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Does streaming service help or hurt game companies?

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Abstract

With the fast development of technologies, the gaming industry becomes more and more diverse, profitable, and competitive. With the unprecedentedly growing gaming industry, the game streaming industry also expands and develops constantly. The previous research agrees that game streaming tends to benefit the game companies by increasing game's popularity, either directly through promotionally demonstrating game contents to the audiences, or indirectly through benefiting game's word-of-mouth. However, they did not consider that game streaming may also hurt the game companies. For instance, the streaming audiences may feel less interested and motivated to play the games after watching the game streaming because the game streaming may spoil too much game contents, which is known as the cannibalization effect.

As a result, in order to accurately express and reflect the potential cannibalization effect of game streaming, this research needs to study and consider the relationships between game streaming, game's popularity, and word-of-mouth of the games in a big picture jointly. In short, this research quantifies these three areas of interest and studies their interactions between each other. Firstly, this research uses the Vector Autoregression model which allows for the simultaneous treatment of game's popularity, game streaming, and word-of-mouth regarding each game instance. However, this research expects that the existence of cannibalization effects depends on the game categories, including "single-player" and "multi-player" which the first model is not able to capture. Therefore, this research proposes a Linear Mixed-Effects Regression model, which can better incorporate such a moderation effect of game categories as well as other game characteristics.

After relevant hypothesis testing, our results show that although game streaming in general helps to improve game's popularity, we observe an obvious existence of the cannibalization effect of game streaming for "single-player" games. Besides, this research also reflects on the implications of the results. For instance, this research recommends game companies to strengthen positive reviews of the games to increase game's popularity, because the result also suggests a strong positive effect of word-of-mouth on game's popularity, especially when the game genre is "Racing".

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1. Introduction

As one of the most critical and innovative sectors, the gaming industry poses a magnified influence on culture, social networking, and entertainment. Global video game revenues will rise by 20% to nearly $180 billion in 2021 as a projection, while the American games alone account for $56.9 billion of spending which is larger than the revenues of the entire global movie industries (Takahashi, 2018). However, only about 5% of video games across all platforms are making a profit, from which we can observe a profitable but highly competitive gaming market (Reisinger, 2018).

The question of how to survive in such a competitive gaming industry and remain profitable haunts the game company's mind. The game companies compete with an increasing number of games introduced by their direct rivals in the gaming industry. In addition, game companies also face fierce competition from other substitute entertainment, such as short-form videos, episodes and outdoor activities. According to South African Cultural Observatory (2019), nearly 37% of 800 million games have not even been loaded once on one of the gaming platforms, Steam. From this perspective, we can infer that game companies are facing high competition in both the internal and external environment. As a result, game companies may find it difficult to attract more players and make a profit.

On the other hand, gamers have a wide variety of games to choose from in this buyer's market as opposed to the market dominated by game companies. Game players can easily quit playing the games that are not impressive, and then quickly switch to another game in the diverse gaming market. Thus, to attract gamer's attention, game companies have to compete with millions of games from other competitive game companies, and they have to find a realistic way to build their brand awareness and increase their revenue.

Therefore, boosting the number of gamers in the game is a necessity for game companies to earn a profit in this competitive industry. Thus, game companies need to come up with innovative and creative methods to entice the game's popularity. One of the attractive actions that game companies take to bring various games closer to the game players is through game streaming services. With the advancement of encoding technologies such as hardware-accelerated engines and developments in handheld device capabilities (Saman, Steven, Saeed, Sebastian, & Garsten 2020; Changqiao et al., 2015), Game streaming allows the audience to select the content to watch, for example, the audience can choose to watch the game streaming based on the program's name or the game types. Game streaming is also almost accessible to all the audience throughout the entire Internet. For example, a user in the United States can access a European game streaming both live and on-demand (Cranor et al., 2001).

Gamers found a place where they can share ideas with an enormous gamer base, upgrade game skills and seek for high-quality game content with the emergence of the game streaming. Generating a diverse community with enriched gaming content, the game streaming also leads to the creation of various web services just for streaming video games. Therefore, in parallel with the game industry's exponential growth, game streaming serves as a new form of online entertainment which is expanding at a swift pace. Take Twitch, one of the game streaming platforms, as an example, Twitch contributed to 1.8% of the total Internet traffic and was ranked the fourth in United States Internet Traffic in 2014, which is higher than the Internet traffic of Valve, Facebook and Amazon (Twitch, 2014). In short, watching game streaming of various video games is becoming an increasingly popular way of entertainment (Nascimento et al., 2014).

As a result, we observe the fast development of both the gaming industry and the game streaming industry. Most importantly, these two areas are also likely to be related to each other and complement each other. However, despite the fact that some game companies successfully used game streaming to appeal to more gamers as mentioned above, this research aims to explore in detail how game streaming can influence the game companies. Therefore, this research will further exemplify and elaborate game streaming's probable impacts on the game companies.

Potential Impacts of Game Streaming on Game Companies

The game streaming sets up several successful examples that the game streaming services help to increase game player's participation in the games. To illustrate, some combinations between game companies and game streaming are "E-sports", "Speedrunning" and "Let's play". In detail, "E-sports" focused on streamed games played by highly skilled gamers and huge tournaments (Taylor, 2015); the

“Speedrunning” aims to finish a game as quickly as possible (often to beat a world record) on the streaming platform, and the “Let’s play” brings spectators and viewers together in the game (Smith, 2013). These sub-communities resulted in an aggregation of internet traffic on the streaming platform, attracted a large amount of games’ popularity, and promoted sales for various games. For example, when the game “Rocket League” was launched on Twitch, one of the streaming platforms, its unusual combination of football (or soccer) played with cars instead of human sportspeople proved to be strikingly and unexpectedly popular on the platform. In the first month after launch, Rocket League went from the 165th most-watched game to the top 5th, resulting in over 5 million download sales (Maestas, 2015). Therefore, it is essential to understand why the streaming service can integrate itself quickly into the gaming industry and how positively the game streaming is influencing the games’ popularity.

On the other hand, on top of the positive effects that game streaming may bring to the game companies, there may also exist a cannibalization effect incurred by game streaming on the game companies. In the gaming industry, the cannibalization effect represents that the game streaming services decrease game’s popularity unexpectedly and hurts game sales eventually. Pearce (2018) explained the cannibalization effect as that once a content anchor completes the “single-player” games, the audiences might not watch the relevant game streaming, or even play the game on their own. Therefore, although game streaming may help to attract more audiences and gamers by streaming the games, yet those audiences who have already gone through the content of the streamed games may have less incentive to buy games. Such a cannibalization effect may happen because the streaming audiences might consider that what they experienced on the streaming platforms has no differences from what they could experience by playing the games themselves. Under such circumstances, the game streaming services may prevent the potential gamers from playing the game, which hurts the game companies.

Electronic Word-of-mouth Effects on the Game Streaming Services

Meanwhile, the electronic word-of-mouth also exists in game streaming. Electronic word-of-mouth refers to any positive or negative statement from potential, actual or former customers about a product or company that is made available to multiple people and/or institutions and spread over the internet (Cheung & Thadani, 2010).

Sometimes, the streaming audience may only take a first glimpse of the streamed games, which may lead to an incomprehensive understanding of the streamed game. As a result, the audiences may leave negative comments based on their biased or incomplete opinions of the games. These arbitrary judgments could demotivate potential players who were following the streamed games. As a consequence, these negative reviews may result in a drop in game's popularity and game sales, which hurts the game companies. On the other hand, positive reviews and commentaries from the audience are usually likely to help the game streaming to appeal to more players, and eventually increase game players, which benefits the game companies.

As illustrated, the reviews and comments of the streaming content of one game also play the role of electronic word-of-mouth which affects both the game streaming services and the game companies. Therefore, reviews and comments, acting as electronic word-of-mouth, potentially play both positive or negative roles on game streaming and game's popularity.

The Interaction between Game streaming, Electronic Word-of-mouth, and Game's Popularity

Therefore, game streaming and electronic word-of-mouth both can influence the game's popularity, which directly affect the revenue of game companies. Thus, it is profitable and crucial to investigate how the interaction exists. Specifically, game streaming may directly influence game's popularity; game streaming may also generate electronic word-of-mouth effects from the reviews of viewers; the reviews from the players are also likely to affect the number of players of one game. To summarize, game streaming and electronic word-of-mouth could positively or negatively impact game's popularity.

Hence, addressing the direct effects of game streaming and electronic word-of-mouth on game's popularity is important to increase the game's popularity, which is also crucial to the game companies. A step further, the investigation on the relationships between game streaming and electronic word-of-mouth also deserves attention. Furthermore, will there be an interaction existing among game streaming, electronic word-of-mouth and game's popularity.

We will then in detail elaborate the interactions of the three areas by combining a study conducted by Johnson & Woodcock (2019) from a big picture. We will introduce several unique features that the game streaming brings to the gaming industry, namely Reviewing and Visibility, to illustrate the possible existence of the interaction.

Reviewing: game streaming brings real-time electronic word-of-mouth

Game streaming allows more people to review the games, which enriches the content of games that players can experience without buying the games. In addition, the streaming platforms have their unique advantages that after-sales reviews cannot match. To illustrate, streaming platforms enable the audience to speak directly to the game companies or streamers so that they can observe more of the game before making a choice whether to purchase the game or not (Johnson & Woodcock, 2019). Hence, the game streaming offers a privilege for the potential players to share their opinions before any purchase. These real-time reviews on the streaming platforms contribute to the electronic word-of-mouth, potentially giving the audiences a deeper understanding of the game prior to purchasing. From another perspective, game companies can enhance this real-time communication and engage more potential gamers into the streaming channels, desiring to drive game sales.

Visibility: everything is visible in game streaming. Positives and Negatives.

Streaming services has become an important site for boosting the visibility of independent games, whereby streamers serve in lieu of a larger formal advertising budget and labour is performed by streamers who benefit both themselves and the game companies through their actions (Johnson & Woodcock, 2019). In the gaming streaming, everything is visible and directly impart information to the game's popularity. Consequently, positive or negative electronic word-of-mouth brought by the game streaming could severely twist buying motives.

If gamers show strong interests in the streamed game, they are likely to introduce more audience into the streaming channel and share thoughts. The volume of electronic word-of-mouth would be increasing in a relative way. With an increasing number of audience and reviews, game streaming makes the positives of the game visible to every audience and exposes the positives of games to an enlarged group of gamers. When the base of potential gamers expands, game companies improve game’s attractions to gamers.

However, the game's visibility can also break a game. If the audience does not appreciate the content of the game, they may express their passive opinions or give up the idea of purchasing the game. That is because the gamers have too many options when choosing a game in this competitive market. From this perspective, game streaming broadcasts the negatives of the game to almost every audience who has access to the game streaming. As a result, the desire to increase the game's popularity may not be as immense as expected. Therefore, from this perspective, the passive reviews may also deteriorate the gamer’s motive to buy a game.

As mentioned above, Firstly, game streaming brings real-time electronic word of mouth from gamers into light. Secondly, the interaction among game streaming, electronic word-of-mouth, and game’s popularity magnify the positives and negatives of one game and relatively influence game sales. During this process, game streaming unreservedly presents the positives and negatives of one game to gamers while gamers also express their unreserved opinions on the streaming platforms. Thus, game streaming, game popularity and electronic word-of-mouth work jointly to help or hurt game companies.

