.41351),(1.55149, 1.82372), (2.18835, 2.10544), (3.02168, 2.36738), (3.97019, 2.53542), (4.88506, 2.65145), (5.84934, 2.7747), (6.88331, 2.88142), (7.94682, 2.9585), (9,3), (10,3))
Units: Dmnl

(042) Graph 3([(0,0) - (1.67984,10.6777)], (0,0), (0.0846548, 0.0301423), (0.186824, 0.0964553), (0.397318, 0.2926),(0.552272, 0.528568), (0.719146, 0.755097), (0.96151, 0.981626),(1.00018, 1.00202), (1.29921, 1.15233),(1.60012, 1.25682), (2.17007, 1.3497), (2.77189, 1.40776), (3.39141, 1.45748), (3.99322, 1.49346))
Units: Dmnl

(043) Graph 4([(0,0) - (100,0.012)] ,(0, 0.003), (2.25, 0.0037), (4.3, 0.0045),(6.2, 0.0055),(10 , 0.0066),(17, 0.008), (26, 0.009), (40, 0.01), (60, 0.0106), (80, 0.011), (100, 0.011))
Units: Dmnl

(044) Graph 5([(0,0) - (1.5,4)], (0,0), (0.165789, 0.0909091), (0.315789, 0.227273), (0.489474, 0.454545), (0.647368, 0.772727), (0.8, 1.1855), (0.971053, 1.80303), (1.12895, 2.33333), (1.26316, 2.80303), (1.5, 3.33333), (1.8, 3.66667), (2.12368, 3.86364), (2.5, 3.938), (3, 3.938))
Units: Dmnl

(045) Graph 6([(0,0)-(10,10)],(0,0),(100,2.8))
Units: Dmnl

(046) Graph 7([(0,0) - (60.0408, 2.54063)], (0, 1.288), (0.9, 1.288), (0.952965, 1.30137), (1.0016 , 1.32534), (1.09708, 1.40753), (1.16013, 1.51027), (1.28623, 1.66438), (1.38171, 1.7363), (1.54924 1.81507), (1.8681, 1.885), (2.2374, 1.93836))
Units: Dmnl

(047) Graph 8([(0,0) - (100,6)], (0,0), (4.60235, 0.143911), (9.79045, 0.420664), (16.5258, 0.756957), (24.9573, 1.20223), (34.3331, 1.70315), (43.5741, 2.30427), (50.4954, 2.93455), (59.8679, 3.92971), (68.8687, 4.6869), (81.4878, 5.41538), (99.8291, 5.74359))
Units: Channel/People

(048) Inflation Growth Fraction= 0.0177/12
Units: Dmnl

(049) Information Delay of PLE= 3
Units: Month

(050) Initial addicted gamers= 5.28e+07
Units: People

(051) Initial beginner gamers= 1.455e+07
Units: People

(052) Initial moderate gamers= 4.78458e+08
Units: People

(053) Initial neutral gamers= 8.44416e+07
Units: People

(054) "Initial non-gamers"= 1.39936e+08
Units: People

(055) Initial Number of FPS and MMORPG Games= 785
Units: Games

(056) Initial potential gamers= 1.56104e+09
Units: People

(057) "Initial pre-addicted gamers"= 4.4e+07
Units: People

(058) INITIAL TIME = 0
Units: Month The initial time for the simulation.

(059) Initial treated gamers= 0
Units: People

(060) "Moderate Gamers (M)"= INTEG (Gaming Adoption Rate, Initial moderate gamers)
Units: People

(061) Money Spent Coefficient for AG= 5
Units: Dmnl

(062) Monthly Advertisement Expense= Delayed Monthly Revenue*Fraction of Revenue used for Advertisement
Units: Dollar/Month

(063) Monthly Advertisement Ratio= Monthly Advertisement Expense/Normal Monthly Advertisement
Units: Dmnl

(064) Monthly Revenue= Avg Money Spent*Money Spent Coefficient for AG* "Addicted Gamers (I)"+Avg Money Spent *("Moderate Gamers (M)"+"Pre-Addicted Moderate Gamers (PI)")*(1+Inflation Growth Fraction)$^{(}Time/TimeCoefficient)$
$Units: Dollar/Month$

