Modeling the epidemics of the internet gaming disorder with system dynamics approach

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Abstract

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 relationships such as family and friends. To explore the global dynamics of Internet Gaming Disorder, we constructed a population-level system dynamics simulation model, also 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 tested and validated between 2010 and 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 in 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.

1 Introduction

Video gaming has evolved significantly since the coin-operated arcade gaming machines in gaming centers where people play and socialize. In time, digital gaming machines have become more accessible and compact such as home consoles and personal computers. Today, people can play sophisticated video games anytime on platforms like mobile phones, and personal computers (PC). Thanks to technological accessibility, even though the number of gamers was 2.03 billion in 2015, it is expected to reach 3.5 billion by 2025 (Newzoo International 2019, 2020, 2021, 2022).

The interactions with virtual worlds and other global players have changed by the popularity of PC games. These games can be classified as single-player or multiplayer which can be either offline or online. Especially, online games provide an extraordinary opportunity for social interaction and entertainment. With its attractive visuals and addictive gameplay, 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(DFC Intelligence 2021; Capcom 2023). The sustained growth in revenue has led to an increase in the prevalence of online gaming with a wide range of game genres, including strategy, adventure, memory, casual, and social games. Moreover, these games provide opportunities for social interaction, learning, stress relief, exploration, and skill development.

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Player types can be expressed as moderate, tenacious, frequent, and heavy players by the average duration and weekly frequency of sessions (Kolo and Baur 2004). The gaming duration 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 Games (MMORPG) (Young 2009). These games provide interaction with others and players can achieve tasks faster by creating a party of a limited number of online friends and in guilds. The popularity of these games has increased over the last decades (Meredith et al. 2009). Alongside playing multiplayer online games, playing First Person Shooter (FPS) games and time spent watching video gaming content are also important indicators and contribute to addiction(Ünal et al. 2022). Online game addiction can cause undesirable consequences since game addicts may play for more than ten or twenty hours and, they intentionally might not sleep, eat, and interact with offline friends to play more (Young 2009). 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 (American Psychiatric Association 2013):

- 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.

Considering the growing gaming industry, the increasing number of gamers, and the negative impacts of excessive gaming behavior on individuals and society, the rise in the proportion of individuals with Internet Gaming Disorder poses a significant threat. This research aims to construct a population-level model of IGD to explore the long-term effects of addictive game genres, streamed video gaming content, and treatment to mitigate the proportion of individuals with the disorder. For this study, more addictive gaming genres of FPS and MMORPG are chosen and the model is established using data gathered from the Twitch streaming platform. After validating the reference dynamics of the global gamer population, different scenarios and policies 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.

2 Related literature

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 IGD. While some researchers examine its prevalence in different age groups, societies, and regions, others attempt to understand the dynamics of IGD by constructing system dynamics models. This literature review will investigate these various approaches and the key findings in the existing literature.

2.1 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% (Feng et al. 2017). 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%(Paulus et al. 2018). 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'(Darvesh et al. 2020). 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%)(Darvesh et al. 2020). All these studies highlight the importance of IGD, even if they utilize different methodologies for measurement.

2.2 The Epidemics of Internet Gaming Disorder

Early system dynamics studies in the addiction field are primarily focused on topics such as problematic alcohol use, drug misuse, and problematic gambling. After IGD is defined, studies about internet-related addictions have increased. Park and Ahn explore and suggest policy changes for dealing with online game addiction and its societal implications by using a system dynamics methodology(Park and Ahn 2010). 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(Hwang and Park 2016). 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(Brammer and Viehweger 2010). Wang explores the growth and competition dynamics of the online game market in Taiwan considering the effect of Research and Development capacity(Wang and Tseng 2010). However, there exists a literature gap in studies encompassing the gaming industry and video content production.

3 Model description

As gaming became more popular and sophisticated, there has been a notable increase in the number of individuals who dedicated their time to gaming.

3.1 Overview of the model

The model is built upon the conventional Susceptible-Exposed-Infected-Recovered-Quitted (SEIRQ) epidemiologic model. Figure 1 demonstrates a simplified version of the stock-flow diagram. There are eight stocks within the population:

- Potential Gamers do not engage in gaming activities,
- Beginner Gamers have been exposed to gaming through word of mouth and advertisements,
- Neutral Gamers 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 play games for more than one hour and less than sixteen hours per week but do not exhibit addictive tendencies,
- Pre-Addictive Moderate Gamers 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 play games for more than twenty hours per week, indicating an important impact on their daily lives. According to investigations of King and Delfabbro (2018), playing video games for thirty hours or more a week usually has negative effects on most users,
- Treated Gamers were previously addicted to gaming but have undergone treatment or intervention to address their addiction,
- Non-Gamers do not have an interest in gaming and abstain from playing.

Lapsed Gamers as individuals who previously played games but currently do not, often due to time constraints. Some of them may consider returning to gaming after six months, though exact data on this fraction is lacking. Therefore, their inclusion is assumed to have minimal impact on analyses.

The causal structure presents 6 reinforcing and 4 balancing loops.

Exposure to Gaming (R1): Potential Gamers commence their gaming journey through word-of-mouth (WoM), and flow into Beginner Gamers. Beginner Gamers 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 to Neutral Gamers. Over time, Neutral Gamers discontinue playing, with some of the population preferring to quit and others reverting to the Potential Gamers.

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. As the Beginner Gamers 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 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. 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 exposed to advertisements may initiate gaming. Some fraction of these individuals move through Neutral, Moderate, and Pre-addicted Moderate Gamers to eventually become Addicted Gamers. Notably, Moderate, Pre-Addicted, and Addicted Gamers all exhibit spending behavior while gaming, however, the most financial contribution comes from Addicted Gamers. Increases in Monthly Advertising Expenses and Advertising Effectiveness are correlated with a rise in Monthly Revenue. This positive feedback loop promotes a continuous increase in the Adoption from Advertisements.

Addictive Genres and New Game Production (R5 & B2): The revenue generated from gamers 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 FPS and MMORPG in the market is especially noteworthy, as it leads to a higher percentage of Beginner Gamers moving to the Pre-addicted Moderate Gamers instead of the Moderate Gamers. This shift creates a reinforcing loop, amplifying the numbers of Pre-addicted and Addicted Gamers. This also creates a balancing loop with the decline in Moderate Gamers.

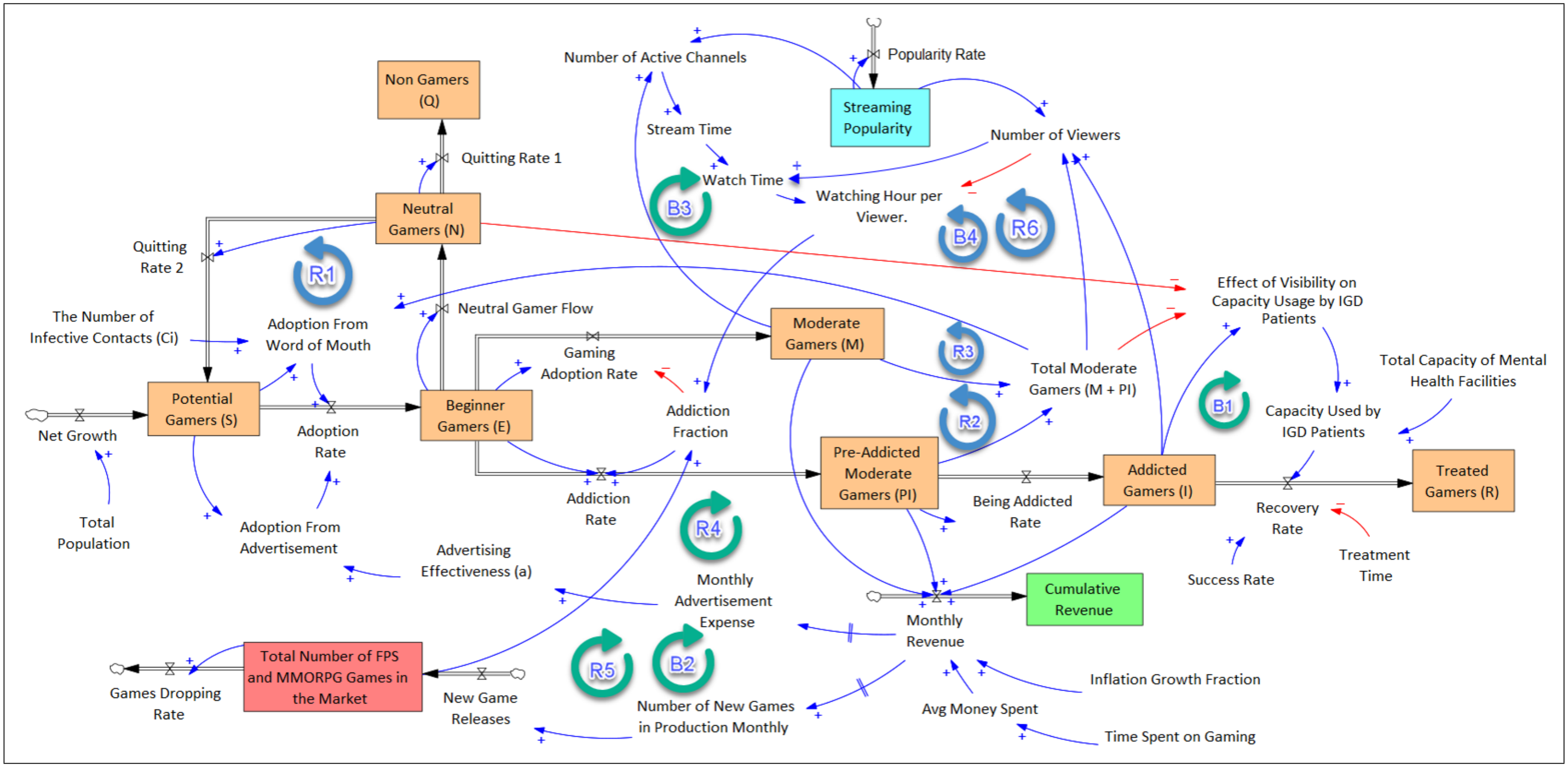


Figure 1: The simplified structure of the S-F diagram and causal loops.