Summary

Therefore, this research aims to investigate in detail whether the game streaming can help or hurt the game companies regarding their game's popularity. In short, game streaming may both improve a game's popularity and damage the game's popularity by generating the cannibalization effect which causes the tension on the games. In detail, the game streaming may lead the audience to solely watch the game streaming instead of playing the games themselves, which may hurt game's popularity. Therefore, this potential tension is of great interest to this research. Apart from the effect of game streaming on the game's popularity, this research will also take electronic word-of-mouth into consideration. That is because this research is also interested in the possible effects that game reviews may bring to the relevant game streaming services or the game companies, as mentioned above. Therefore, this research will cover the content of the relationship between the game streaming and game's popularity, the relationship between the electronic word-of-mouth and game streaming, as well as the relationship between game electronic word-of-mouth and game's popularity.

2. Literature review

This paper draws from three research topics: game streaming, electronic word-of-mouth, and game's popularity. We will describe the relevant literature in the following and point up the common and differences in the findings.

Game streaming on the games' popularity

Many studies have strived to find the effect game streaming has on the game's popularity. One of studies measured the effect of game streaming on game's popularity, the authors introduced a way to rank users by game's popularity using qualitative data (Kaytoue et al., 2012). Other studies also built the connection between game streaming and game's popularity by combining data from streaming and players' history to detect the impact of game streaming on a player's game performance and engagement (Matsui, Sapienza & Ferrara, 2020).

By far, existing studies have mainly emphasized the positive side of game streaming on game's popularity but did not manage to find or quantify the dark side of game streaming, which is the cannibalization effect, referring to a reduction in game sales. On the positive side, Sjöblom et al. (2017), discovered the relevant features such as influential streamers on the streaming platform are attractive to the game's popularity. To give the audience more influence, Pascal et al. (2017) highlighted the enhanced communications between game's popularity and game streaming could positively boost game popularity. Similarly, Conceptual research shows that streaming platforms embody a predominantly socially enjoyable experience and a space to interact with peers having the same interest in an easily joinable community (Smith, Obrist & Wright, 2013). However, unlike prior work, we focused on the positive influence the streaming effect can bring to the game's popularity but also attempted to find the dark side of the streaming effect via cannibalization.

Little studies dive into the cannibalization effect of the streaming platforms. For example, Smith, Obrist & Wright (2013) have found neglected malleability between the active and passive roles in users' experiences but could not split them or provide quantitative evidence. Staying on the conceptual level, Pearce (2018) merely observed a phenomenon - When the interactive experience on the streaming platform plays out almost the same for every player and lasts only a few hours, gamers may not want to buy it.

However, Smith, Obrist & Wright (2013) and Pearce (2018) only pointed out that streaming platforms can potentially ruin game sales but failed to provide quantitative or empirical evidence. By measuring the number of streamers, our research adds on previous work results by using quantitative data to investigate the negative impact of game streaming on game's popularity via cannibalization. Meanwhile, our approach expects to verify whether game streaming positively impacts game's popularity, as prior studies illustrated.

Electronic word of mouth on the gaming's popularity

Electronic word-of-mouth plays an essential role in influencing consumer attitudes and, consequently, affecting consumer choice, loyalty, and brand switching (Wangenheim, Florian, Bayón & Tomás, 2004). For example, one of the studies showed how electronic word-of-mouth influences switching decisions, and concluded that expertise and similarity affect perceived power, customers' attitudes, and subsequent decision making (Wangenheim, Florian, Bayón & Tomás, 2004). Moreover, Yayli, Ali, Bayram & Murat (2012) structured the electronic word-of-mouth, which is the online consumer review on purchasing decisions, stating that consumer reviews have a causal effect on consumer purchasing behaviour and affect consumer product choices. In both cases, prior works highlighted the significant impact of electronic word-of-mouth on the purchase decision.

When prior work integrates electronic word-of-mouth into the game industry, they found some gamers get an idea of what games they might like to buy intuitively, while others go with electronic word-of-mouth based on the game reviews (Feng & Xiaoquan, 2006). This statement proved that electronic word-of-mouth influences consumers' decisions, but they could not measure to what certain degree. Based on the relationship between gamer's popularity and electronic word-of-mouth, prior study specifically stated that electronic word-of-mouth significantly influences the sales of video games. For example, a one-point increase in the average rating is associated with a 4% increase in-game sales. Furthermore, negative ratings have a more considerable impact than positive ratings (Feng & Xiaoquan, 2006).

However, although previous studies investigated the impact of electronic word-of-mouth on the game's popularity, previous research barely divided electronic word-of-mouth into the electronic word-of-mouth volume and electronic word-of-mouth valence to find the respective impact on the game's popularity (Anastasiei, Bogdan, Dospinescu & Nicoleta, 2019). For example, one game can receive countless game reviews, in other words, a large volume of electronic word-of-mouth. However, the game's popularity could still decrease suffering a lower electronic word-of-mouth valence, meaning that negative reviews take over most of the total reviews. Likewise, little literature examines whether the game's popularity will increase when the volume of electronic word-of-mouth volumes is huge, the number of game reviews will boost games' popularity regardless of the positive review or the negative review. Therefore, we will focus on these two dimensions of electronic word-of-mouth: electronic word-of-mouth valence, the percentage of positive game reviews in total game reviews, and electronic word-of-mouth volume, the total amount of game reviews, and attempt to find each impact on game's popularity.

The interplay between game streaming, electronic word-of-mouth and game's popularity

If the online game firms cannot satisfy the core values of their players, the players will be unwilling to recommend and share this game with others (Shu-Hsien, Chih-Chuang, Retno & Ying, 2012). Hence, game streaming is a significant new force in the games industry to help gamers realize the core value of games, creating new links between developers and influencers and shifting our gameplay and game design expectations (Johnson & Woodcock, 2019).

Prior works therefore identified game streaming and electronic word-of-mouth as two significant impacts on game's popularity. Firstly, game companies can collect data regarding their customers to create better products and more personalized experiences via streaming platforms. Secondly, game companies can leverage the Word-of-mouth phenomenon to increase visibility and awareness about their service, their products and create long-term customer relationships (Foster, Lisa, Dunn & Robert, 2020). This related study claimed that electronic word-of-mouth and gaming streaming function jointly on the game's popularity. However, Foster, Lisa, Dunn & Robert (2020) only took the positive impacts of game streaming and electronic word-of-mouth into consideration and did not investigate the interplay between game streaming and electronic word-of-mouth.

In other research, previous works give the opposite points on the respective impact on game's popularity in terms of game streaming and electronic word-of-mouth. Portas, Karla, Reyes & Pável (2018) stated that electronic word-of-mouth is more critical in affecting games' popularity than game streaming. By the brand community commitment from the sender's perspective, electronic word-of-mouth has a more prominent role than perceptions on innovation attributes in influencing users' attitudes and intentions to continue using the video streaming platform. On the contrary, Lindsay (2016) discovered that while electronic word of mouth could offer more consistent recommendations within streaming services, game streaming exists as the most effective form. The research above has opened the door for further discussion in this area - whether the impact of game's streaming supersedes the impact of electronic word of mouth on the game's popularity.

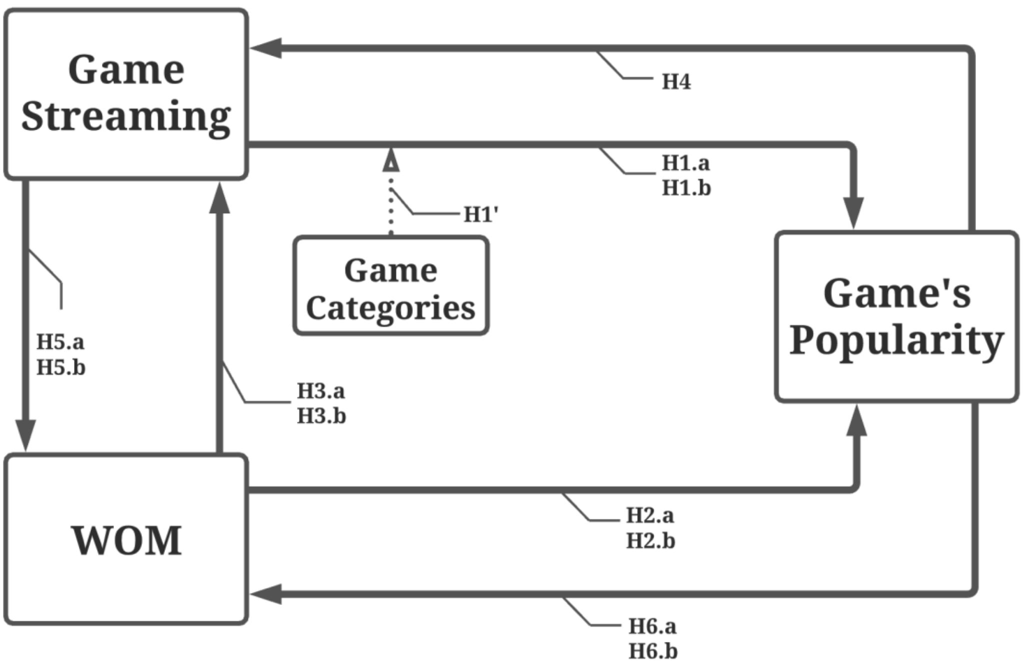
Overall, it is a vital step further based on previous studies to determine the positive or negative effect of game streaming and electronic word-of-mouth on the game's popularity. Even further, when distinguishing games into different categories, whether the impact of game streaming and the impact of electronic word-of-mouth varies on the games' popularity. Equally important, with regards to game streaming and electronic word-of-mouth, which one is more helpful to improving game's popularity? Whether the interaction of game streaming, electronic word-of-mouth, and game's popularity exist? We build several hypotheses in the theory part and seek for the answer based on the literature gaps.

3. Theoretical Framework

As discussed above, game streaming can usually help to display and advertise the content of the games to the audience, which often helps the games attract more players. However, sometimes streaming may also spoil too much content of the game, which may make the audience play less games. In addition to the streaming services, word-of-mouth (this research will also refer to it as WOM) also tends to have a crucial impact on the number of game players. Good word-of-mouth may help games gain more supportive players, while bad word-of-mouth usually turns down gamers. Largely based on the number of active game players and how much they play the games, we can estimate a game's popularity. In other words, we believe that a more popular game will have more concurrent players than the less popular games. And this research will concentrate on game streaming and WOM as two substantial areas that affect game popularity. More precisely, as the interest of the research topic, we will study and explain the positive or negative effects that game streaming and WOM may bring to the game's popularity.

The theoretical framework below will speculate and define the game's popularity, followed by the effects incurred by game streaming and WOM respectively (*Figure 1.*). Next, this research will discuss and explain various effects that the game streaming, WOM, and the game's popularity may have on each other as well as corresponding hypotheses.

Figure 1. Theoretical Framework



3.1. Areas of Interest

This part of the research will define and describe the three areas that this research will focus on, namely, game's popularity, game streaming, and WOM.

3.1.1. Game's Popularity

The area that we are the most interested in is the game's popularity. Game's popularity reflects game-play intensity. Different from the game sales records, the game's popularity can better and more realistically represent the player's participation in the games. In other words, a high game's popularity usually indicates a higher number of active players. The other way round, the number of concurrent players is possible to imply a game's popularity as well. For instance, a game that has more players is also likely to have a higher game's popularity. Therefore, the first area that this research addresses is the game's popularity, which is also crucial for game companies.