(065) Monthly Revenue Ratio= Delayed Monthly Revenue/Normal Monthly Revenue

Units: Dmnl

(066) Net Growth= (Net Growth Fraction*Total Population/Net Growth Time)
Units: People/Month

(067) Net Growth Fraction= 0.00024
Units: Dmnl

(068) Net Growth Time= 1
Units: Month

(069) Neutral Gamer Flow= “Beginner Gamers (E)”*Neutral Gamer Fraction/ Gamer Adoption Time
Units: People/Month

(070) Neutral Gamer Fraction= 0.69
Units: Dmnl

(071) “Neutral Gamers (N)”= INTEG (Neutral Gamer Flow-Quitting Rate 1-Quitting Rate 2, Initial neutral gamers)
Units: People

(072) Neutral to Potential Fraction= 0.1
Units: Dmnl

(073) New Game Flow= Effect of Monthly Revenue on New Game Production*Normal Number of New Games in Production
Units: Games/Month

(074) New Game Releases= Games WIP/Game Production Delay
Units: Games/Month

(075) “Non Gamers (Q)”= INTEG (Quitting Rate 1, “Initial non-gamers”)
Units: People

(076) Normal Addiction Fraction= 0.1
Units: Dmnl

(077) Normal Advertising Effectiveness= 0.01/12
Units: 1/Month

(078) Normal Ave Money Spent= 1.3
Units: Dollar/Month/People

(079) Normal Monthly Advertisement= Normal Monthly Revenue* Fraction of Revenue used for Advertisement
Units: Dollar/Month

(080) Normal Monthly Revenue= 13.5/12*10^9
$Units : Dollar/Month$

(081) Normal Number of Games in the Market= 920
Units: Games

(082) Normal Number of New Games in Production= 8.7
Units: Games/Month

(083) Normal Watching Hour per Viewer= 500
Units: Hour/People

(084) Number of Active Channels= “Moderate Gamers (M)”* Delayed Pandemic Lockdown Effect on Streaming Channel Opennings *Channel per Moderate Gamers
Units: Channel

(085) Number of Viewers= ("Addicted Gamers (I)"+"Total Moderate Gamers (M + PI)")*Viewer Coefficient *Delayed Pandemic Lockdown Effect on Twitch Viewership
Units: People

(086) Pandemic Lockdown Effect on Adoption= IF THEN ELSE(Time $\geq$ $Pande-mic\,start : AND : Time < Pandemic\,start + Duration, 3.5, 1)$
$Units : Dmnl$

(087) Pandemic Lockdown Effect on Playing Time and Money Spent= IF THEN ELSE(Time$\geq$ $Pandemic\,start : AND : Time < Pandemic\,start + Duration * 2 + 1, 1.3, 1)$
$Units : Dmnl$

(088) Pandemic Lockdown Effect on Streaming Channel Opennings= IF THEN ELSE(Time$\geq$ $Pandemic\,start : AND : Time < (Pandemic\,start + Duration * 2 + 1), 1.4, 1)$
$Units : Dmnl$

(089) Pandemic Lockdown Effect on Streaming Popularity= IF THEN ELSE (Time $\geq Pandemic\,start : AND : Time < (Pandemic\,start + Duration * 2 + 1), 4, 1)$
$Units : Dmnl$

(090) Pandemic Lockdown Effect on Twitch Viewership= IF THEN ELSE (Time $\geq Pandemic\,start : AND : Time < (Pandemic\,start + Duration * 2 + 1), 1.5, 1)$
$Units : Dmnl$

(091) Pandemic start= 120-3
Units: Month

(092) PI to I Fraction= 0.05
Units: Dmnl

(093) Popularity Goal= IF THEN ELSE(Time¡=18, 0 ,100)
Units: Dmnl

(094) Popularity Increase Delay= 1
Units: Month

(095) Popularity Rate= (Popularity Goal-Streaming Popularity)*Streaming Popularity Fraction/Popularity Increase Delay
Units: Dmnl/Month