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

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

3.2 The stock and flow diagram

The model consists of three sectors: (1) Gamer, (2) Gaming Business, and (3) Streaming. In this section, mathematical equations, and effect functions of each sector are discussed. The background information and assumptions behind the model are summarized.

3.2.1 Gamer Sector

With the widespread use of online communication tools, allowing people to connect. This connectivity made gaming a more communal activity. With the increasing popularity, the number of online PC gamers reached nearly 1.8 billion in 2022 (DFC Intelligence 2021). Particularly, young people are becoming more interested in gaming because of technological advancements. Almost 60% of gamers are under 30 (Entertainment Software Association 2022).

Many individuals were obliged to stay indoors and find comfort and entertainment during the COVID-19 pandemic. Hence, more people began to use online games for social interaction and entertainment. %7 of people spent more than 20 hours playing video games weekly in the United States in 2020 and 2022 (Statista 2020; Limelight Networks 2021). Contrary to small differences in the 1-5 and 6-10 hour playing time groups, 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 could be an increase in the number of people suffering from IGD.

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.

Figure 2 demonstrates the stock flow structure for population stocks of various gamer types. The number of *Potential Gamers*(people) who are susceptible to experience the act of playing a game due to the growing number of the *Total Population*(people).

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

$$Adoption\ Rate = Adoption\ from\ Advertising + Adoption\ from\ WoM. \tag{1}$$

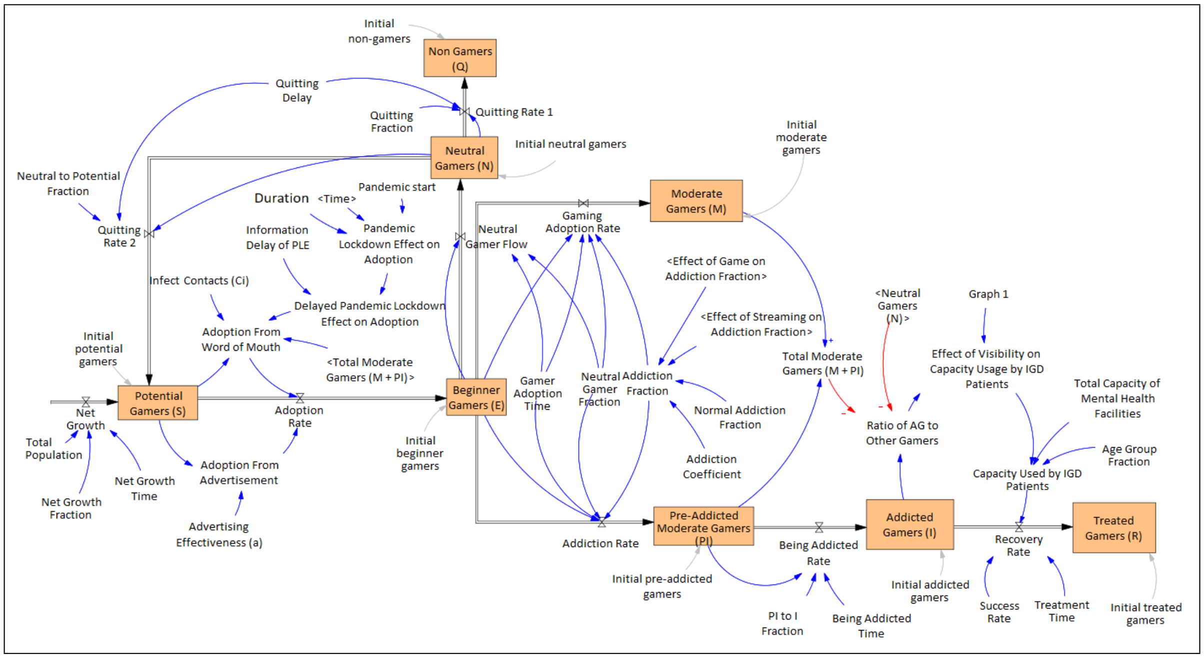


Figure 2: Gamer sector and population stocks.

The first way to adopt gaming is through advertisements as the Bass Diffusion Model. 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(Sterman 2000). The *Adoption from Advertisement (A)* is represented as

$$Adoption from Advertisement(A) = Potential\ Gamers(S) \times Advertising\ Effectiveness\ (a) \tag{2}$$

where *Advertising Effectiveness* (1/month) is the fractional adoption rate from advertising (Sterman 2000).

The second way to adopt gaming for *Potential Gamers* is adoption from Word-of-Mouth. The number of people contacted per person over a given period is called the Contact Rate. The term *Infectivity (i)* describes how likely it is for an individual to get a disease after coming into contact with an infectious person (Sterman 2000). Within the gaming community, *Potential Gamers* contact other moderate gamers with the *Contact Rate (C)*. Besides, *Addicted Gamers (I)* do not establish contact with Potential Gamers 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(Newzoo International 2022, 2021, 2020, 2019).

$$\begin{aligned} Adoption\ from\ WoM =& Potential\ Gamers(S) \times Infect\ Cont(Ci) \\ & \times \frac{Total\ Moderate\ Gamers(M+PI)}{Potential\ Gamers(S)\ +\ Total\ Moderate\ Gamers(M+PI)} \\ & \times Delayed\ Pandemic\ Lockdown\ Effect\ on\ Adoption \end{aligned} \tag{3}$$

by using *Delayed Pandemic Lockdown Effect on Adoption*(unitless) as a third-order delayed version of *Pandemic Lockdown Effect on Adoption*(unitless) (see Section 3.2.4). Moreover, the Equation (3) is analogous to traditional Susceptible-Infected-Recovered (SIR) models with "Infected" people including a summation of *Moderate Gamers* and *Pre-addicted Moderate Gamers* (people).

A constant fraction called *Neutral Gamer Fraction*(unitless) of *Beginner Gamers* only plays less than 1 hour in a week after the first exposure whereas the remaining is split between *Moderate*

Gamers and *Pre-addicted Moderate Gamers* 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.

In general, the outflows from the gamer stocks are calculated as

$$Outflow = \frac{Gamer\ Stock}{Adjustment\ Time} \times Gamer\ Fraction. \tag{4}$$

The *Beginner Gamers* flow into Neutral Gamers. There are two outflows from the *Neutral Gamer* stock. Some *Neutral Gamers* flow into the *Non-Gamer* with the *Quitting Rate 1* (People/Month), while some of them flow into the *Potential Gamer* with the *Quitting Rate 2* (People/Month). Besides, *Beginner Gamers* flow into *Moderate Gamers* via *Gaming Adoption Rate* (People/Month) and flow into *Pre-addicted Moderate Gamers* stock via *Addiction Rate* (People/Month). These flows are calculated as

$$Neutral\ Gamer\ Rate = \frac{Beginner\ Gamer(E)}{Gaming\ Adoption\ Time} \times Neutral\ Gamer\ Fraction, \tag{5}$$

$$\begin{aligned} Gaming\ Adoption\ Rate = &\frac{Beginner\ Gamer(E)}{Gaming\ Adoption\ Time} \times (1 - Neutral\ Gamer\ Fraction) \\ &\times (1 - Addiction\ Fraction), \end{aligned} \tag{6}$$

and

$$\begin{aligned} Addiction\ Rate = &\frac{Beginner\ Gamer(E)}{Gaming\ Adoption\ Time} \times (1 - Neutral\ Gamer\ Fraction) \\ &\times Addiction\ Fraction. \end{aligned} \tag{7}$$

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

$$\begin{aligned} Addiction\ Fraction = &Normal\ Addiction\ Fraction + Addiction\ Coefficient \\ &\times (Effect\ of\ Game\ on\ Addiction\ Fraction \\ &+ Effect\ of\ Streaming\ on\ Addiction\ Fraction) \end{aligned} \tag{8}$$

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.