3.1.2. Game Streaming

Another concept of great significance is the game streaming. Similar to game's popularity, we use game streaming to represent streaming and watching intensity. Game streaming also expresses the extent to which streamers and audiences are involved with relevant game streaming. In other words, a high degree of game streaming usually implies a more popular game streaming, which more streamers would broadcast, and more audiences would watch. Besides, a high level of game streaming also indicates more time that people would spend streaming or watching the game streaming. In general, the level of game streaming directly reflects the extent of effects that streaming services bring to the relevant game. As a result, this research will also take the game streaming into consideration, and we will also try to explore game streaming's probable impacts on other areas of interest, such as game's popularity.

3.1.3. WOM - WOM Volume and WOM Valence

There are also many other methods that game companies can adopt to increase game's popularity, for instance, game companies sometimes also consider the word-of-mouth effects. Therefore, this research will mention the other factor that may affect game's popularity, which is WOM. When it comes to the gaming industry, the reviews of the game can largely reflect and decide the game's WOM, which may further influence the game's popularity. As a result, this research will utilize game’s online reviews to stand for the WOM effects (Godes & Mayzlin, 2004). However, both the number and tones of the reviews can reflect WOM. Therefore, we will divide the game’s electronic WOM into two dimensions to indicate its influence on the game's popularity, namely volume, and valence (Anastasiei & Dospinescu, 2019).

Firstly, WOM Volume is defined as the frequency with which people communicate the game reviews, while WOM Valence is considered as a term that summarizes the type of positive or negative reviews (Harrison-Walker, 2001). The reason why this research aims to separate the two aspects out of only one review rating is that a single review score cannot afford to reflect both the number and the polarity of the review’s conditions. To illustrate, the game with 1 positive review out of 10 total reviews is different from the game with 10 positive reviews out of 100 reviews. Therefore, this research will separately deal with WOM Volume and WOM Valence based on the game’s reviews posted from the players to represent the effects of WOM on game’s popularity. In short, if a game has high WOM Volume, then it means that this game has a large number of comments from the players. On the other hand, the higher WOM Valence a game has, the more positive reviews this game receives compared to the negative ones.

3.2. Hypotheses

After discussing and briefly introducing the three main areas of interest, which are game’s popularity and game streaming, and WOM (volume and valence), this part of the research will elaborate on their interrelation. After that, we will propose different hypotheses regarding each specific relationship.

3.2.1. Game Streaming’s Direct Effect on Game’s Popularity

As described above, live streaming can provide customers with an immersive experience, and enrich information such as reviews and demonstrations, which can drastically drive product sales (Hallanan, 2021). Game streaming can also play the role of marketing campaigns that advertise and promote the games to the audience, which is likely to appeal to the audience and acquire more players. Game streaming helps to demonstrate and show off the gaming experience, game content, and game quality, which may convince the streaming audience and turn themselves into players. Besides, game streaming can provide another opportunity for the players to engage in the games even when they cannot play the games right away. In other words, game streaming can keep the players constantly interested and involved in the games as well. From this perspective, we tend to believe that game streaming sometimes acts an unignorable role in improving a game's popularity.

As a result, we propose hypothesis **H1.a** to represent the possible benefit that game streaming may bring to game's popularity mentioned above.

H1.a: One game's game streaming will increase this game's popularity.

With **H1.a**, we will be able to test the hypothesis in the model result part to verify whether game streaming can improve game's popularity.

Apart from that, it is of central interest to this research to study whether game streaming helps or hurts game's popularity. Apart from the positive effects that game streaming may bring to the game's popularity, game streaming may also prevent the audience or the players from playing the games (Matsui, Sapienza & Ferrara, 2020), which damages the game's popularity. To illustrate, game streaming sometimes may expose too much content of a game for the audience, especially for the single-player games if the game content is based on a narrative story (Pearce, 2018). In other words, it is less likely for the audience to play the same game if they have watched the streamers playing through the games. Therefore, as mentioned above, the game streaming sometimes may also spoil the game content and decrease the player's interest in the game, which eventually decreases game's popularity.

As a result, we will propose hypothesis **H1.b** to represent the possible negative cannibalization effect that game streaming may bring to game's popularity.

H1.b: One game's game streaming will decrease this game's popularity.

With **H1.b**, we will be able to test the hypothesis later in the model result part to verify whether game streaming will hurt game's popularity.

3.2.1.1. Game Category's Moderating Effect

After proposing the competing hypotheses **H1.a** and **H1.b** as mentioned above, this research is also interested in exploring under which more precise circumstances game streaming may have weaker positive effects on or even negative effects on the game's popularity. In other words, certain factors may affect the impacts of game streaming on game's popularity, and this research is interested in perceiving and discovering the factor that may affect or moderate the relationship between game streaming and game's popularity. In essence, this research will concentrate on the possible moderating effects incurred by game categories, which include "single-player" and "multi-player" games, the reasons are as below.

Take movie spoilers as an example, movie spoilers usually disclose the essential content of the movies, which is likely to decrease the audience's interest in the films (Falls, 2014). Similarly, the games categorized as "single-player" games mostly focus on the player's individual indulging experience, while game streaming is likely to disclose too much content of the games to the viewers. In other words, the audience can obtain the same gaming experience through the streaming, which may decrease their incentives to play the games. Consequently, playing a similar role of the spoiler, game streaming may have subtler positive or even negative impacts on game's popularity. On the other hand, addressing player's sharing and cooperation, "multi-player" games usually attach high importance to the communication and interactions among players (Caroux, Isbister, Bigot, & Vibert, 2015), and game streaming can serve as an online platform where different players can interact with each other. As a result, "multi-player" games may strengthen game streaming's advantages in encouraging player's sharing and collaboration, which is likely to help the games to appeal to more players.

From this perspective, different game categories may influence the impacts that game streaming has on game's popularity. As a result, we propose hypothesis **H1'** to explore the probable moderating effects that game categories may have on the relationship between game streaming and game's popularity.

H1': Game streaming is more helpful in increasing the game's popularity for multiplayer games, compared to single-player games.

With **H1'**, we will be able to test the hypothesis in the model results to verify whether multiplayer games' popularity benefits more from game streaming.

3.2.2. WOM Volume and WOM Valence's Direct Effect on Game's Popularity

Similar to the customers of the offline stores, online game players can comment and share their reviews in respect to different games. Game lovers may then come across game reviews or comments, and then get to know the game. In addition, people's recommendations or reviews regarding different games may also help the gamers who know the game to make the decision whether to become a player or not. Sometimes word-of-mouth activities may have a more long-term and persuasive benefit for the game's popularity compared to other promotional methods (Livingston, Nacke & Mandryk, 2011). For instance, the more WOM Volume that a game has, the more comments and reviews that a game tends to have, therefore, the more likely other gamers can be aware of the game or even play the game. From this perspective, WOM Volume is likely to get more people to know and play the game, benefiting the game's popularity.

Therefore, this research will propose **H2.a** to test WOM Volume's effect on game's popularity.

H2.a: A game's WOM Volume will increase this game's popularity.

With **H2.a**, this research can test the hypotheses in the model result part to verify whether WOM Volume can improve the game's popularity.

It is usually expected that positive WOM Valence tends to bring benefits for the products or services. Take the hotel industry as an example, positive WOM Valence increases the number of hotel bookings compared to negative WOM Valence (Ye, Law & Gu, 2009). A game's high WOM valence implies that this game receives mostly positive reviews from the players, which is more likely to be more attractive and raise more players interest (Trusov, Bodapati & Bucklin, 2010). As a result, high WOM Valence is likely to increase the game's popularity. Conversely, a negative WOM Valence usually describes the disadvantages of the products or services, which may damage customer's satisfaction and expectation and result in a less purchase tendency (Shi, Tang, Zhang, Gao & Zhu, 2016). In other words, a relatively low WOM valence indicates a non-supportive attitude of most players towards the game, which may dissatisfy the players and decrease the game's popularity. Therefore, we will also propose the hypothesis to test the relationship between WOM Valence and the game's popularity.

Therefore, this research will propose **H2.b** to test WOM Valence's effect on game's popularity.

H2.b: A game's WOM Valence will increase this game's popularity.

With **H2.b**, this research can test the hypotheses in the model result part to verify whether WOM Valence can improve the game's popularity.

However, it is also worth mentioning that sometimes high WOM Volume and WOM Volume may also have an unexpected negative effect on game's popularity. For instance, an intention to spread positive WOM about the products can backfire on the organization and decrease sales if the incentives are not used properly (Anghelcev, 2013). There are also circumstances where positive reviews decrease and negative reviews increase customer's purchase intention (Reimer & Benkenstein, 2016). The situations mentioned above may happen if gamers are behaving out of anticonformity. To illustrate, when a certain group of people observe a large number of positive game reviews (high WOM Volume and Valence), instead of showing conformity with the majority group of players and play the game, they conversely trust less in the comments and become less interested in the game (Willis, 1965). Therefore, WOM Volume and WOM Valence may also damage the game's popularity. However, we will not propose additional separate hypotheses, because **H2.a** and **H2.b** are already sufficient to test the impacts of WOM Volume and WOM Valence on the game's popularity.

3.2.3. WOM Volume and WOM Valence's Cross Effect on Game Streaming

This research also expects a reciprocal effect from WOM Volume and Valence on game streaming. For instance, there may be circumstances that some reviews under a game can raise gamer's interest in the games. On top of the interest in the game itself, a gamer may also develop curiosity in relevant streaming channels related to the game. In other words, a large quantity of reviews (WOM Volume) or the high percentage of positive reviews (WOM Valence) may both make the gamers entertained and desire to know more about the game, while one of the best solutions to know the game better is to watch game streaming (Burstin, 2021). From this perspective, WOM Volume and WOM Valence may indirectly increase game streaming. Moreover, there may even be occasions that the players leave comments directly referring to or promoting the streaming services. From this point of view, WOM (volume and valence) can directly affect game streaming. Therefore, overall WOM Volume and WOM Valence are likely to have an effect on the game streaming services.

We propose hypotheses **H3.a** and **H3.b** to represent the possible benefits that WOM (volume and valence) may bring to corresponding game streaming.

H3.a: A game's WOM Volume will improve this game's game streaming.

H3.b: A game's WOM Valence will improve this game's game streaming.

With **H3.a** and **H3.b**, we will be able to test the hypothesis in the model result part to verify whether WOM can improve game streaming.

3.2.4. Game's Popularity's Feedback Effect on Game Streaming

In addition to the impacts that game streaming and WOM may have on the game's popularity, the game's popularity is also likely to have a reciprocal impact on game streaming and WOM as the feedback effect. Product or service's popularity, as an important indicator of the quality of the products or services, can both represent the perceived value and lead to herd behaviors (Caminal & Vives, 1996; Kang, Lu, Guo & Li, 2021). In explanation, higher popularity is likely to appeal to more potential customers and raise their interest. For example, an increase in the game's popularity is accompanied with a raise in the number of active players. Assuming that there is a certain percentage of newly acquired players, who are involved with the game streaming, then an increase in the number of players usually indicates an increase in the game streaming. Therefore, an increase in the game's popularity may enhance game streaming.

As a result, we propose hypothesis **H4** to represent the possible benefit that the game's popularity may bring to game streaming.

H4: One game's popularity will improve this game's game streaming.