(096) "Potential Gamers (S)"= INTEG (Net Growth+Quitting Rate 2-Adoption Rate, Initial potential gamers)
Units: People

(097) "Pre-Addicted Moderate Gamers (PI)"= INTEG (Addiction Rate-Being Addicted Rate, "Initial pre-addicted gamers")
Units: People

(098) Quitting Delay= 3
Units: Month

(099) Quitting Fraction= 0.016
Units: Dmnl

(100) Quitting Rate 1= "Neutral Gamers (N)"*(Quitting Fraction)/Quitting Delay
Units: People/Month

(101) Quitting Rate 2= "Neutral Gamers (N)"*Neutral to Potential Fraction/ Quitting Delay
Units: People/Month

(102) Ratio of AG to Other Gamers= “Addicted Gamers (I)”/(“Total Moderate Gamers (M + PI)”+“Addicted Gamers (I)” +“Neutral Gamers (N)”)

Units: Dmnl

(103) Recovery Rate= Capacity Used by IGD Patients/Treatment Time*Success Rate

Units: People/Month

(104) Revenue Information Delay= 3

Units: Month

(105) SAVEPER = 1

Units: Month [0,?] The frequency with which output is stored.

(106) Streaming Hours= Number of Active Channels*Streaming Time per Channel

Units: Hour

(107) Streaming Popularity= INTEG (Popularity Rate, 0)

Units: Dmnl

(108) Streaming Popularity Fraction= Graph 4(Streaming Popularity)*Delayed Pandemic Lockdown Effect on Streaming Popularity

Units: Dmnl

(109) Streaming Time per Channel= 700

Units: Hour/Channel

(110) Success Rate= 0.1

Units: Dmnl

(111) “Infect Contact (Ci)”= 0.12/12
Units: People/People/Month

(112) Time Coefficient= 1
Units: Month

(113) TIME STEP = 0.0625
Units: Month [0,?] The time step for the simulation.

(114) Total Capacity of Mental Health Facilities= 1.13024e+06
Units: People

(115) “Total Moderate Gamers (M + PI)”= “Moderate Gamers (M)”+“Pre-Addicted Moderate Gamers (PI)”
Units: People

(116) Total Number of FPS and MMORPG Games in the Market= INTEG (New Game Releases-Games Dropping Rate, Initial Number of FPS and MMORPG Games)
Units: Games

(117) Total Population= “Addicted Gamers (I)”+“Beginner Gamers (E)”+ “Potential Gamers (S)”+“Total Moderate Gamers (M + PI)”+“Neutral Gamers (N)”+“Non Gamers (Q)”+“Treated Gamers (R)”
Units: People

(118) “Treated Gamers (R)”= INTEG (Recovery Rate, Initial treated gamers)
Units: People

(119) Treatment Time= 3
Units: Month

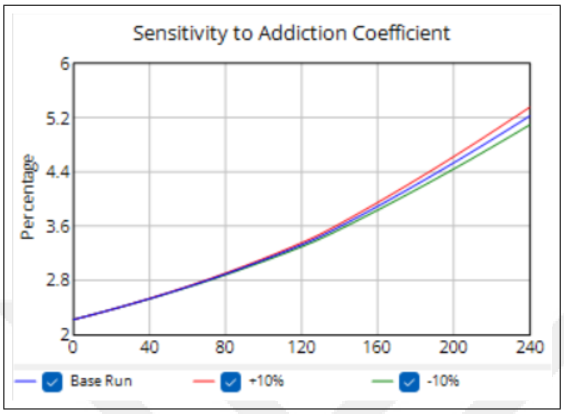
(120) Viewer Coefficient= Graph 6(Streaming Popularity)/975
Units: Dmnl

(121) Watching Hour per Viewer= ZIDZ(Watching Hours,Number of Viewers)
Units: Hour/People