As the visibility of the addiction increases, various treatment centers worldwide provide interventions to restore their health. When the proportion of *Addicted Gamers* to other gamers increases, the addiction becomes more visible and turns into a priority. Therefore, the allocated capacity for patients who suffer from IGD increases. *Recovery Rate* and *Capacity Used by IGD Patients* are determined by

$$Recovery\ Rate = \frac{Capacity\ Used\ by\ IGD\ Patients \times Success\ Rate}{Treament\ Time}, \tag{9}$$

and

$$\begin{aligned} Cap.\ Used\ by\ IGD\ Patients = &Age\ Group\ Fraction \times Eff.\ of\ Visibility\ on\ Capacity\ Usage \\ &by\ IGD\ Patients \times Total\ Cap.\ of\ Mental\ Health\ Facilities. \end{aligned} \tag{10}$$

The *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

$$Ratio\ of\ AG\ to\ Other\ Gamers = \frac{Addicted\ Gamer\ (I)}{Total\ Moderate\ Gamers\ (M + PI) + Neutral\ Gamers\ (N)} \tag{11}$$

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

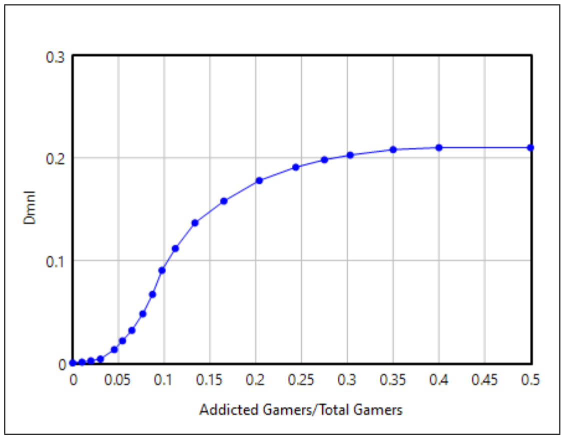


Figure 3: Graphical function of effects of visibility on capacity usage.

The S-shape graphical function demonstrated in Figure 3 is increasing since the rise of addiction creates a need to use more capacity. If the proportion of *Addicted Gamers* to other gamers is less than 10%, society might not recognize the addiction. Capacity usage is limited to around 20% as it will also be used for other kinds of addictions and psychological diseases.

3.2.2 Gaming Business Sector

The market value of online PC gaming increased and reached $42 billion in 2022 due to the rising number of online games and inflation rate (Ian Webster 2023; Capcom 2023). Some of the revenue is allocated to marketing expenses to attract more people into the gaming world. Figure 4 demonstrates the stock flow diagram of this sector.

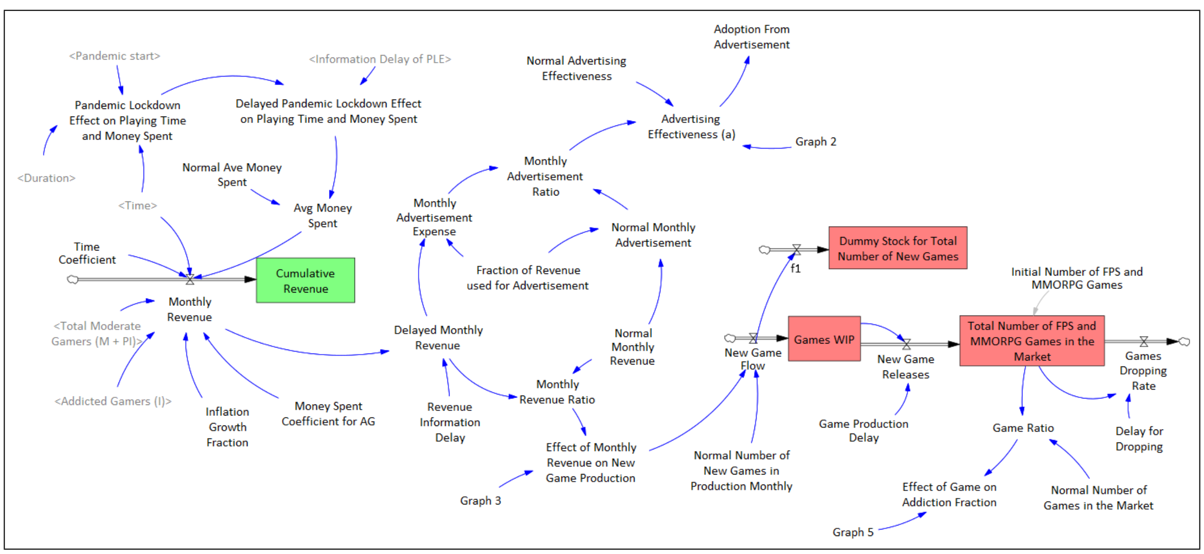


Figure 4: Gaming business sector.

Among all genres, FPS and MMORPG genres are especially significant as they have been related to IGD (Ünal et al. 2022). Other genres have less probability of being addictive compared to

FPS and MMORPG. As indicated in Table 1, the odds ratios provide insights into the relationship between gaming genres and IGD status.

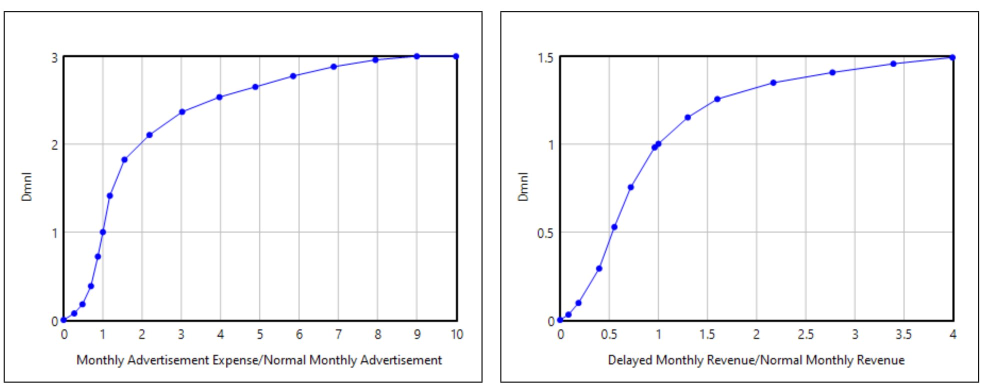
Table 1: Odd ratios of IGD for different genres (data from (Ünal et al. 2022)).

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)

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

$$\begin{aligned} Monthly\ Revenue =& Avg\ Money\ Spent \times (1 + Inflation\ Growth\ Fraction)^{\frac{Time}{Time\ Coefficient}} \\ & \times [Money\ Spent\ Coeff.\ for\ AG \times Addicted\ Gamers\ (I) \\ & + Total\ Moderate\ Gamers\ (PI + M)] \end{aligned} \tag{12}$$

given that *Money Spent Coeff. for AG*(unitless) represents that *Addicted Gamers* spend twice as much time as other gamers(Ünal et al. 2022). 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* is consists of the product of *Normal Ave Money Spent* (\$/Month) and *Delayed 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 (see Section 3.2.4).



(a) Effect of monthly advertisement expenses on advertisement effectiveness

(b) Effect of monthly revenue on new game production

Figure 5: Graphical functions in 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

$$Monthly\ Advertisement\ Ratio = \frac{Monthly\ Advertisement\ Expense}{Normal\ Monthly\ Advertisement} \tag{13}$$

where *Monthly Advertisement Expense* is a fraction of *Delayed Monthly Revenue* and *Advertisement Effectiveness (a)* (1/Month) is derived from a graphical function illustrated on Figure 5a as

$$\begin{aligned} Advertising\ Effectiveness\ (a) =& f(Monthly\ Advertisement\ Ratio) \\ & \times Normal\ Advertisement\ Effectiveness \end{aligned} \tag{14}$$

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

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 5b 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

$$\begin{aligned} New\ Game\ Flow =& Normal\ Number\ of\ New\ Games\ in\ Prod.\ Monthly \\ & \times Eff.\ of\ Monthly\ Revenue\ on\ New\ Game\ Production \end{aligned} \tag{15}$$

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

$$Monthly\ Revenue\ Ratio = \frac{Delayed\ Monthly\ Revenue}{Normal\ Monthly\ Revenue} \tag{16}$$

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(Ünal et al. 2022).

The *Effect of Games on Addiction Fraction*(unitless) is derived from a graphical function of *Game Ratio*(unitless) that is computed by dividing *Total Number of FPS and MMORPG Games in the Market* to *Normal Number of Games in the Market* (Games) which is 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 6.

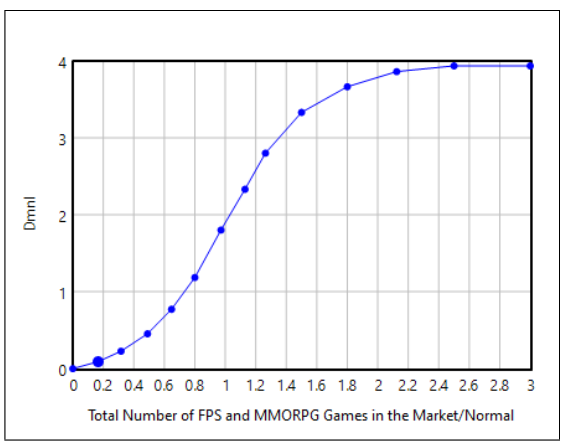


Figure 6: Graphical function of effects of games on addiction fraction.