With **H4**, we will be able to test the hypothesis in the model result part to verify whether the game's popularity improves game streaming.

3.2.5. Game Streaming's Cross Effect on WOM Volume and WOM Valence

Although game streaming is likely to have a major impact on the game's popularity, there may also be certain cross effects that game streaming have on WOM (Volume and Valence). To illustrate, live streaming in general provides a platform where the streamers can encourage and convey their opinions and reviews about the products to the audience (Hallanan, 2021). Therefore, there may be circumstances that the streamers or the streaming content would strike a chord with the audience when they are watching game streaming. More than only motivating people to play the games themselves, the game streaming may also directly remind the players to express their thoughts and opinions regarding the games. For instance, if the players feel the same way as the game streamer while watching the game streaming, these players may later share their comments on the game. Therefore, more players may be prompted to share their reviews and comments regarding the games while watching game streaming. From this perspective, game streaming is likely to affect WOM Volume.

Therefore, we propose hypothesis **H5.a** to represent the possible benefits that game streaming may bring to WOM Volume.

H5.a: One game's game streaming will improve this game's WOM Volume.

Apart from that, when it comes to the WOM Valence, this research expects a positive impact from game streaming as well. As mentioned, streaming usually can promotionally advertise for the products or services, and the positive reviews largely reflect whether the streaming is effective. For instance, streamers often tend to demonstrate the advantages of the products or services, while encouraging the audience to leave a good comment and review, which is because the positive reviews from the users are then likely to confirm the quality of the streamed products or services (Hallanan, 2021). Similarly, from this perspective, this research expects that game streaming can also improve WOM Valence.

Therefore, we propose hypothesis **H5.b** to represent the possible benefits that game streaming may bring to WOM Valence.

H5.b: One game's game streaming will improve this game's WOM Valence.

With **H5.a** and **H5.b**, we will be able to test the hypothesis based on the model results to verify whether game streaming can improve WOM Volume and WOM Valence respectively.

3.2.6. Game's Popularity's Feedback Effect on WOM Volume and WOM Valence

The popularity of products or services can affect their word-of-mouth (Hartini & Mardhiyah, 2020), high product or service's popularity indicates more customers, which in return may bring in more reviews and comments from them. Similar to the game's popularity's effect on game streaming, the more players that a game has, the more comments and reviews that a game is likely to receive. For instance, if we assume that the percentage of players who are willing to contribute to the WOM (volume and valence) by sharing their reviews is the same among all players, then an increase in the number of players may also suggest a change in WOM Volume and WOM Valence. Therefore, the game's popularity is very likely to pay back the effects on the WOM (volume and valence).

As a result, we propose hypotheses **H6.a** and **H6.b** to represent the possible benefit that game's popularity may bring to WOM Volume and WOM Valence.

H6.a: One game's popularity will improve this game's WOM Volume.

H6.b: One game's popularity will improve this game's WOM Valence.

With **H6.a** and **H6.b**, we will be able to test the hypothesis in the model result part to verify whether the game's popularity can benefit WOM.

3.2.7. Reinforcement Effects

All the three areas mentioned above, namely game's popularity and game streaming and WOM (volume and valence), tend to have a reflexive future effect, which means that each of the three areas in the past will have an effect on themselves in the future. To illustrate, an increase in game streaming usually entails that the corresponding game is getting more and more popular among the streamers and audience. Therefore, it is expected that more streamers and audiences may take the trend and participate in that game streaming, which is highly likely to lead to an even higher game streaming in the following future. Similarly, both game's popularity and WOM (volume and valence) tend to have the same reinforcement effects on themselves. An increase in game's popularity or WOM (volume and valence) are likely to appeal to more players and result in a further increase in the following time, which is also known as the herd behaviors (Parthasarathy & Bhattacherjee, 1998). As a result, this research will take the three reinforcement effects incurred by the three areas of interest into consideration in the empirical analysis. However, we will not formulate separate hypotheses for these effects specifically, since such carry-over effect's implications are not of central theoretical interest in our research.

Summary

We will conclude all the hypotheses that this research proposed in the table as below (*Table 1.*).

Table 1. Summary of Hypotheses

Hypothesis	Content
H1.a	One game's game streaming will increase this game's popularity.
H1.b	One game's game streaming will decrease this game's popularity.
H1'	Game streaming is more helpful in increasing the game's popularity for multiplayer games, compared to single-player games.
H2.a	A game's WOM Volume will increase this game's popularity.
H2.b	A game's WOM Valence will increase this game's popularity.
H3.a	A game's WOM Volume will improve this game's game streaming.
H3.b	A game's WOM Valence will improve this game's game streaming.
H4	One game's popularity will improve this game's game streaming.
H5.a	One game's game streaming will improve this game's WOM Volume.
H5.b	One game's game streaming will improve this game's WOM Valence.
H6.a	One game's popularity will improve this game's WOM Volume.
H6.b	One game's popularity will improve this game's WOM Valence.

4. Methodology

We will develop the methodology from two steps, which are respectively data collection and model construction. Firstly, this research will describe how we quantify game's popularity, game streaming, WOM Volume, and WOM Valence, as well as how this research collected relevant data. Secondly, we will describe the process of how this research selects the appropriate models, as well as the model construction process. In the end, after implementing the models, we will derive corresponding model results, with which we can interpret the coefficients and test the hypotheses that we proposed as above.

4.1. Data collection

This research sets out to collect relevant data that is able to represent the areas of interest, namely game's popularity, game streaming, WOM Volume, and WOM Valence. Besides, we will also describe other relevant data that we collected, which this research will use in the models as well. And we will mention the methods that we utilized for data collection, data cleaning, with a descriptive summary table.

4.1.1. Game's Popularity

When it comes to the game's popularity, there are many criteria that can imply whether a specific game is prevalent among the players. For instance, the sales of a game, or the number of people who own the game both reflect the game's popularity. However, on one hand, the price of the games may affect the monetary sales which cannot accurately indicate the game's popularity. In other words, one game may have better monetary sales due to a high price, which does not explain the popularity of the game. On the other hand, there may be circumstances that a gamer merely purchases a game out of a discount without playing. As a consequence, such sales or owners' data cannot accurately represent the active players of the game, nor the game's popularity.

As a result, in order to better reveal the dynamic popularity level of different games in time, this research will utilize the monthly concurrent players to represent the game's popularity per month. In detail, we accessed the daily maximum number of concurrent players, and then we calculated the average of the daily peak numbers over all days within the month to express the game's popularity of that month. The number of concurrent players realistically displays the player's actual participation in the games. Therefore, the higher the number of concurrent players of a game is, in general, the more active players a game will have, and the more popular the game is. Most importantly, regardless of the number of newly acquired players that are in the game, the number of concurrent players includes both new and existing players that altogether reflect the active players level, which expresses the game's popularity.

In short, when it comes to data collection, this research turned to Steam regarding the data related to the gaming industry. Steam is a world-wide video game digital distribution service platform where hundreds of millions of players can play games. And we expect that we can estimate a relatively accurate game's popularity with the help of such an influential platform as Steam. Then, this research made use of Python to extract the average concurrent players per month for the 500 games that have the greatest number of players from the Steam database. The reason why we considered the 500 most popular games is because these games are more representative in the gaming industry. It will be of less value for this research to focus on the games that have very few players, which are likely to demonstrate non-significant or even biased results. In addition to the data collection of average concurrent players, which represents the game's popularity, we also collected and recorded other game's characteristics, such as the game genre, categories, discount, and others.

4.1.2. Game Streaming

When it comes to the game streaming data, this research will utilize one of the most famous live streaming services called Twitch. We expect Twitch to be influential enough which can help us draw representative results in the game streaming industry. This research made use of JavaScript when accessing Twitch streaming. Similarly, in order to acquire the game streaming information that better represents game streaming's impacts, this research will retrieve relevant streaming information for the 500 games that have the most viewers. The reason why we did not include more games' streaming levels is that the remaining streamed games tend to have too few viewers per month, which may be less accurate and representative to stand for game streaming's real impact.

It is of great significance that the 500 games that this research chose in terms of game streaming may be different from the 500 games chosen based on game's popularity. Therefore, regarding the table that contains 500 most-played games and the table that contains 500 most-viewed games respectively, we further carried out a left outer join between the two tables. In other words, the joined result combined the two tables of 500 games based on the 500 games chosen out of game's popularity. Therefore, we can still observe the 500 most-played games as well as their detailed information after the outer join, however, we may not be able to possess the game streaming data of a few games because they are not among the 500 most-viewed streamed games. The reason why this research carried out the outer join based on the 500 most-played games is because the game's popularity is the essence of the research. On the other hand, if the game streaming data is not present, then we consider that game streaming level is 0, which has no impact on others.

It is also worth mentioning that this research has observed five important indicators from Twitch which all reflect the monthly game streaming level. The five indicators include the average number of daily streamers per month, the average number of daily viewers, the average number of channels per month, the average streamed time for the game in hours per month, and the average watched time for the game in hours per month. However, instead of using all of the indicators, we will use the average number of streamers to represent the game streaming level. The reason why we utilized the number of streamers is because the streamers are also the game players. On the other hand, the number of streamers to some extent also reflects the game streaming level of a game. For instance, if there are more streamers broadcasting one specific game, then it is more likely for the audiences from the streaming platform to notice the streamed game, which indicates a higher level of game streaming impacts. In detail, after acquiring the daily maximum number of streamers, we then calculate the average number of streamers by taking the average of the daily peak numbers over all days within a month to express the game streaming level of that month.

4.1.3. WOM Volume and WOM Valence

Similar to the data collection process for the game's popularity, we made use of the Steam platform again with the help of the Steam Application Programming Interface (API). After that, we were able to note down the reviews of different games by the users, which include both the number and the content of the reviews. The content of the reviews also include whether the player recommends the game or not. Next, this research will divide the WOM effects into WOM Volume and WOM Valence based on the quantity and the sentiment of the reviews respectively.

WOM Volume

This research recorded all the reviews that a game received from the players, and we estimated the WOM Volume of one game based on the total amount of reviews that a game has regardless of whether the review is positive or negative.

WOM Valence

Apart from the WOM Volume, we use the ratio of the number of positive reviews out of the total number of reviews that a game has as the WOM Valence. If the player recommends the game, then we expect the relevant review to be positive. In other words, if the player's review stated that the player does not recommend the game, then we treat the review as negative. The reason why we consider the percentage of positive reviews is because this research is interested in knowing the general sentiment of the player's reviews, where a high WOM Valence implies that the most reviews, or players, support the game.

4.1.4. Other Relevant Data

In addition, we will also specify and summarize other important information that we collected, which includes game categories, game genres, game tags, and discount records.

Firstly, as mentioned above, game category describes the properties of the games. The game category divides all the games into two groups, which are the "single-player" and "multi-player" games. And this research is interested in including the game categories as the categorical variable to study the moderating effects of game categories on the relationship between game streaming and game's popularity.

Secondly, this research also collected the game genres data from the game store, which is the game classification method that the game store decides based on the gameplay characteristics. Gaming platforms, such as Steam that we refer to in this research, can classify the games based on different styles of the game which are the game genres. It is the gaming platform that decides the game genre that a game belongs to, and one game can only belong to one primary game genre that suits the game the most. Therefore, instead of considering the game genres as a game’s variable, this research tends to regard the game genres as the grouping method. As a result, we will include the game genre in order to control the possible impacts related to different game genres groups, which we will discuss in detail in the modeling part later in this research.