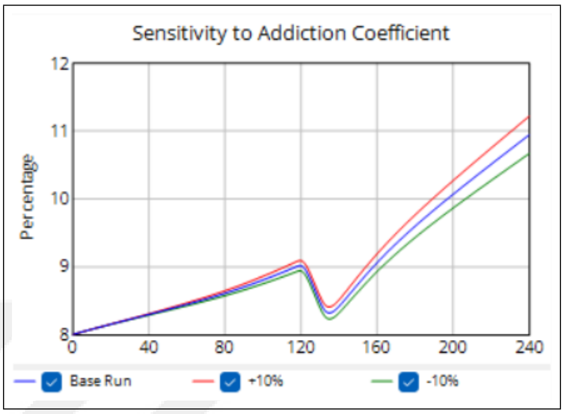
(122) Watching Hours= Streaming Hours*Watching Hours Fraction
Units: Hour

(123) Watching Hours Fraction= ZIDZ("Addicted Gamers (I)"*2+"Total Moderate Gamers (M + PI)",("Addicted Gamers (I)" +"Total Moderate Gamers (M + PI)"))*25
Units: Dmnl

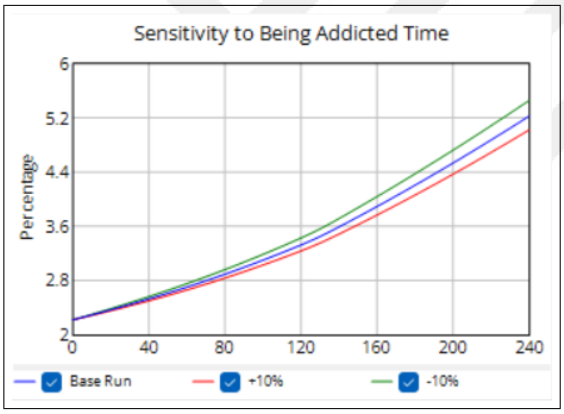
APPENDIX B: SENSITIVITY TEST RESULTS



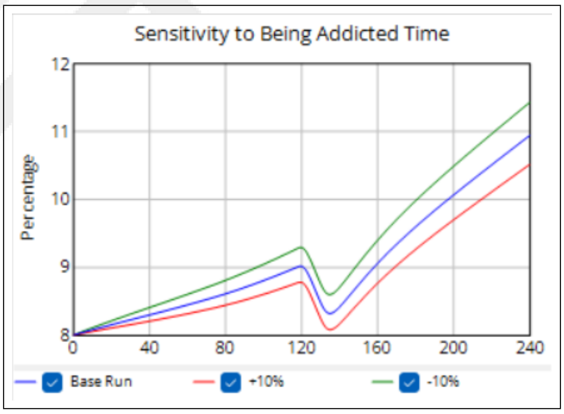