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.

3.2.3 Streaming Sector

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 have been essential in this cultural transformation. The rise in viewers is evidence of the increased interest in video game content.

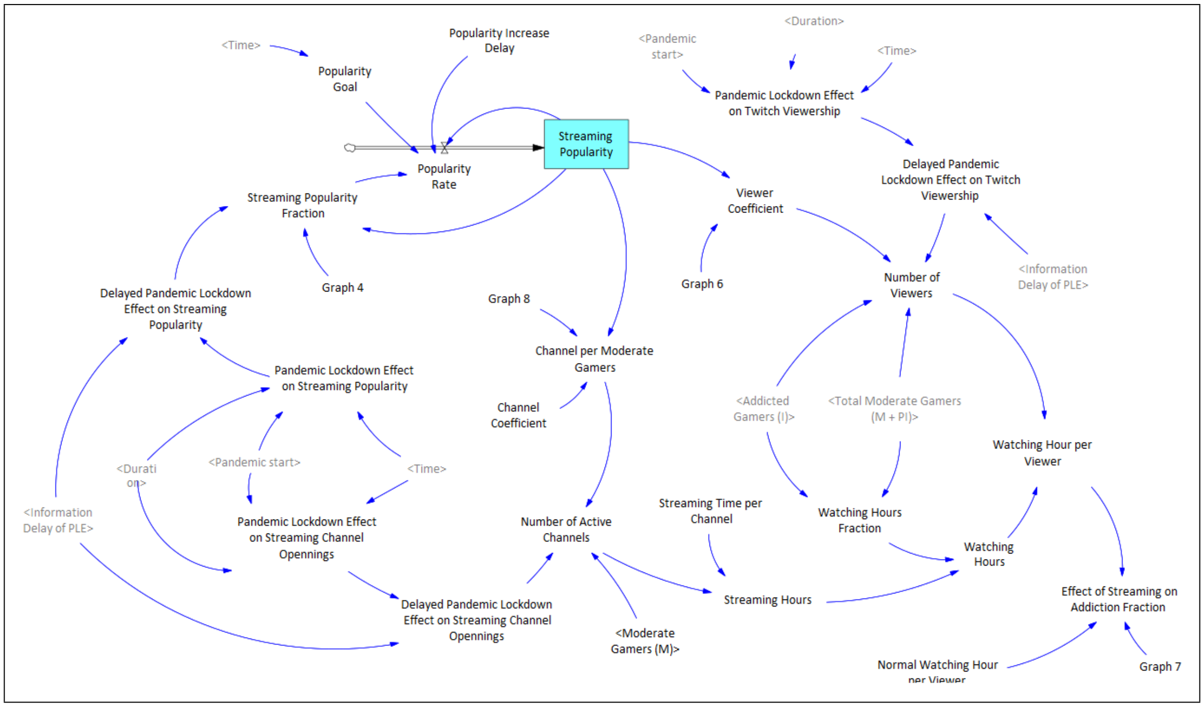


Figure 7: Streaming sector.

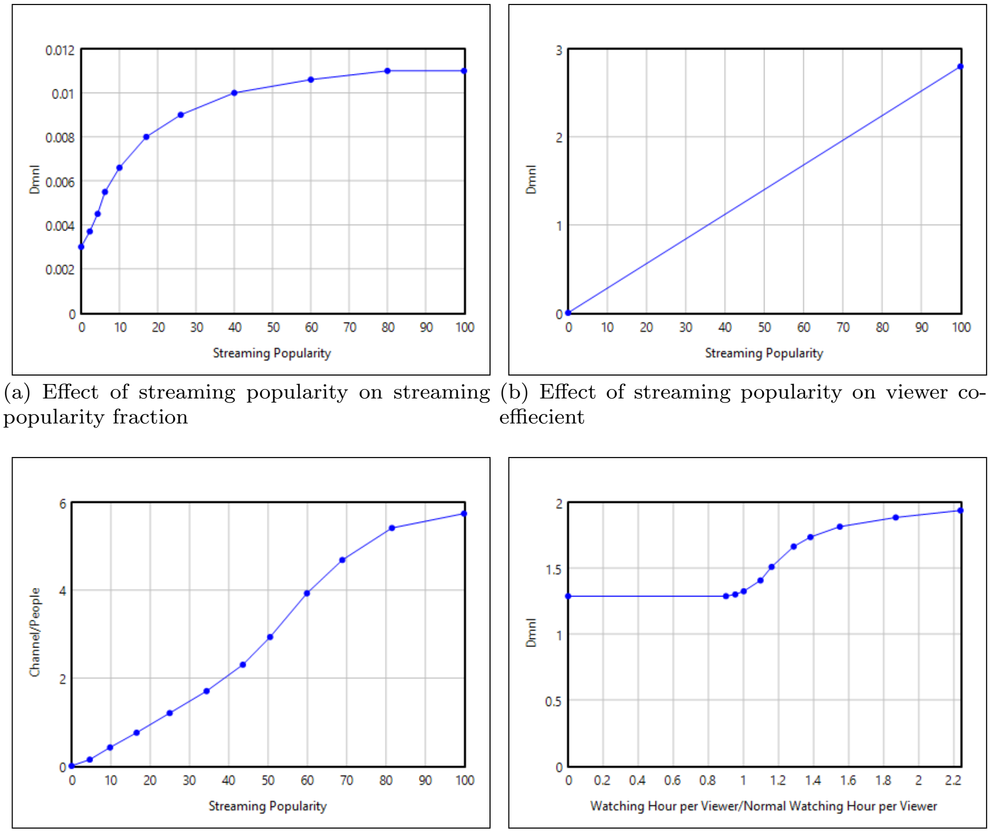
Figure 7 portrays the stock flow structure for the channels, broadcast time, viewers, and watch time of the video gaming content considering the popularity increase of Twitch streaming along with related effect equations.

Our model begins in the year 2010, and within the initial eighteen months, only YouTube Gaming platform 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 8 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.

Figure 8a 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

$$Popularity\ Rate = (Popularity\ Goal - Streaming\ Pop.) \times \frac{Streaming\ Popularity\ Fraction}{Popularity\ Increase\ Delay} \quad (17)$$

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 8a.



(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 8: Graphical functions in streaming sector.

Figure 8b and 8c 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:

$$\begin{aligned} Number\ of\ Active\ Channels &= Channel\ per\ Moderate\ Gamers \times Moderate\ Gamers\ (M) \\ &\times (Delayed\ Pandemic\ Lockdown\ Effect\ on\ Streaming\ Channel\ Opennings) \end{aligned} \tag{18}$$

and

$$\begin{aligned} Number\ of\ Viewers =& (Addicted\ Gamers + Total\ Mod.\ Gamers) \times Viewer\ Coefficient \\ &\times (Delayed\ Pandemic\ Lockdown\ Effect\ on\ Twitch\ Viewership) \end{aligned} \tag{19}$$

by using delayed effects (unitless) as a third-order delayed versions(see Section 3.2.4). *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

$$Streaming\ Hours = Number\ of\ Active\ Channels \times Streaming\ Time\ per\ Channel \tag{20}$$

and

$$Watching\ Hours = Streaming\ Hours \times Watching\ Hours\ Fraction \tag{21}$$

where

$$Watching\ Hours\ Fraction = 25 \times (\frac{2 \times Addicted\ Gamers + Total\ Moderate\ Gamers}{Addicted\ Gamers + Total\ Moderate\ Gamers}) \tag{22}$$

given that a standard rate of twenty-five times is applied to each hour that is streamed, and *Addicted Gamers* spend twice as much time as other gamers(Ünal et al. 2022). According to Ünal et al. (2022), *Watching Hour per Viewer* (Hour/people) is a significant indicator of addiction that is calculated as

$$Watching\ Hour\ per\ Viewer = \frac{Watching\ Hours}{Number\ of\ Viewers} \tag{23}$$

so as to evaluate *Effect of Streaming on Addiction Fraction*(unitless). Figure 8d 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.

3.2.4 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* 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* 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:

$$\begin{aligned} Pandemic\ Lockdown\ Effect\ on\ ... =& IF\ THEN\ ELSE(Time >= Pandemic\ start : AND : \\ & Time < Pandemic\ start + Duration, X, 1) \end{aligned} \tag{24}$$

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

$$\begin{aligned} Delayed\ Pandemic\ Lockdown\ Effect\ on\ ... =& DELAY3(Pandemic\ Lockdown\ Effect\ on\ ..., \\ & Information\ Delay\ of\ PLE) \end{aligned} \tag{25}$$

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

4 Model estimation and validation

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 30 years (2010 to 2040) was conducted and analyzed. Moreover, the pandemic period between 2020 and 2022 is taken into account in validation.