Apart from the game genre that is up to the gaming platform’s decision, this research will include another perspective of game characteristic, which is the game tag. Game tags also tend to indicate and describe different styles of games. However, compared to the game genre, both the game companies and the players can contribute to the game tags of a game. For instance, the game companies and the players can propose different tags of the game, and then the gaming platform will display a few most popular user-defined tags for the game. It is also worth mentioning that a game can have several game tags. Most importantly, some user-defined game tags of a game may better help the game to appeal to the players, which helps the game to increase the game's popularity (Drachen, Sifa & Thurau, 2014). On the other hand, certain game tags may also increase the audience’s interest in the game streaming, and WOM (volume and valence) (Baker, 2019). Therefore, this research is also interested in including some of the popular game tags as variables in the modeling part. In detail, we will choose three most popular game tags out of all the game tags that this research collected as the categorical variables, aiming to explore their possible impacts on the game’s popularity, game streaming, WOM Volume, and WOM Valence. The three game tags are “Action”, “Indie”, and “Simulation”.

Last but not least, apart from the information related to the game characteristics, this research will also take discount records of the game into consideration. To illustrate, a game's discount is very likely to benefit games sales and players, which increases game's popularity (Choi & Chen, 2019). Therefore, this research is also interested in including discount records as the continuous variable to discover its influences on game's popularity, game streaming, WOM Volume, and WOM Valence in the modeling part. Briefly, we collected the discount information in the form of a decimal number which falls into the range from 0 to 1, and the value of the discount variable represents the percentage to take off from the original price. For instance, if the discount of a game is equal to 0.2000, then it means that a player can purchase the game at 80% of the original price. Above all, if the game is free, then the discount will remain 0 all the time.

4.1.5. Data Preparations

Log transformation

We observed the skewed distribution when it comes to the data related to game's popularity, game streaming, WOM Volume, and WOM Valence. The skewed distribution is likely to degrade the accuracy of the model fit, leading to less valid model results. Therefore, we will also carry out the log transformation for the data related to the four areas. As a result, after the log transformation, we managed to decrease the variability of data and make data conform more closely to the normal distribution (Feng et al., 2014). It is also worth mentioning that when applying the log transformation to the relevant data, we can operate directly on the data related to the game's popularity and WOM Valence. However, this research increased WOM volume and game streaming variables by one unit to avoid the zero value, which does not support log transformation.

4.1.6. Descriptive Analysis

As a result of the operationalization and data collection process as mentioned above, this research managed to acquire the necessary data to represent various variables that we will use in the model building step. In this part of the research, we will carry out a brief descriptive analysis regarding the quantified and pre-processed variables, especially for game's popularity, game streaming, WOM Volume, and WOM Valence. In addition, we will also summarize other important information that we mentioned above, which refers to game categories, game genres, game tags, and discount records.

Before reaching the descriptive summary table, we will also summarize all the game genres groups that this research used. As discussed, we divided different games into groups based on their primary genre, which describes the game's style. We collected in total 12 different game genres groups, which we expect to be sufficient for the study on different random-effects among various groups (Theobald, 2018), which we will also discuss in detail in the modeling part. We will demonstrate 12 different game genres as well as the number of games that each game genre contains in the table below. And the observation in the table refers to each data row instance that contains game-related information in a specific month, or in short, the game-time combination information.

Table 2. Number of games in each group i by Primary Genre

Game Genre	Number of Observations	Number of Games
Action	3861	82
Strategy	1417	27
Simulation	1403	17
Free to Play	1262	9
Indie	889	31
RPG	837	22
Massively Multiplayer	437	8
Adventure	407	6
Racing	241	18
Sports	150	3
Early Access	126	3
Animation & Modeling	46	1

According to the table above (*Table 2.*), we can conclude from the column "Number of Observations" that we have in total 11,076 data records. In addition, we include in total 227 games in the dataset, suggested by the column "Number of Games" which represents the actual number of games per genre. Next, we will summarize all the variables we introduced above in the table below (*Table 3.*).

Table 3. Description of Variables

Variables	Measurement	Definition
CP_{ijt} (Game's Popularity)	Number of concurrent players	CP_{ijt} refers to the game's popularity of game j in group i at time t.
STR_{ijt} (Game Streaming)	Number of game streamers	STR_{ijt} describes the game streaming of game j in group i at time t.
$WOMVolume_{ijt}$ (WOM Volume)	Number of total game reviews	$WOMVolume_{ijt}$ describes the WOM Volume of game j in group i at time t.
$WOMValence_{ijt}$ (WOM Valence)	The ratio of positive game reviews over all reviews	$WOMValence_{ijt}$ describes the WOM Valence of game j in group i at time t.
$Action_{ij}$	Tags of the game from the game store	$Action_{ij}$ is a binary variable that is equal to 1 when the game j in group i in the game store has the tag "Action", otherwise 0.
$Indie_{ij}$	Tags of the game from the game store	$Indie_{ij}$ is a binary variable that is equal to 1 when the game j in group i in the game store has the tag "Action", otherwise 0.
$Simulation_{ij}$	Tags of the game from the game store	$Simulation_{ij}$ is a binary variable that is equal to 1 when the game j in group i in the game store has the tag "Action", otherwise 0.
$Discount_{ijt}$	Sales discount history from the game store	$Discount_{ij}$ indicates the percentage of price deduction for game j in group i at time t.
$Categories_{ij}$	Game category information from the game store	$Categories_{ij}$ is a dichotomous variable that takes the value of 0 if game j in group i is "multi-player" game, $Categories_{ij}$ is equal to 0 if the game is "single-player".

The table above includes the relevant information regarding the four areas of interest to this research (*Table 3.*). Most importantly, the “Measurement” column explains the operationalization of corresponding variables that this research uses to quantify the areas of interest. In addition, as mentioned above, we include the game categories as the dichotomous variable to study its moderating effect on the relationship between game streaming and game’s popularity. And we included the 3 most popular game tags as three variables, namely “Action”, “Indie”, and “Simulation”.

Table 4. Summary Statistics of Numeric Variables

Variables	Mean	Standard Deviation	Min	Max
CP_{ijt} (Game’s Popularity)	8.001	1.446	1.864	14.276
STR_{ijt} (Game Streaming)	5.082	4.030	0	12.591
$WOMVolume_{ijt}$ (WOM Volume)	6.515	1.402	0	12.384
$WOMValence_{ijt}$ (WOM Valence)	0.609	0.072	0.154	0.693
$Action_{ij}$	0.549	0.498	0	1
$Indie_{ij}$	0.312	0.463	0	1
$Simulation_{ij}$	0.355	0.478	0	1
$Discount_{ij}$	0.201	0.255	0	0.978

The table above summarizes the numeric variables with their mean, standard deviation, minimum, and maximum information. The minimum value for STR_{ijt} and $WOMVolume_{ijt}$ are 0, which means that the effects of game streaming and WOM Volume for some games in certain months may be 0. In terms of the three game tags variables, $Action_{ij}$, $Indie_{ij}$, and $Simulation_{ij}$, the mean value also represents the percentage of the appearance of the relevant game tag among all the game-time combination observations among the dataset. For instance, the mean value of $Action_{ij}$ is 0.549, which means that 54.9% of the data rows refer to the game which people attach the “Action” tag to. When it comes to $Discount_{ij}$, the maximum value of 0.978 means that the highest discount that a game has from our dataset is 97.8% off the original price.

Table 5. Summary Statistics of Game Categories

Variable	**Value**	**Observations**	**Number of Games**
$Categories_{ij}$	Multi-Player	1896	39
	Single-Player	9180	188

The table above summarizes the dichotomous variable $Categories_{ij}$. The column “Observations” indicates the number of observations of the data rows that contains one game’s information in a specific month, which belongs to either the “multi-player” or the “single-player” category. The “Number of Games” represents the actual amount of games for each category (*Table 5.*). We can notice that there are many more games that belong to the “single-player” category, and the “single-player” game category also contains more data records.

4.2. Model Building

4.2.1. Model Choices

As discussed above, this research deals with the information that includes several perspectives, which include the game's popularity, game streaming, and WOM (volume and valence) aspects. Meanwhile, this research also intends to explore the dataset from two perspectives, namely time-series and game genre which is the classification assigned to video games. Therefore, the model that this research intends to use should be capable of addressing the interactions among the areas of interest. Out of all the suitable models, this research will firstly make use of the Vector Autoregression (VAR) model to capture the relationships among game's popularity, game streaming, WOM Volume, and WOM Valence. Above all, the VAR model allows these variables to influence each other, meaning that each variable can act as a dependent variable and as an independent variable to explain the other variables. For example, we aim to test the effects of game streaming on the game's popularity, as well as the effect of game's popularity on the game streaming reversely.

In addition, the VAR model enables us to predict the value of variables in the current time period, which we can use again as regressors in the prediction for the next period (Schilegel & Gordon, 1985). Therefore, the VAR model is capable of helping this research to observe the interactions of the three areas of interest as they change over time (Asteriou & Hall, 2011). After adopting the VAR model for each individual game, we will be able to obtain an overview of the multivariate relationships among the game's popularity, game streaming, as well as the WOM effects (volume and valence) from the perspective of each separate game. We will in detail introduce how we would adopt the VAR model for the purposes of the research in the following part of the methodology.

However, The VAR model limits the scope on verifying the game's popularity, game streaming WOM Volume, and WOM Valence per one game over time but failed to aggregate game genres. This means that the VAR model does not have the ability to tell whether game streaming helps or hurts game popularity at a group level. Hence, the result from the VAR model per game is not sufficient. Alternatively, the linear mixed effect model can capture multiple games based on game genres and present the relations between game streaming, games' popularity, WOM Volume, and WOM Valence on an aggregated level.

Therefore, this research needs to come up with another model to complement the VAR model above. And the second model that this research will use is the Linear Mixed-Effect Regression model (LMER). With the help of the second regression model, we can analyze the game's popularity as well as all other relevant information of all the games over time. Frankly speaking, we can use the linear mixed-effects model to fit all the data and draw the conclusions in terms of the hypotheses from a bigger picture. Besides, this research is also able to include other game characteristics in the second regression model, such as the game genres, discount information, and others. Therefore, the second regression model manages to be the complementation of the first model in terms of the categorization by game genres.

In conclusion, instead of building a sophisticated model that includes all the content all at once, this research will make use of the advantages from both the VAR model and the LMER model. In detail, the VAR model mainly considers the time series forecasts but lacks the capability of explaining certain game information, such as the game genres. Alternatively, the LMER model is able to complement the VAR model and provide a more general result that we can apply for other games that this research does not cover. Thus, we can take the advantage of both models, which contribute to a more comprehensive research result. We will also briefly summarize the differences of the two models in the table below (*Table 6.*).

Table 6. Comparison of Two Models

	Advantages	**Disadvantages**
VAR Model	- Allow interactions of different variables in the model.	- Must build the VAR model on each individual game at a time.
LMER Model	- Take game genres and other information into consideration. - Can include all the game relevant data from a big picture.	- Not able to indicate the interactions of the variables in one model.

4.2.2. Vector Autoregression Model (VAR)

As discussed above, we will first implement the VAR model based on each individual game. Due to the large quantities of model results, which include the estimated coefficients, standard errors, p-values, and other information, we will not display the results for all the games. However, this paper will present an aggregated version of the model results across all games and interpret certain variable's impacts with relevant hypothesis testing processes.