(a) Addiction coefficient



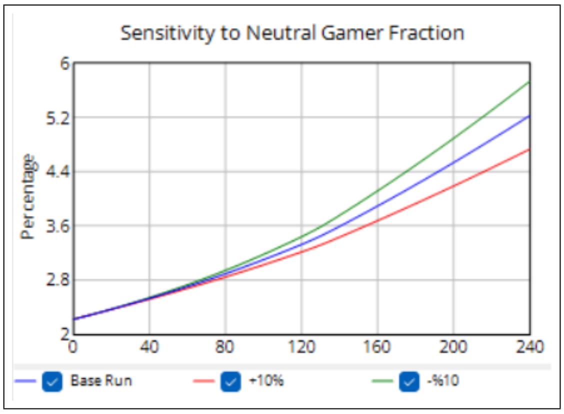
(b) Addiction coefficient



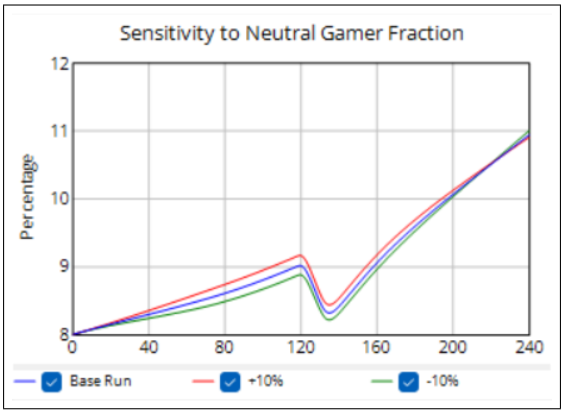
(c) Being addicted time



(d) Being addicted time

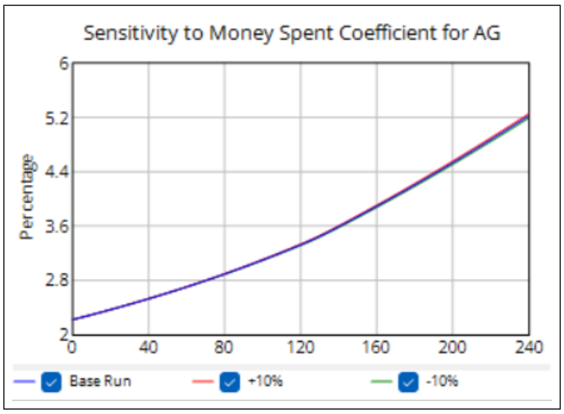


(e) Neutral gamer fraction

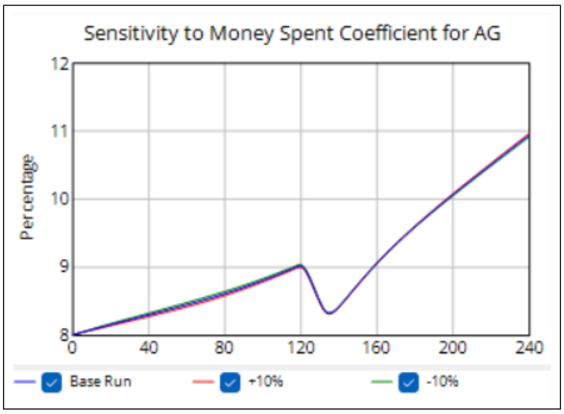


(f) Neutral gamer fraction

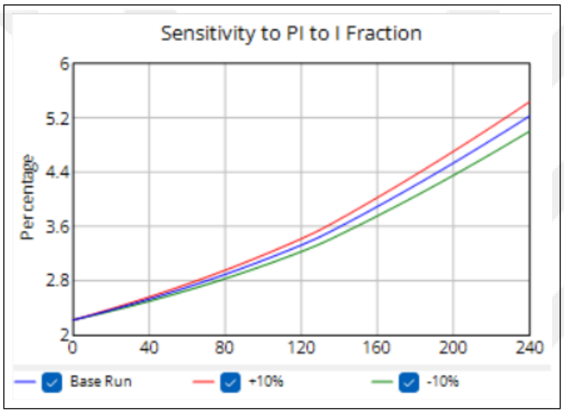
Figure B.1. Sensitivity tests - 1.