4.1 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(DFC Intelligence 2021; Entertainment Software Association 2022). We computed the number of Potential Gamers by extracting the PC gamer population from the overall population aged from 10 to 29 (The World Bank Group 2023). The allocation of initial values for gamer stocks is calibrated based on gaming habits and the time spent by individuals in gaming activities (Statista 2020; Limelight Networks 2021).

Worldwide mental health facility capacity is estimated at 14.5 beds per 100,000 people(WHO 2021). 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)(SAMHSA 2021).

The total number of FPS and MMORPG games is 785 which is also the initial value in our model(FANDOM 2023). 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) (Capcom 2023).

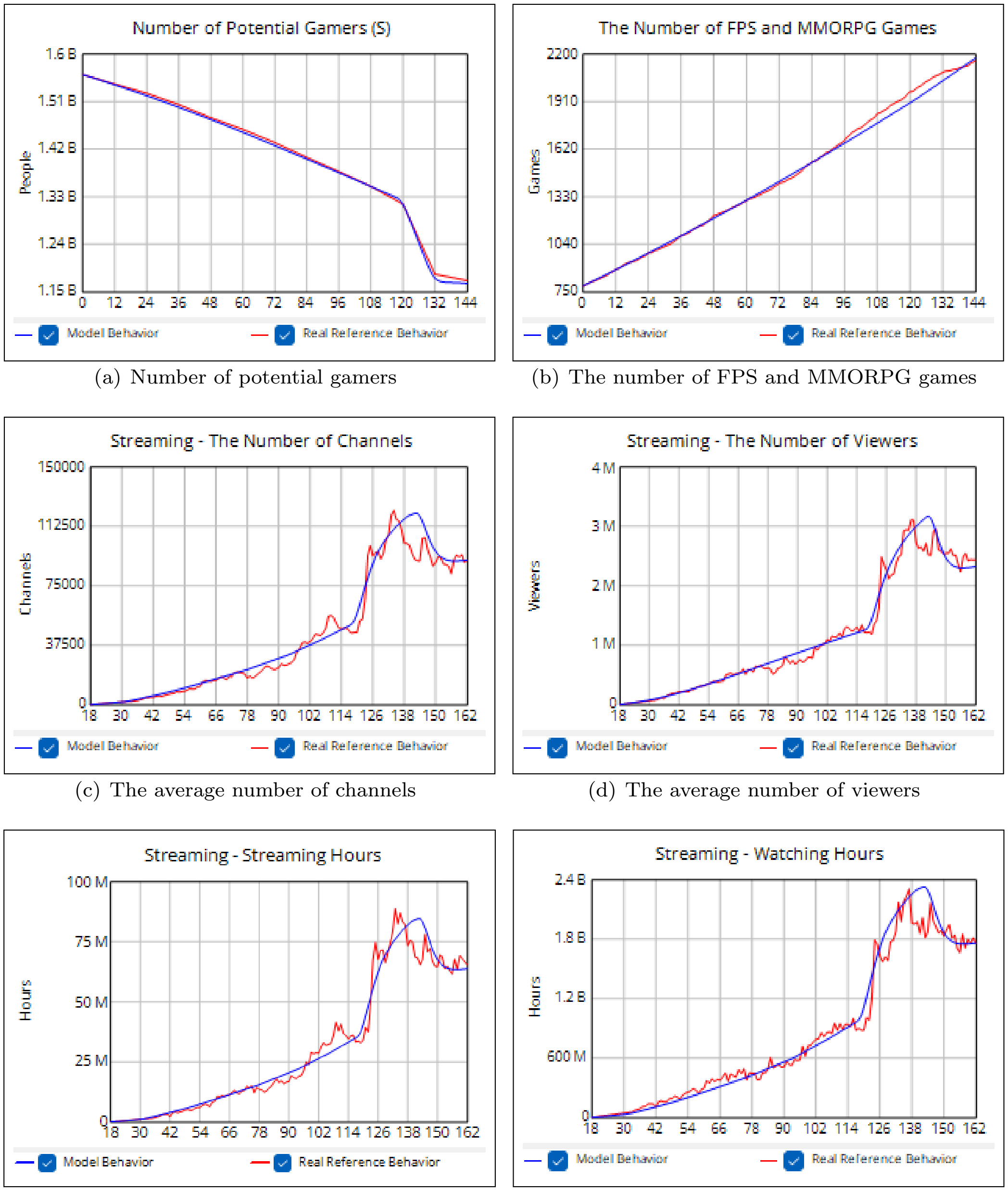
The data utilized for the number of active channels, streaming time, the number of viewers, and watch times pertains to the Twitch platform (Twitch Tracker 2023). As Twitch started broadcasting in June 2011, the initial values are considered as zero. Information regarding other platforms has not been taken into account as it is deemed less significant compared to Twitch.

Our simulation spans the thirty-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 (DFC Intelligence 2021; Capcom 2023) and monthly data from (FANDOM 2023; Twitch Tracker 2023) 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.

4.2 Model Credibility

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 (Barlas 1996). In this context, the model structure is constructed based on the 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. All parameters have meaningful real-world equivalents, and assumptions or simplifications are explicitly explained. For acceptable numerical accuracy, the simulation time step (dt) is chosen as 0,0625.

Output behavior tests are devised to compare the primary pattern components in the model behavior with those observed in the actual behavior. The initial parametrization is calibrated to align with real data spanning from 2010 to 2022. The decline in the number of Potential Gamers parallels the real data as shown in Figure 9a. As depicted in Figure 9b, the number of FPS and MMORPG games are changing similarly to the cumulative game counts in real data. Figure 9c-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.



(a) Number of potential gamers

(b) The number of FPS and MMORPG games

(c) The average number of channels

(d) The average number of viewers

(e) Streaming hours per month

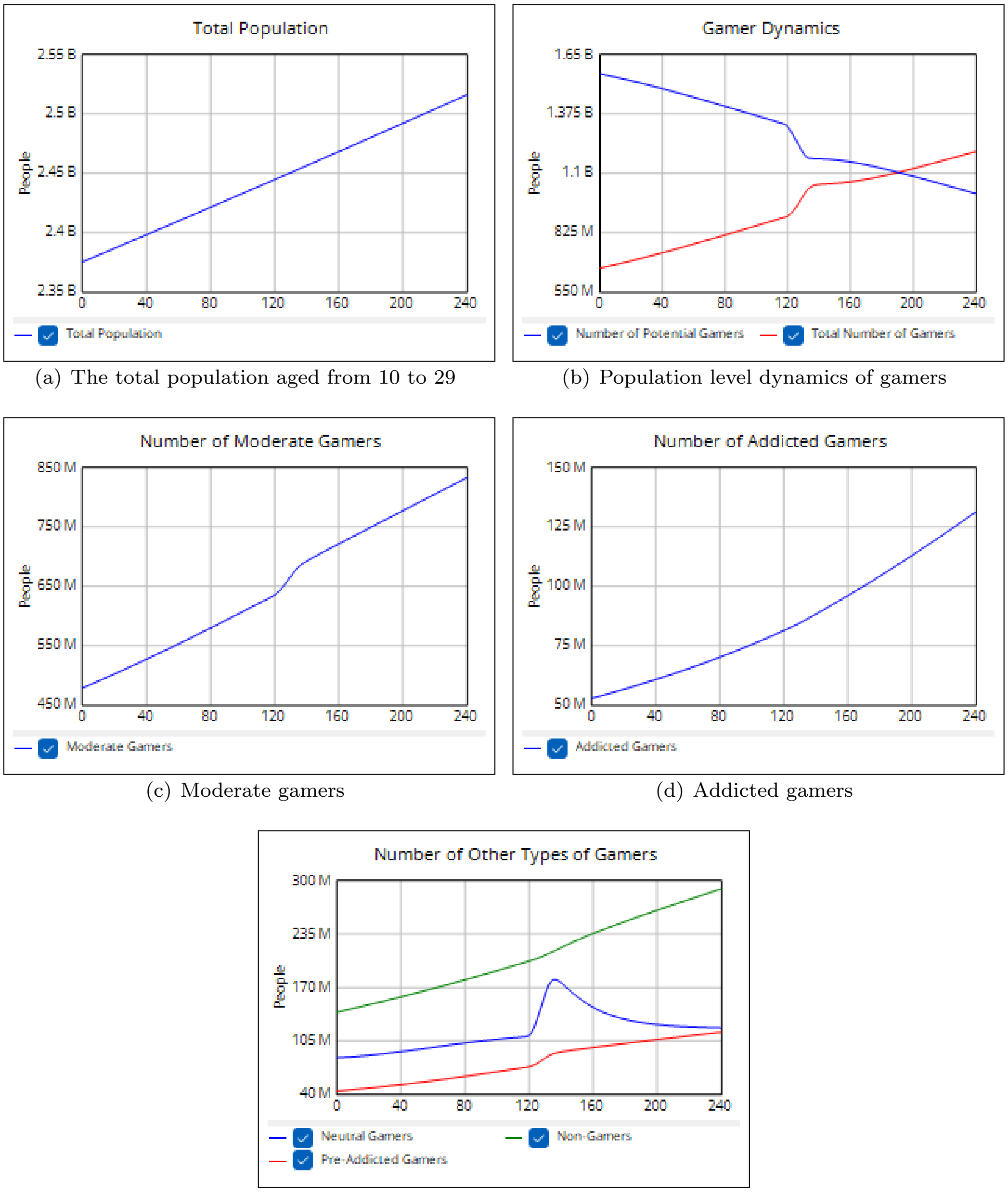
(f) Watching hours per month

Figure 9: Behavior validity of the model (data from (DFC Intelligence 2021; Entertainment Software Association 2022; The World Bank Group 2023; Statista 2020; Limelight Networks 2021; FANDOM 2023; Twitch Tracker 2023)).