4.2.2.1. VAR Preparation

It is worth mentioning that when applying the VAR model to every individual game, we are also supposed to carry out necessary testing procedures to ensure the feasibility and credibility of the VAR approach. For instance, we have to make sure that the game's popularity, game streaming, WOM Volume, and WOM Valence records for a game are all stationary. Data stationarity is an important criterion to reflect how we perceive and predict the data, which indicates how constant the overall behavior of the data is. In other words, if we want to acquire an accurate VAR model and result, the time series data should not move to permanently different levels over time so that deviations are essentially temporary, and the mean of data is revertive.

To verify whether the time series data is stationary and determine how well the model fits the data, R-squared from the model result is a skeleton key. However, Unit roots inside the dataset can drive a non-stationary pattern. Technically speaking, the time series dataset is not mean-reverting alongside a high R-squared value when data is uncorrelated. Consequently, the unit-roots can cause a serious issue throughout the analysis, indicating that the time series is not mean-reverting, and the result from any model is not reliable. Therefore, we applied the Augmented Dickey-Fuller Test (ADF test) before implementing the VAR model to identify and resolve the existence of unit roots. The ADF test proposes the null hypothesis that there are unit-roots inside the dataset. After that, we were able and managed to observe the stationarity of the data in our research, featured by mean-reverting (Selva Prabhakaran, 2019).

Meanwhile, this research also tried different methods to improve the stationarity of the data, and the method we used is differencing the data by subtracting the previous observation from the current observation. Differencing can help stabilize the mean of a time series by removing changes in the level of a time series, therefore, we can reduce or even eliminate the trend and seasonality (Hyndman & Athanasopoulos, 2018).

4.2.2.2. VAR Equation

As a result of the discussion above, this part of the research will introduce the equation of the VAR model. We will firstly include four test variables in the VAR model, namely, game's popularity, game streaming, WOM Volume, and WOM Valence, which are respectively $CP_t, STR_t, WOMVolume_t WOMValence_t$. Driven by the underlying function of the VAR model, predicting the current value based on the previous observations, an accurate selection on lag order is necessary to model building. The Bayesian information criteria (BIC) is the optimal method to select lag order for a short period of time. (Schilegel & Gordon, 1985). After adopting the BIC test instead of an arbitrary selection, we believe that one time period of lagged effect is sufficient as indicated in the result of the BIC test.

The variables as well as the mathematical equation of the VAR model that this research will implement on each individual game are as below.

CP_t: the indicator of the game's popularity at time t;

STR_t: the indicator of the game's streaming at time t;

$WOM\ Volume_t$: the indicator of WOM Volume of the game at time t; and

$WOM\ Valence_t$: the indicator of WOM Valence of the game at time t.

$$\begin{pmatrix} CP_t \\ STR_t \\ WOMVolume_t \\ WOMValence_t \end{pmatrix} = \begin{pmatrix} a_{10} \\ a_{20} \\ a_{30} \\ a_{40} \end{pmatrix} + \sum_{l=1}^{p} \begin{pmatrix} a_{11}^l\ a_{12}^l\ a_{13}^l\ a_{14}^l \\ a_{21}^l\ a_{22}^l\ a_{23}^l\ a_{24}^l \\ a_{31}^l\ a_{32}^l\ a_{33}^l\ a_{34}^l \\ a_{41}^l\ a_{42}^l\ a_{43}^l\ a_{44}^l \end{pmatrix} \begin{pmatrix} CP_{t-l} \\ STR_{t-l} \\ WOMVolume_{t-l} \\ WOMValence_{t-l} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{pmatrix}$$

And we will consider the value of p as 1, because this research will only take into consideration one period lag effect of game's popularity, game streaming, WOM Volume, and WOM Valence.

4.2.2.3. VAR Model Result

After repeatedly applying the VAR model to every individual game, we are able to obtain different coefficients and corresponding standard errors related to specific correlations among game's popularity, game streaming, WOM Volume, and WOM Valence. Take a specific game "X", for example, we can formulate the VAR model regarding the four variables of game "X" and then observe the coefficients and relevant p-values of the estimated coefficients. According to statistically significant coefficients from the summary table below (*Table 7.)*, we can interpret the model result and test the hypotheses.

Table 7. Overview of Number of Significant VAR Results

	CP_{t-1}	STR_{t-1}	$WOMVolume_{t-1}$	$WOMValence_{t-1}$
CP_t	90	12	52	25
STR_t	43	147	39	19
$WOMVolume_t$	20	12	73	29
$WOMValence_t$	17	15	23	124

A summary of the number of games from which we observe a statistically significant lagged effect of one specific variable (columns) on corresponding present variables (rows), at 5% significance level.

The results presented an overview of all the results of the relations among game's popularity, game streaming, WOM Volume, and WOM Valence among 227 games for each individual game. For instance, the VAR results of 52 games out of all 227 games proved a statistically significant lagged effect of WOM Volume on game's popularity; 43 games out of all 227 games indicated that game's popularity poses statistically significant lagged effects on game streaming; WOM valence has a statistically significant lagged effect on WOM Volume in 29 games out of all 227 games. It is also worth mentioning that the estimated carry-over effect, the advance contribution of the old period to growth in the current period (Lewis-Beck, Bryman & Futing, 2004), was also observed from the result. However, the carry-over effect is not of center interest to this research, and we would only consider the interactions among game streaming, game's popularity, WOM Volume, and WOM Valence.

On the other hand, on average we only observed a small amount of significant estimated coefficients that stand for the lagged effects of game's popularity, game streaming, WOM Volume, and WOM Valence on each other out of all 227 games. Therefore, this research is only able to draw rough conclusions regarding the hypotheses proposed, based on games with statistically significant coefficients. As a result, we will further decompose the significance results of various lagged effects into the positive effects and negative effects, and further elaborate what they entail as below.

Table 8. Significant VAR Results for CP_t

	CP_{t-1}	STR_{t-1}	$WOMVolume_{t-1}$	$WOMValence_t$
Positive Coefficient	20	8	47	16
Negative Coefficient	70	4	5	9

A summary of the number of positive and negative coefficients of corresponding variables in the CP equation only regarding the significant results.

H1.a One game's game streaming will increase this game's popularity

Results: 8 out of 227 game's game streaming had statistically significant positive estimated coefficients on the game's popularity at 5% significance level. In other words, we observe 8 games that demonstrate significant positive lagged effects of game streaming on the game's popularity. Therefore, this research found strong evidence to support **H1.a** from 8 games among all 227 games.

H1.b One game's game streaming will decrease this game's popularity

Results: 4 out of 227 game's game streaming had statistically significant negative estimated coefficients on the game's popularity at 5% significance level. In other words, we observe 4 games that demonstrate significant negative lagged effects of game streaming on the game's popularity. Therefore, this research found evidence to support **H1.b** from 4 games among all 227 games.

H1'. Game streaming is more helpful in increasing the game's popularity for multiplayer games, compared to single-player games

Results: The VAR model does not support this hypothesis since results only focus on the individual game, but the moderation effect will only be visible when the model aggregates games by group in this case. We cannot conclude anything on this hypothesis since the VAR model does not take the different game categories into consideration. Linear mixed effect model fits well in this case.

H2.a A game's WOM Volume will increase this game's popularity.

Result: 47 out of 227 game's WOM Volume had statistically significant positive estimated coefficients on the game's popularity at 5% significance level. In other words, we observe 47 games that demonstrate significant positive lagged effects of the game's WOM Volume on the game's popularity. Therefore, this research found evidence to support **H2.a** from 47 games among all 227 games.

H2.b A game's WOM Valence will increase this game's popularity.

Result: 16 out of 227 game's WOM Valence had statistically significant positive estimated coefficients on the game's popularity at 5% significance level. In other words, we observe 16 games that demonstrate significant positive lagged effects of the game's WOM Valence on the game's popularity. Therefore, this research found evidence to support **H2.b** from 16 games among all 227 games.

Table 9. Significant VAR Results for STR_t

	CP_{t-1}	STR_{t-1}	$WOMVolume_{t-1}$	$WOMValence_t$
Positive Coefficient	34	11	17	7
Negative Coefficient	9	136	22	12

A summary of the number of positive and negative coefficients of corresponding variables in the STR equation only regarding the significant results.

H3.a. A game's WOM Volume will improve this game's game streaming

Result: 17 out of 227 game's WOM Volume had statistically significant positive estimated coefficients on the game's game streaming at 5% significance level. In other words, we observe 17 games that demonstrate significant positive lagged effects of the game's WOM Volume on the game's game streaming. Therefore, this research found evidence to support **H3.a** from 17 games among all 227 games.

H3.b. A game's WOM Valence will improve this game's game streaming.

Result: 7 out of 227 game's WOM Valence had statistically significant positive estimated coefficients on the game's game streaming at 5% significance level. In other words, we observe 7 games that demonstrate significant positive lagged effects of the game's WOM Valence on the game's game streaming. Therefore, this research found evidence to support **H3.b** from 7 games among all 227 games.

H4. One game's popularity will improve this game's game streaming.

Result: 34 out of 227 game's popularity had statistically significant positive estimated coefficients on the game's game streaming at 5% significance level. In other words, we observe 34 games that demonstrate significant positive lagged effects of the game's popularity on the game's game streaming. Therefore, this research found evidence to support **H4** from 34 games among all 227 games.

Table 10. Significant VAR Results for $WOMVolume_t$

	CP_{t-1}	STR_{t-1}	$WOMVolume_{t-1}$	$WOMValence_t$
Positive Coefficient	1	7	8	22
Negative Coefficient	19	5	65	7

A summary of the number of positive and negative coefficients of corresponding variables in the WOM Volume equation only regarding the significant results.

H5.a. One game's game streaming will improve this game's WOM Volume.

Results: 7 out of 227 game's game streaming had statistically significant positive estimated coefficients on the game's WOM Volume at 5% significance level. In other words, we observe 7 games that demonstrate significant positive lagged effects of the game's game streaming on the game’s WOM Volume. Therefore, this research found evidence to support **H5.a** from 7 games among all 227 games.

H6.a. One game’s popularity will improve this game’s WOM Volume.

Result: 1 out of 227 game’s popularity had statistically significant positive estimated coefficients on the game’s WOM Volume at 5% significance level. In other words, we observe 1 game that demonstrates significant positive lagged effects of the game's popularity on the game’s WOM Volume. Therefore, this research found evidence to support **H5.b** from 1 game among all 227 games.

Table 11. Significant VAR Results for $WOMValence_t$

	CP_{t-1}	STR_{t-1}	$WOMVolume_{t-1}$	$WOMValence_t$
Positive Coefficient	4	7	14	10
Negative Coefficient	13	8	9	114

A summary of the number of positive and negative coefficients of corresponding variables in the WOM Valence equation only regarding the significant results.

H5.b. One game’s game streaming will improve this game’s WOM Valence.

Result: 7 out of 227 game’s game streaming had statistically significant positive estimated coefficients on the game’s WOM Valence at 5% significance level. In other words, we observe 7 games that demonstrate significant positive lagged effects of the game's game streaming on the game’s WOM Valence. Therefore, this research found evidence to support **H5.b** from 7 games among all 227 games.

H6.b. One game’s popularity will improve this game’s WOM Valence.