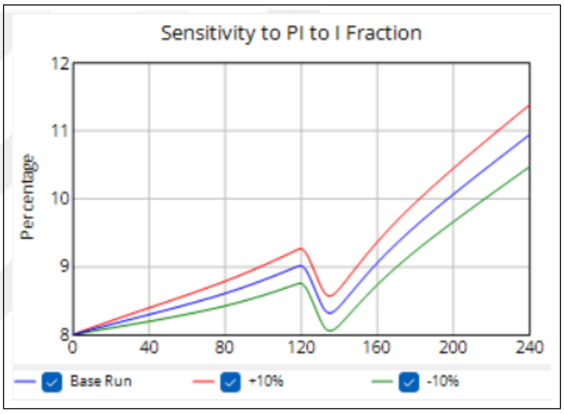
(a) Money spent coefficient for AG



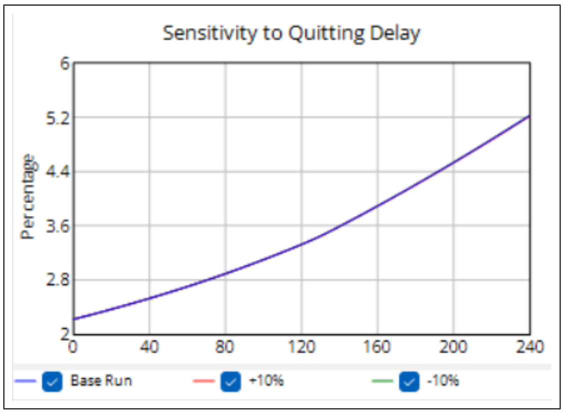
(b) Money spent coefficient for AG



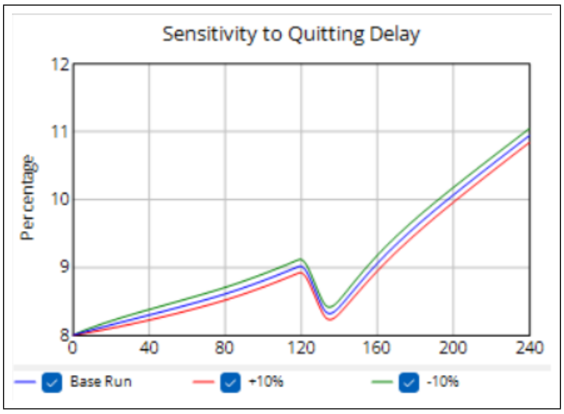
(c) PI to I fraction



(d) PI to I fraction

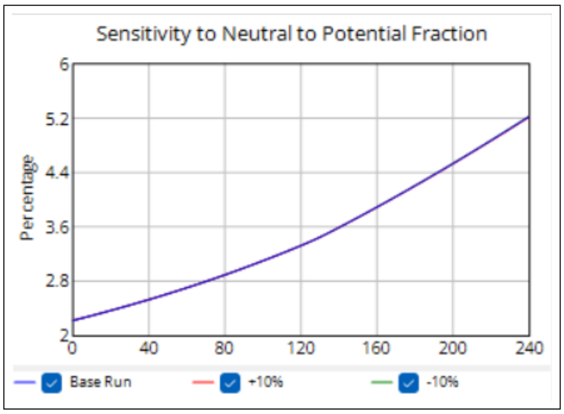


(e) Quitting Delay

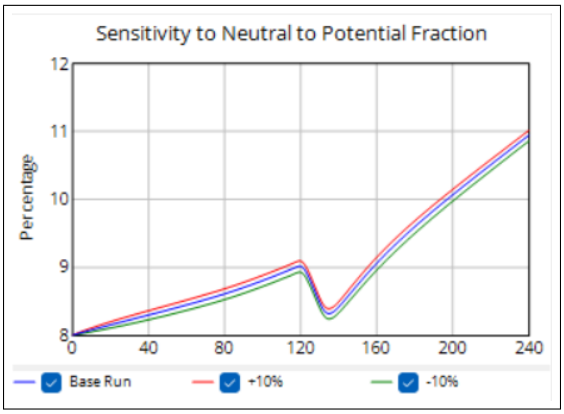


(f) Quitting Delay

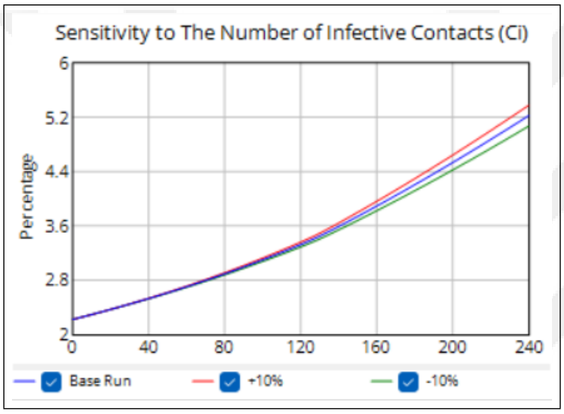
Figure B.2. Sensitivity tests - 2.