4.3 Base Run

The model is simulated for 20 years starting from 2010 to 2030 in the Base Run. Additionally, a sensitivity analysis has been implemented to examine the effects of changes in parameters on the model. Population-level dynamics are illustrated in Figure 10. According to the base run, the total population aged between 10 and 29 will surpass 2.5 billion people within 20 years. While the number of Potential Gamers decreases to almost 1 billion, the total number of gamers will reach 1.2 billion people in 2030.

According to our model, an increase is observed in all of the gamer stocks. As shown in Figure 10e, the number of Neutral Gamers shows a gradual increase over time, especially experiencing a significant increase during the pandemic period. However, in the post-pandemic period, the number of Neutral Gamers exhibits a downward trend after reaching 170 million in the 136th month (the year 2023) of simulation. The number of Moderate Gamers reaches 830 million, while the number of Pre-Addictive Moderate Gamers reaches 115 million. Addicted Gamers, demonstrates a rapid increase at an accelerated pace and reach 130 million people by the end of the year 2030.



(a) The total population aged from 10 to 29

(b) Population level dynamics of gamers

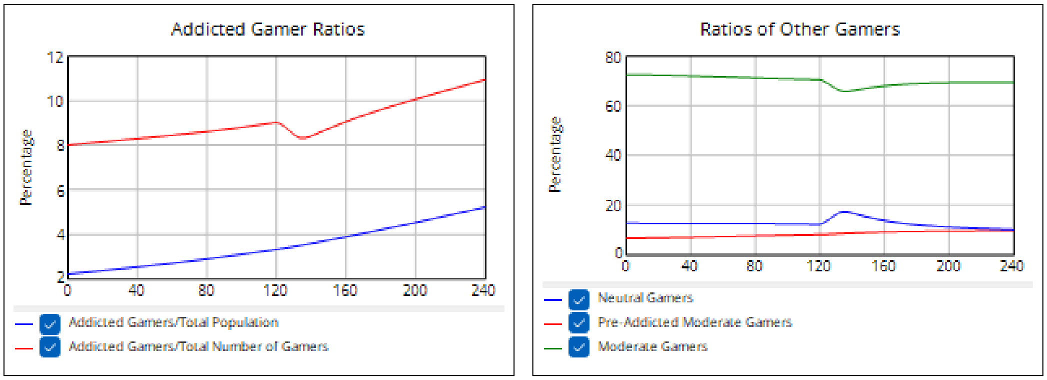
(c) Moderate gamers

(d) Addicted gamers

(e) Various gamers

Figure 10: Population-level dynamics.

The data in Figure 11a points to the fact that the Addicted Gamer ratios are increasing in time. However, during the pandemic period, a decline is observed in the ratio of Addicted Gamers to the overall gamer population since many people have experienced gaming due to time spent in lockdowns. Figure 11b 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 11: Ratios of gamers.

4.4 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%. As depicted in Table 2, the parameters that most significantly influence the ratios of addicted gamers to total population and total number of gamers are as follows:

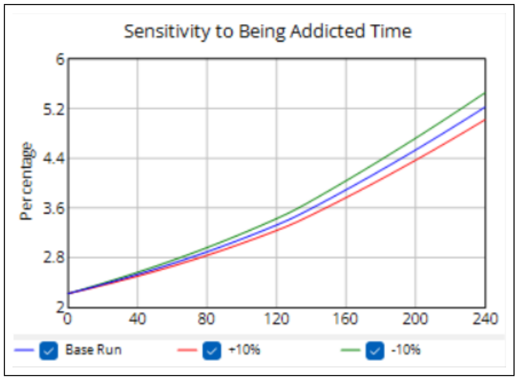
Table 2: Selected parameters by sensitivity analysis, units, and values.

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

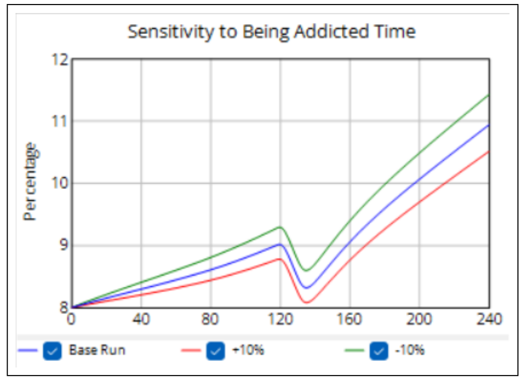
Complete outcomes of the sensitivity analysis are provided in Appendix B, while significant runs are discussed in this section. The model exhibits consistent behavior concerning both model assumptions and real-world expectations.

We obtained different behaviors and results for both outcomes of interest. Figure 12 demonstrates the most impactful parameter which is Being Addicted Time in terms of influencing changes. Since the changes in this parameter influence the Addicted Gamers ratios. 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.

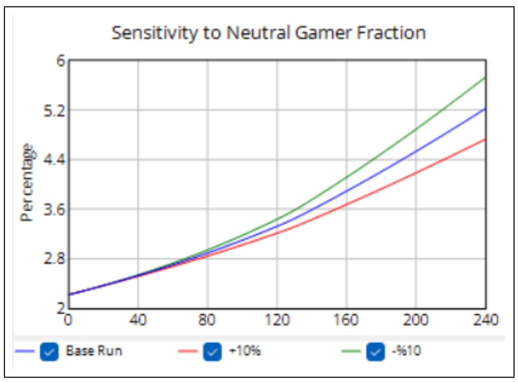
The changes in infect contacts (Ci) result in the expected impact on the ratio of addicted individuals to the total population. While the influence of a 10% increase or decrease in this parameter is significant until the pandemic period, its effect has declined afterward. This decline can be attributed to the increase in the number of players during the pandemic period. 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 compared to the sensitivity tests of other parameters.



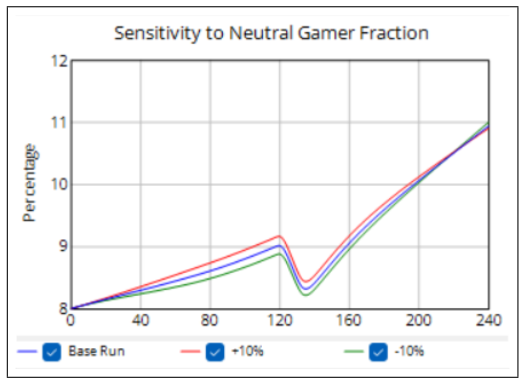
(a) The ratio of addicted to total population (being addicted time)



(b) The ratio of addicted to tot. number of gamers (being addicted time)



(c) The ratio of addicted to total population (neutral gamer fraction)



(d) The ratio of addicted to tot. number of gamers (neutral gamer fraction)

Figure 12: Sensitivity tests.

Table 3 indicates the outcomes of interest that we will focus on in simulation experiments in the following chapters.

Table 3: Outcomes of interest after the base and sensitivity runs.