Result: 4 out of 227 game’s game popularity had statistically significant positive estimated coefficients on the game’s WOM Valence at 5% significance level. In other words, we observe 4 games that demonstrate significant positive lagged effects of the game's popularity on the game’s WOM Valence. Therefore, this research found evidence to support **H6.b** from 4 games among all 227 games.

In conclusion, this research is able to use the VAR results to interpret and test different hypotheses proposed above. We carried out the hypothesis testing with the model result that is built on each individual game, of which the results are as below (*Table 12.*). For instance, the "Number of Games that Provides Evidence for the Hypothesis" represents the number of games from which we observe a statistically significant coefficient that provides strong evidence to support relevant hypotheses.

Table 12. Summary of Hypotheses tested by VAR Model

Hypothesis	Path	Number of Games that Provides Evidence for the Hypothesis
H1.a	Streaming → Popularity	8
H1.b	Streaming → Popularity	4
H1'	single-player Categories → Streaming ↓ Popularity	Not Applicable
H2.a	Volume → Popularity	47
H2.b	Valence → Popularity	16
H3.a	Volume → Streaming	17
H3.b	Valence → Streaming	7
H4	Popularity → Streaming	34
H5.a	Streaming → Volume	7
H5.b	Streaming → Valence	1
H6.a	Popularity → Volume	7
H6.b	Popularity → Valence	4

However, as mentioned above, we were only able to observe a few significant results out of all 227 games regarding different relationships among game's popularity, game streaming, WOM Volume, and WOM Valence. As a consequence, we did not manage to find strong evidence to support whether in general the relationships among game's popularity, game streaming, WOM Volume, and WOM Valence were significant. Hence, this research will propose the LMER model as below to treat all the game relevant data in a big picture, while taking into consideration other game related information such as game genres, which may help to provide stronger evidence to support the hypotheses.

4.2.3. Linear Mixed-Effects Model (LMER)

As discussed above, this part of the research will put forward an additional linear regression model to capture the information that VAR is not able to obtain, such as the differences of games from different game categories, game genres. It is worth mentioning again the reason why this research proceeds with LMER instead of a simple linear regression is because we expect different estimated effects of interest for the different games and genres. In other words, we believe that the effects of lagged game's popularity, game streaming, WOM Volume, and WOM Valence on game's popularity may vary across different game genres groups. And this research aims to build a model that we can apply to other games out of the collected data sample as well. Therefore, this research will extend the simple linear model, and take into consideration both the fixed-effects and random-effects of the lagged effects of game's popularity, game streaming, WOM Volume, and WOM Valence. In short, this research will use the mixed-effects model to include likely random-effects, which indicates the varying levels and impacts of game's popularity, streaming, WOM Volume, and WOM Valence across different groups. And this research will use game genres for grouping purposes.

In detail, to explain the linear mixed-effects model, we will briefly define the fixed-effects and random-effects relevant to this research. As far as this research's concern, fixed-effects refer to the stable impacts that the game-related variables have, which are independent of other factors such as game genres or time. In short, the fixed-effects model assumes that the coefficient for one variable across all game genre groups is the same. Most importantly, this research uses random-effects to represent the impacts of the variables that may differ among different groups. For instance, if game streaming has different effects on game's popularity among different game genres, then this research will be able to capture such a random-effect by using LMER. As a result, with the help of LMER, this research will be more capable to deal with random-effects and increase model accuracy (Peng & Lu, 2012). Next, we will implement the linear mixed-effect model.

4.2.3.1. LMER of Game's Popularity

As mentioned above, firstly, we would consider the game's popularity as the target of the linear mixed-effects model. We will then use different explanatory variables to represent various lagged effects that game streaming, WOM Volume, and WOM Valence may have on the game's popularity. For instance, we will include the direct effects from the game streaming by considering the lagged game streaming as one of the independent variables. In addition, we will include the potential moderating effect of game categories in the game's popularity model too. The mathematical equation is as below.

The model for game's popularity (CP Model):

$$\begin{aligned} CP_{ijt} = {} & \beta_0 + \beta_1 CP_{ijt-1} + \beta_2 STR_{ijt-1} + \beta_3 Categories_{ij} \\ & + \beta_4 STR_{ijt-1} * Categories_{ij} \\ & + \beta_5 WOMVolume_{ijt-1} + \beta_6 WOMValence_{ijt-1} + \beta_7 Action_{ij} + \beta_8 Indie_{ij} \\ & + \beta_9 Simulation_{ij} + \beta_{10} Discount_{ijt} + b_{i1} + b_{i2} CP_{ijt-1} + b_{i3} STR_{ijt-1} \\ & + b_{i4} WOMVolume_{ijt-1} + b_{i5} WOMValence_{ijt-1} + \varepsilon_{ij} \end{aligned}$$

$(i = 1, \dots, m;\ j = 1, \dots, n_i;\ t = 1, \dots, T_{ij})$

where

- β_0 is the fixed intercept for the regression model.

- $\beta_1, \beta_2, \dots, \beta_{10}$ represent the fixed-effects coefficients of corresponding fixed-effects variables. These fixed-effects are identical for all groups.

- m is the number of groups decided by game genres.

- n_i stands for the size of cluster, which is the number of games within group i.

- T_{ij} is the number of periods of records available for the game j in group i.

- b_{i1} is the random-effects parameter, representing random intercept for group i.

- $b_{i2}, b_{i3}, b_{i4}, b_{i4}$ are the random-effects parameter, which represent the random slope for the lagged effects of game's popularity (CP), game streaming (STR), WOM Volume, and WOM Valence for group i respectively.

- ε_{ijt} is the error term for game j in group i at time t.

Explanation of Fixed-Effects and Random-Effects using CP Model

It is also worth mentioning that this research considers the game genre as the random-effects regressor. We will not directly use such a regressor as the game genre as the independent variable in the equation, however, we will use the game genre to divide the data records into different groups (*Table 2.*). After that, we can involve the random intercept and random slopes through different groups.

To elaborate more about the fixed-effects and random-effects that this research focuses on, we will use the coefficients from the equation above for a clearer illustration. The linear mixed-effects model above includes $\beta_1, \beta_2, \beta_3 \ldots$ to represent the fixed-effects, while using $b_{i1}, b_{i2}, b_{i3}, b_{i4}, b_{i5}$ to indicate the random-effects related to the game genre group i. In detail, b_{i1} refers to the random intercept while the rest represents the random slopes.

For instance, after inputting the values of various variables, such as CP_{ijt-1}, STR_{ijt-1}, into different analytical tools, we are able to fit the regression model and obtain the estimated coefficients of the variables from the result. We can then observe the consistent fixed-effects incurred by variables through the coefficients $\beta_1, \beta_2, \beta_3 \ldots$, which is because $\beta_1, \beta_2, \beta_3 \ldots$ are unchanged regardless of which game genre groups that game j belongs to. To illustrate, STR_{11t-1} and STR_{21t-1} represent respectively the first game's game streaming in game genre group 1, and game genre group 2. These two different game streaming have the same and universal coefficient β_1, expressing that the two games' streaming has the same slope of effects on corresponding game's popularity. Similarly, $\beta_1, \beta_2, \beta_3 \ldots$ all indicate the same fixed-effect that different variables have, regardless of the group that the games are in.

In spite of that, the results of $b_{i1}, b_{i2}, b_{i3}, b_{i4}, b_{i5}$ explains the random-effects among different groups i, which we can also infer from the footnotes of the coefficients. Take b_{i1} for example, b_{i1} can take on different values based on different game genres groups i and stands for the additional intercept for game genre group i. To illustrate, without considering other independent variables, β_0 represents the fixed intercept that remains the same for all the games regardless of the game genres groups. However, b_{i1} serves as the random-effect on the intercept that is additional to the fixed-effect intercept β_0. In other words, after taking the different groups i into consideration, the final intercept for one game in group i would be β_0+b_{i1}. Therefore, if b_{11} is different from b_{21}, then β_0+b_{11} will be different from β_0+b_{21}, which indicates that the games in group 1 will have a different value of intercept in the regression model from group 2, which mainly means that the intercept of game's popularity level of games in genre group 1 will be different from genre group 2. Similarly, $b_{i2}, b_{i3}, b_{i4}, b_{i5}$ respectively represents the additional random-effects that the lagged effects of game's popularity, game streaming, WOM Volume, and WOM Valence will have based on group i.

4.2.3.1.1. Game Categories' Moderating Effect in CP Model

Next, we will further elaborate the moderating effect of game categories by rewriting the CP model equation above without changing the regression.

$$CP_{ijt} = \beta_0 + \beta_2 STR_{ijt-1} + \beta_3 Categories_{ij} + \beta_4 STR_{ijt-1} * Categories_{ij} + \varepsilon_{ij} + Others$$

$$CP_{ijt} = \beta_0 + \beta_3 Categories_{ij} + (\beta_2 + \beta_4 Categories_{ij}) * STR_{ijt-1} + \varepsilon_{ij} + Others$$

In essence, we can use $\beta_2 + \beta_4 Categories_{ij}$ to reflect the moderating effects of game categories that influences the relationship between game streaming and game's popularity, which we can use to test the related hypothesis as well. We will include the relevant discussion in the following parts of the research.

4.2.3.2. LMER of Game Streaming

This research is also interested in the impacts of different areas on game streaming. With the help of the game streaming model, we will be able to study the cross effect that WOM Volume and WOM Valence may have on game streaming. On the other hand, we can explore the feedback effect that game's popularity may have on game streaming. Therefore, in this part of the research, we will build a similar model which uses game streaming as the dependent variable. Besides, all the other explanatory variables will remain the same as in the game's popularity model above. The mathematical equation is as below.

The model for game streaming (STR Model):

$$STR_{ijt} = \beta_0 + \beta_1 CP_{ijt-1} + \beta_2 STR_{ijt-1} + \beta_3 Categories_{ij} \\ +\beta_4 STR_{ijt-1} * Categories_{ij} \\ +\beta_5 WOMVolume_{ijt-1} + \beta_6 WOMValence_{ijt-1} + \beta_7 Action_{ij} + \beta_8 Indie_{ij} \\ +\beta_9 Simulation_{ij} + \beta_{10} Discount_{ijt} + b_{i1} + b_{i2} CP_{ijt-1} + b_{i3} STR_{ijt-1} \\ +b_{i4} WOMVolume_{ijt-1} + b_{i5} WOMValence_{ijt-1} + \varepsilon_{ij}$$

According to the equation, we will include the fixed-effects as well as the relevant random-effects regarding the random intercept and slopes across different game genres groups, which remains the same as the research described in the CP model already (4.2.2.1.).

4.2.3.3. LMER of WOM Volume and WOM Valence

Apart from that, this research will move on to the target of WOM Volume and WOM Valence. We will build two additional models to study the WOM Volume and WOM Valence, by regarding WOM Volume and WOM Valence as the dependent variable respectively. All the other explanatory variables and lagged effects of game's popularity, game streaming, WOM Volume, and WOM Valence remain the same as explained in the first model for game's popularity. And the two mathematical equations for WOM Volume and WOM Valence are as below.