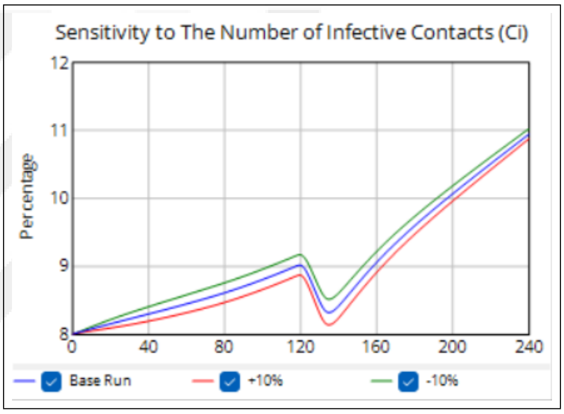
(a) Neutral to potential fraction



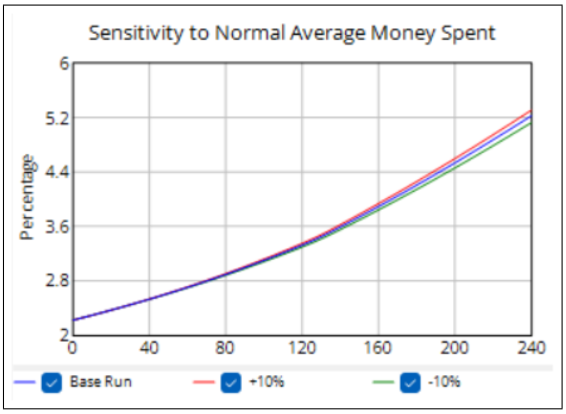
(b) Neutral to potential fraction



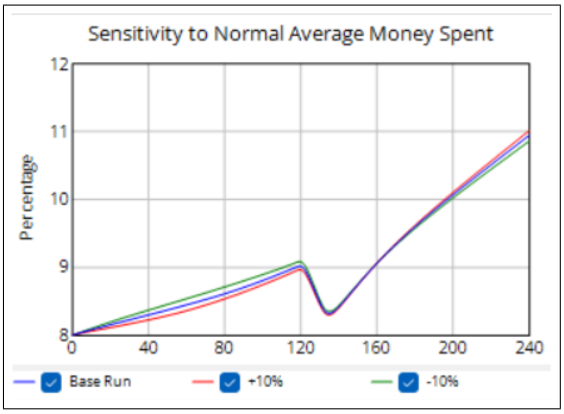
(c) Infect contacts (Ci)



(d) Infect contacts (Ci)



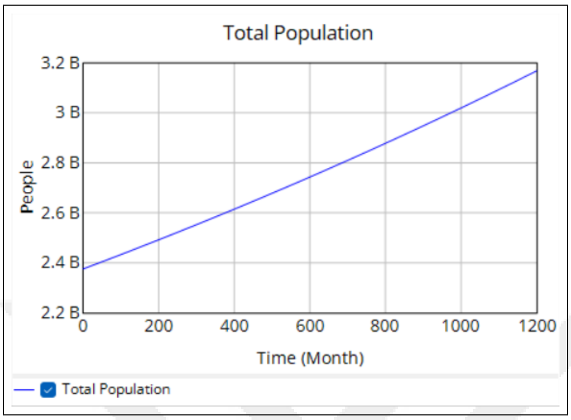
(e) Normal average money spent



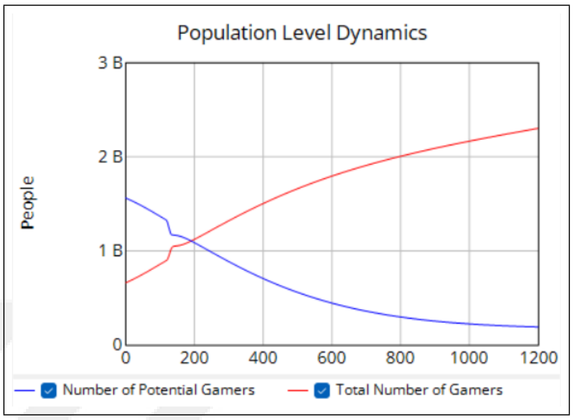
(f) Normal average money spent

Figure B.3. Sensitivity tests - 3.