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

5 Results and Discussion

5.1 Scenario Analysis

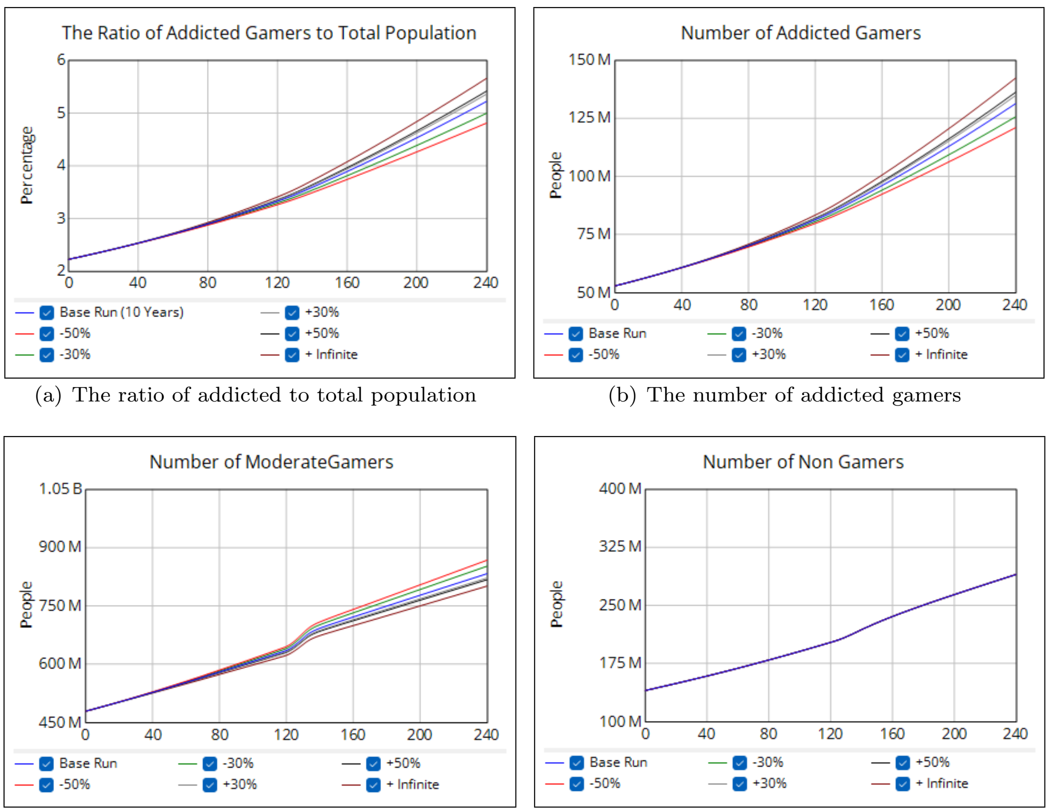
In this section, our objective is to analyze different hypothetical yet possible scenarios and examine changes in the four outcomes of interest. The chosen parameters for the scenario analysis are presented in Table 4. Normal Average Money Spent corresponds to the average money spent on gaming by gamers 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. The results of parameter Delay for Dropping will be examined in this conference paper, and the results of parameters Normal Average Money Spent and Duration can be referenced to master's thesis.

Table 4: 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		%

5.1.1 The Average Life of Games in the Market

Each year, games with larger maps and higher resolutions are released. Hence, old games 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. A scenario analysis has been conducted based on the parameter Delay for Dropping.



(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 13: Scenario analysis using delay time for dropping a game.

Figure 13 indicates that the parameter particularly influences the behavior of outcomes of interest. 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.

5.2 Policy interventions

Policy interventions were implemented to assess their impact on the epidemics of gaming addiction. 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;

$$\begin{aligned} &New\,Value\,of\,the\,Parameter = \\ &IF\,THEN\,ELSE(Time > 144, Initial\,Value \times (1 + C), Initial\,Value) \end{aligned} \tag{26}$$

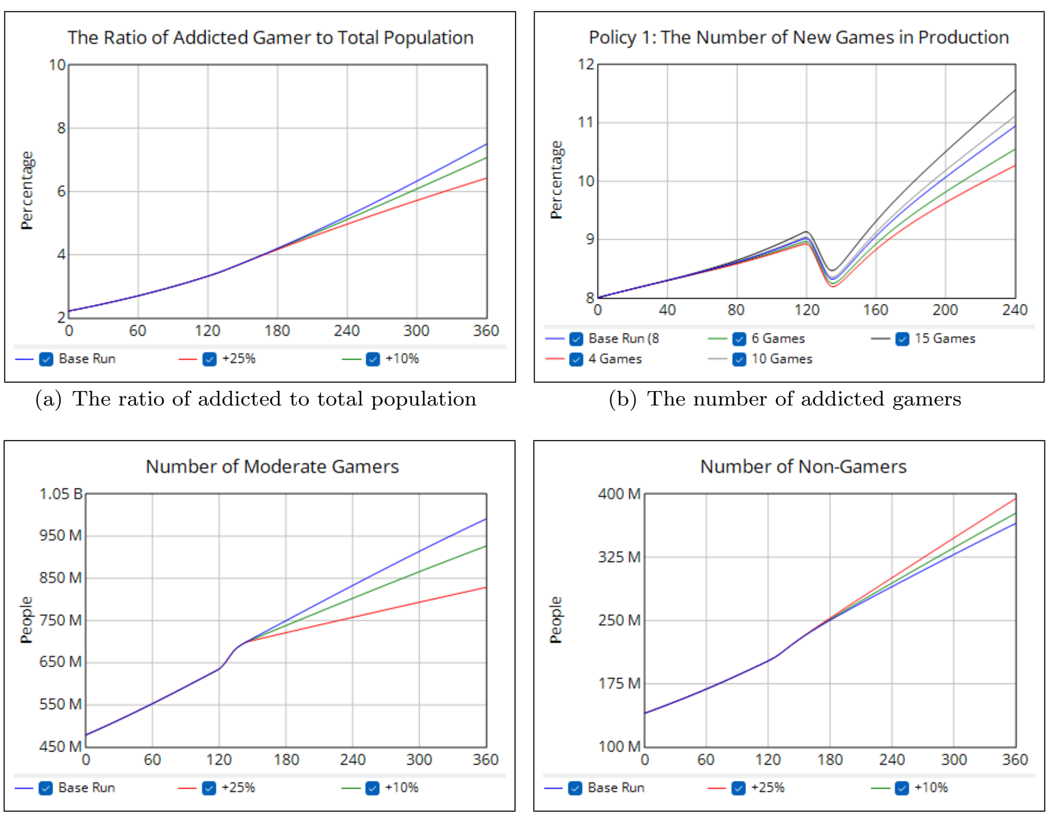
utilizing C as the percentage change on *Initial Value* of the parameter. As seen in Table 5, alterations have been applied to parameters related to gamers.

Table 5: 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	%

5.2.1 The Neutral Gamer Fraction

Each year, various games are released, and an increasing number of Potential Gamers are becoming Beginner Gamers by being exposed to online gaming. This policy investigates how player dynamics will change if Beginner Gamers 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

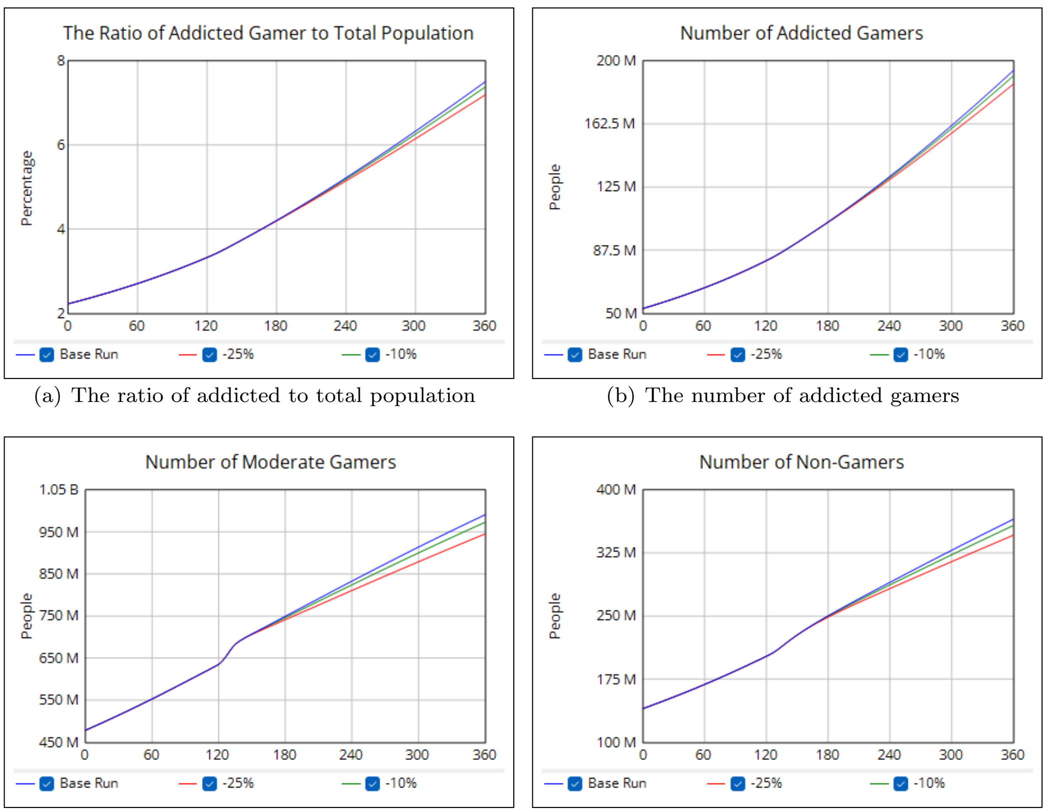
(d) The number of non gamers

Figure 14: Policy intervention using the neutral gamer fraction.

When the Neutral Gamer Fraction increases, there is a rise in the flow from Beginner Gamers to Neutral Gamers. This also increases the number of people joining the Non-Gamer 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 decreases over time. As depicted in Figure 14, the outcomes indicate a decrease in the numbers of Addicted Gamers and Moderate Gamers due to the increase in the Neutral Gamer Fraction. Particularly, the population of Moderate Gamers 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. The impact of this parameter appears to be relatively significant.

5.2.2 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(AdColony and GWI 2021; King and Delfabbro 2018). 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 15: Policy intervention using infect contacts (Ci).

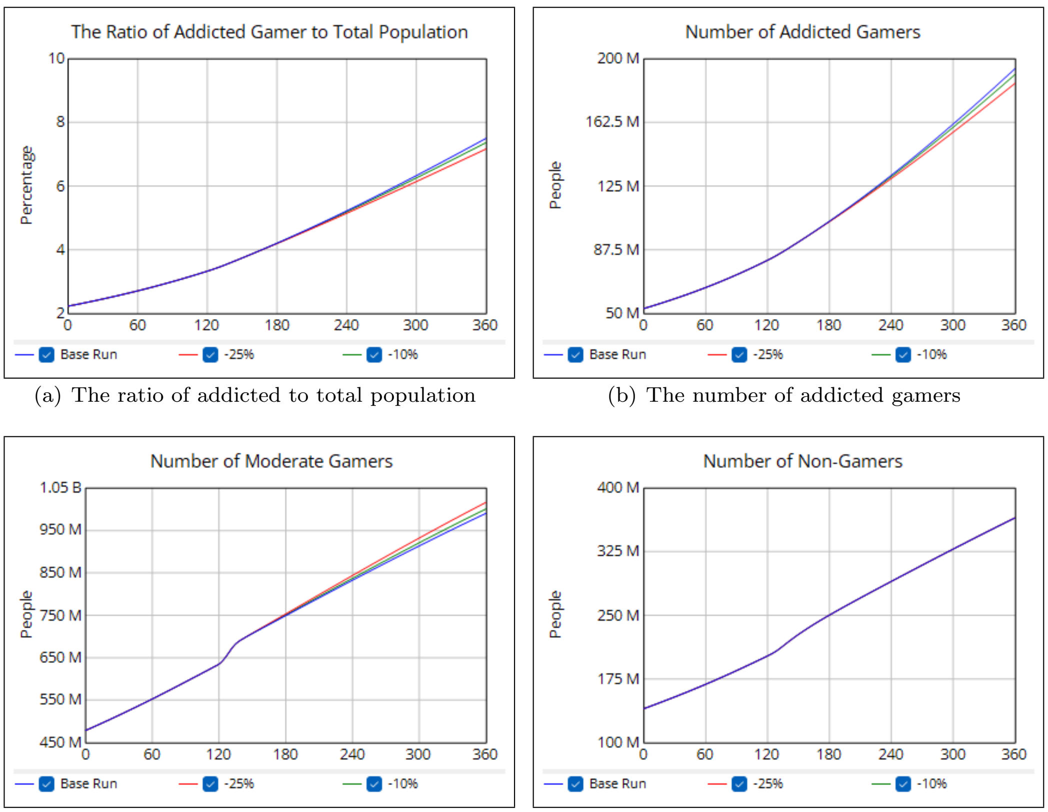
When people engage socially, they listen to stories about their friends' gaming preferences and observe gameplay. When they are sufficiently influenced, they begin playing games to spend time online with their peers. The parameter named infect contacts (Ci) is a critical factor indicating Potential Gamers'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

Figure 15 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 15, the order of the decrease from the greatest to the least is as follows: Non-gamer, Moderate Gamer, Addicted Gamer. The fall in Addicted Gamers 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 become more visible and noticeable among other gamers.

5.2.3 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 who play games for shorter durations instead of becoming Addicted Gamers according to Figure 16. Thus, there is a reduction in the proportion of addicted gamers within society. In contrast, Non-Gamers 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 16: Policy intervention using the addiction coefficient.

5.2.4 Combined Policy Intervention

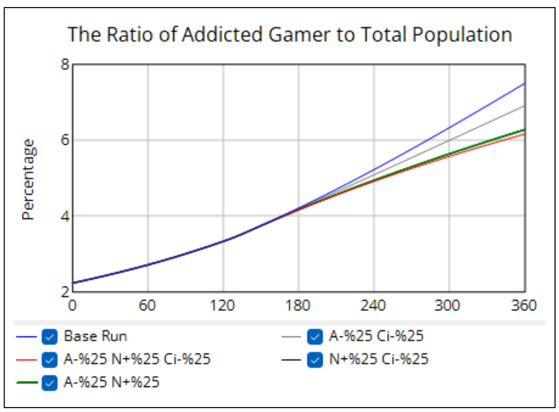
Upon examining Figure 14, 15, and 16, it becomes evident that alterations in each policy parameter yield varying degrees of impact. Considering both triple and double combinations of the prior policy interventions, four experiments were conducted as illustrated in Table 6.

As seen in Table 6, 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 17 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.

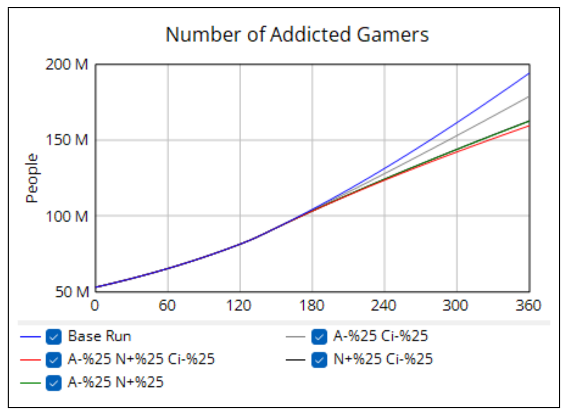
Table 6: Selected parameters for combined policy intervention.

			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	%

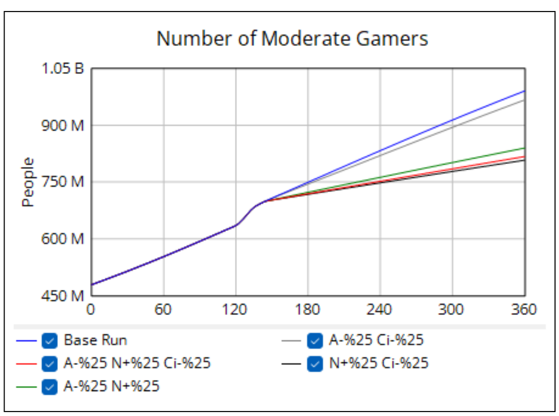
Figure 17c shows that Experiment 2 did not effectively alter the number of Moderate Gamers. While the results of the remaining experiments are considered similar, Experiment 3, unlike Addicted Gamers, resulted in the most significant decrease in the number of Moderate Gamers. Looking at Figure 17d, it is concluded that the experiments resulted in both increases and decreases in the Non-Gamers 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, 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.



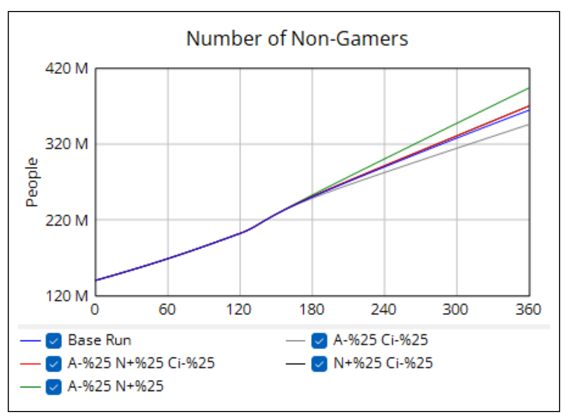
(a) The ratio of addicted to total population



(b) The number of addicted gamers



(c) The number of moderate gamers



(d) The number of non gamers

Figure 17: Combined policy intervention.

Upon examining the outcome named the number of Addicted Gamers in Figure 17b, 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.

6 Conclusion and Recommendations

The widespread popularity and accessibility of online gaming have led to a significant increase in game addiction. To understand the dynamics of worldwide epidemics of IGD, we constructed a population-level system dynamics simulation model. Most studies 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 qualitative and quantitative information from the literature and validated using actual data spanning 12 years. 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), and Addiction Coefficient. Finally, the findings from scenario analyses and policy interventions are discussed.

In the scenario analysis, the average life of games in the market ("Delay for Dropping") has the most substantial impact by increasing the ratio of addicted gamers to the total population and the total number of gamers. For policy analysis, the simulation time horizon is 360 months and interventions start from the 144th month. Policy analysis highlights that adjusting the Neutral Gamer Fraction significantly impacts 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 most substantial impact on the outcomes of interest. Results demonstrate that the effects of FPS and MMORPG games, and streaming of video gaming content are influential. By decreasing their influence people are more likely to become Moderate Gamers. The policy intervention with the Infect Contacts is the third influential one. 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 on the number of Addicted Gamers. With the information collected from policy simulations, we made 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 policy parameters creates the largest decrease in the number of Addicted Gamers. In summary, results indicate that increasing the Neutral Gamer Fraction that leads to a higher proportion of gamers who play less than 1 hour. 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 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, alternative mitigation strategies can be explored and assessed. Another direction for future research studies might be developing an individual-level system dynamics model for the dynamics of addiction, examining the dynamics of becoming an addicted gamer. With the outcomes from this individual-level model and the insights from the literature, agent-based modeling for addiction dynamics can be created to examine interpersonal dynamics.

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