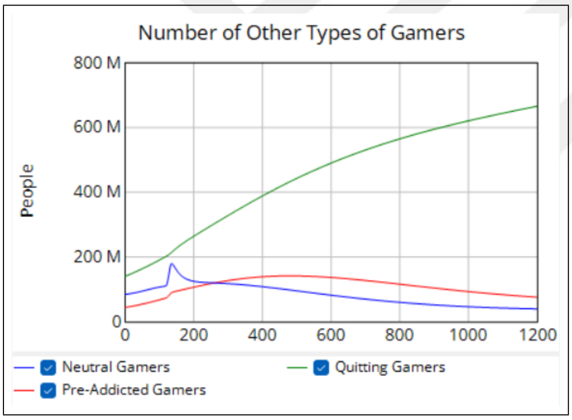
APPENDIX C: BASE RUN SPANNING A CENTURY



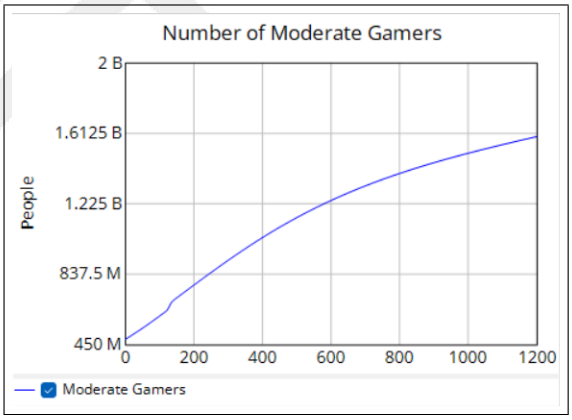
(a) The total population aged from 10 to 29



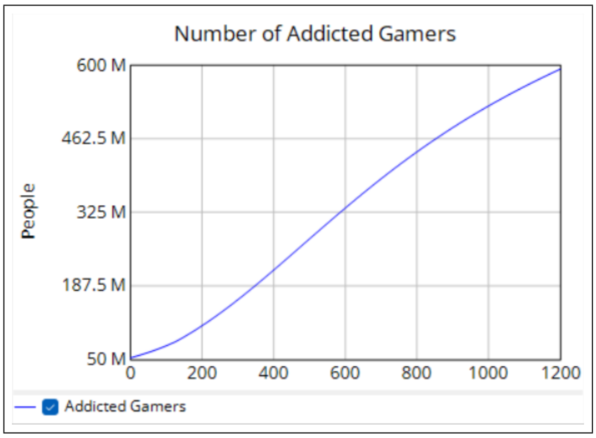
(b) Population level dynamics of gamers



(c) Various gamers

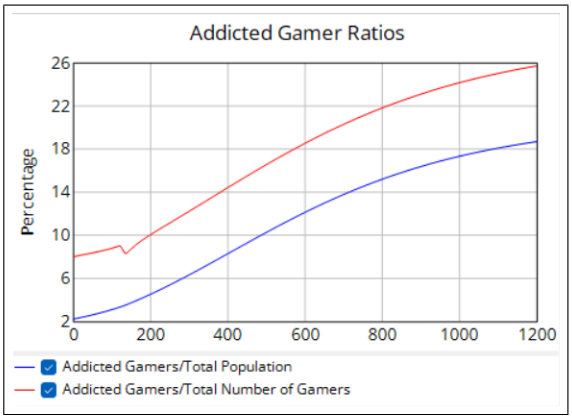


(d) Moderate gamers

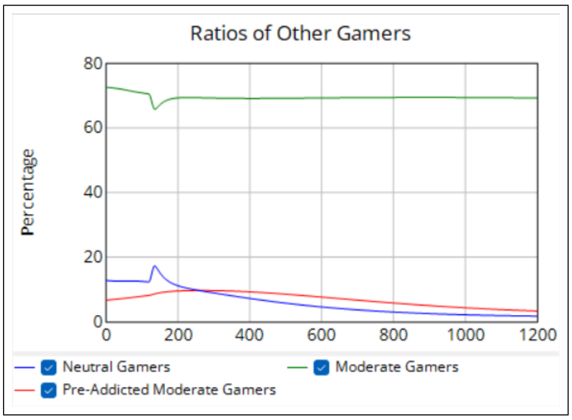


(e) Addicted gamers

Figure C.1. The dynamics of gamers for a base run spanning a century.



(a) Addicted gamers



(b) Other gamers per overall gamers

Figure C.2. Ratios of gamers for a base run spanning a century.