The model for WOM Volume (WOM Volume Model):

$$WOMVolume_{ijt} = \beta_0 + \beta_1 CP_{ijt-1} + \beta_2 STR_{ijt-1} + \beta_3 Categories_{ij} \\ +\beta_4 STR_{ijt-1} * Categories_{ij} + \beta_5 WOMVolume_{ijt-1} \\ +\beta_6 WOMValence_{ijt-1} + \beta_7 Action_{ij} + \beta_8 Indie_{ij} \\ +\beta_9 Simulation_{ij} + \beta_{10} Discount_{ijt} + b_{i1} + b_{i2} CP_{ijt-1} \\ +b_{i3} STR_{ijt-1} + b_{i4} WOMVolume_{ijt-1} + b_{i5} WOMValence_{ijt-1} + \varepsilon_{ij}$$

The model for WOM Valence (WOM Valence Model):

$$WOMValence_{ijt} = \beta_0 + \beta_1 CP_{ijt-1} + \beta_2 STR_{ijt-1} + \beta_3 Categories_{ij} \\ +\beta_4 STR_{ijt-1} * Categories_{ij} + \beta_5 WOMVolume_{ijt-1} \\ +\beta_6 WOMValence_{ijt-1} + \beta_7 Action_{ij} + \beta_8 Indie_{ij} \\ +\beta_9 Simulation_{ij} + \beta_{10} Discount_{ijt} + b_{i1} + b_{i2} CP_{ijt-1} \\ +b_{i3} STR_{ijt-1} + b_{i4} WOMVolume_{ijt-1} + b_{i5} WOMValence_{ijt-1} + \varepsilon_{ij}$$

According to the equations, the variables from both models remain the same as the equation before, where the difference is that we use WOM Volume and WOM Valence as the dependent variable respectively here. We again include the fixed-effects, and the random-effects regarding the random intercept and slope across different game genres groups, which remains the same as the research described in the CP model already (4.2.2.1.).

4.2.4. Model Results

After that, we can obtain corresponding model results, and we are able to test the hypothesis that this research proposed in the theories parts. We will summarize the model coefficients, standard error, significance level, as well as other relevant data separately for each model with corresponding interpretations.

4.2.4.1. Results of CP Model

We will summarize the model results for the fixed-effects and random-effects of the CP model separately as below. We will include the coefficients of the fixed-effects as well as corresponding standard error, with which we will be able to test the hypothesis. In addition, we will include the performance indicators R^2 of the model as well, R^2 briefly indicates the accuracy of the model and the accuracy of the mixed-effects, where a higher R^2 tends to indicate better performance of the model (Gilmour, Thompson & Cullis, 1995). In terms of the random-effects of the intercept and slopes, we will conclude them in another table. The values of the random-effects from the random-effects table will entail additional random effects on the fixed intercept, game streaming, WOM Volume, and WOM Valence among different groups according to the game genres, as explained above. The results for both effects are as below.

Fixed-Effects on Game's Popularity

Table 13. Fixed-Effects of CP Model

	Estimate	**Std. Error**
Intercept	0.0554	0.0390
Lagged CP	0.9554 ***	0.0073
Lagged STR	0.0044 #	0.0024
Lagged WOM Volume	-0.0005	0.0064
Lagged WOM Valence	0.4333 ***	0.0502
Action	0.0011	0.0081
Indie	0.0118	0.0072
Simulation	0.0148 *	0.0075
Discount	0.2246 ***	0.0115
R^2	0.9571	

\# Significant at the 10% level.

* Significant at the 5% level.

** Significant at the 1% level.

*** Significant at the 0.1% level.

Hypothesis Results

With the coefficients and standard error stated above (*Table 13.*), we are able to test the hypotheses regarding the direct effects of game streaming on game's popularity. We can also test the direct effect of WOM Volume and WOM Valence on the game's popularity. In addition, we will also shortly refer back to the results of the VAR model regarding different hypotheses.

H1.a. One game's game streaming will increase this game's popularity.

VAR Result: We find statistically significant evidence from 8 games which support **H1.a** out of 227 games.

LMER Result: The coefficient for the direct effect of game streaming on game's popularity is 0.0044, which is statistically significant at 10%. As a result, this research can conclude that we have evidence to support the hypothesis **H1** that one game's game streaming will increase its popularity. In addition, the coefficient is 0.0044, which means that a 1 percentage improvement in game streaming is expected to lead to a 0.0044 percentage increase in the game's popularity while holding all other variables constant. From this perspective, in general the streaming effects can benefit the popularity of games, although the impacts seem subtle to some extent.

H1.b. One game's game streaming will decrease this game's popularity.

VAR Result: We find statistically significant evidence from 4 games which support **H1.b** out of 227 games.

LMER Result: As the competing hypothesis of **H1.a**, we have already concluded a positive impact of game streaming on game's popularity which is statistically significant at 10% in **H1.a**. As a result, this research finds evidence against **H1.b**, and we can summarize that in general game streaming helps game companies to increase game's popularity.

H2.a. A game's WOM Volume will increase this game's popularity.

VAR Result: We find statistically significant evidence from 47 games which support **H2.a** out of 227 games.

Results: The coefficient for the direct effect of WOM Volume on game's popularity is -0.0005, which is not statistically significant at 10%, providing little evidence to support the hypothesis **H2.a**. Therefore, this research did not find enough evidence and cannot conclude a significant relationship between WOM Volume and game's popularity.

H2.b. A game's WOM Valence will increase this game's popularity.

VAR Result: We find statistically significant evidence from 16 games which support **H2.b** out of 227 games.

Results: The coefficient for the direct effect of WOM Valence on game's popularity is 0.4333, which is statistically significant at 0.1%, providing strong evidence to support hypothesis **H2.b**. In addition, the coefficient is 0.4333, which means that a 1 percentage improvement in WOM Valence is expected to lead to a 0.4321 percentage increase in the game's popularity while holding all other variables constant. Therefore, in general this research finds evidence to support that positive reviews help games to gain popularity.

Moderating Effects of Game Categories

Table 14. Coefficients of Categories-Related Variables in CP Model

	Estimate	Std. Error
Categories Single-player	-0.0281 *	0.0126
STR:Categories Single-player	-0.0057 **	0.0020

\# Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Table 15. Effects of STR on CP After Being Moderated by Game Categories

Categories	β_3	β_1	$(\beta_1 + \beta_3)$
Multi-Player	0**	0.0044#	0.0044**
Single-Player	-0.0057**	0.0044#	-0.0013**

\# Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Referring to the game's popularity's equation, $\beta_1 + \beta_3$ represents the impacts of game streaming on game's popularity moderated by game categories.

Hypothesis Results

With the statistics stated above (*Table 13. & Table 14.*), we are able to test the hypotheses regarding the moderating effects of game categories that affect the impacts of game streaming on game's popularity.

H1'. Game streaming is more helpful in increasing the game's popularity for multiplayer games, compared to single-player games.

Result: Game categories indicate whether the game belongs to "single-player" or "multi-player" categories. We summarized the coefficients and other relevant information in the table above (*Table 13. and Table 14.*). The model results only included the information regarding the "single-player" category because the model considered the "multi-player" category as the benchmark. In other words, considering the coefficient of the moderating effects of game categories as 0 when the category is "multi-player", the coefficient of "STR:Categories Single-player" represents the additional moderating impact that "single-player" category has on the relationship between game streaming and game's popularity, which is -0.0057 (*Table 13.*). Besides, the coefficient of "STR:Categories Single-player" is significant at 1% significance level. Therefore, this research finds strong evidence to support **H1'**. In other words, this research finds strong evidence to support that game streaming is more helpful in increasing the game's popularity for multiplayer games, compared to single-player games.

As a result, after taking the moderating effects of game categories into consideration, the coefficient of the game streaming's impact on game's popularity is 0.0044 for the "multi-player" games, while the estimated coefficient of game streaming's effect on game's popularity is -0.0013 for the "single-player" games. Therefore, not only did this research find strong evidence to support **H1'** that the moderating effects of "multi-player" games increase the benefits that game streaming brings to game's popularity compared to the "single-player" games, we also found evidence that such a moderating effect of "single-player" games makes game streaming hurt game's popularity. As a consequence, this result also refers to the cannibalization effect as mentioned above.

Random-Effects on Game's Popularity

Table 16. Random-Effects of CP Model

Game Genres	Intercept	CP	STR	Volume	Valance
Action	-0.0562	0.0164	0.0019	-0.0144	0.0066
Adventure	0.1251	-0.0364	-0.0074	0.0195	0.0677
Animation & Modeling	0.0279	-0.0081	-0.0016	0.0044	0.0150
Early Access	0.0447	-0.0130	-0.0036	0.0029	0.0512
Free to Play	-0.0081	0.0024	0.0051	0.0175	-0.1278
Indie	-0.0543	0.0158	0.0018	-0.0141	0.0074
Massively Multiplayer	0.0587	-0.0171	0.0005	0.0252	-0.0740
Racing	0.0262	-0.0076	-0.0060	-0.0140	0.1335
RPG	-0.0047	0.0014	-0.0004	-0.0033	0.0145
Simulation	-0.0207	0.0060	0.0002	-0.0075	0.0170
Sports	-0.0614	0.0179	0.0058	-0.0009	-0.0906
Strategy	-0.0772	0.0225	0.0037	-0.0153	-0.0206

We can also observe the random-effects from the model result (*Table 16.*), which have an impact in addition to the fixed-effect based on which genre the game belongs to. For instance, we can observe an additional negative random-effect of game streaming (STR) on game's popularity (CP) for game genres groups "RPG", which is -0.0004. The negative random-effect does not entail that game streaming will have a negative effect on game's popularity for the games from "RPG" game genre. Instead, the negative random-effect represents the additional negative impact to the fixed-effect of game streaming on game's popularity, which is 0.0044 as stated in **H1**. As a result, with the negative random-effects of "RPG", we may infer that game streaming benefits the game's popularity less if one game belongs to "RPG". In detail, taking both the fixed-effects and random-effects into consideration, then the estimated coefficient of the impact of game streaming on game's popularity for "RPG" genre is 0.0040. As a result, game streaming still benefits the game's popularity in the "RPG" genre group, although the additional negative random-effects indicate a decreased benefit. We will explain more random-effects as well as specific implications in the following parts of the research as well.

4.2.4.2. Results of STR Model

In this part of the results, we will conclude the model results of both fixed-effects and random-effects for the game streaming model respectively. We will include the coefficients of different variables as well as their standard error for hypothesis testing purposes. After that, we will also summarize the results of the random-effects regarding the intercept and slopes in another table, whose numbers represent the additional random effects on the fixed intercept, game's popularity, WOM Volume, and WOM Valence among different groups (game genres).

Fixed-Effects on Game Streaming

Table 17. Fixed-Effects of STR Model

	Estimate	Std. Error
Intercept	-2.2189 **	0.5721
Lagged CP	0.3072 **	0.0594
Lagged STR	0.7228 ***	0.0399
Lagged WOM Volume	0.1491 #	0.0671
Lagged WOM Valence	-0.3499	0.5499
Action	0.0099	0.0638
Indie	0.0896	0.0545
Simulation	-0.1250 *	0.0574
Discount	0.0779	0.0852
R^2	0.6920	

\# Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Hypothesis Results

With the help of the model results such as the coefficients, standard error, this research can carry out the hypothesis testing with corresponding significance level. We can test the cross effect of WOM Volume and Valence and the feedback effect of the game's popularity on game streaming. We will omit the repeated tests description, of which the details are as above.

H3.a. A game's WOM Volume will improve this game's game streaming.

VAR Result: We find statistically significant evidence from 17 games which support **H3.a** out of 227 games.

Results: The coefficient for the cross effect of WOM Volume on game's popularity is 0.1491, which is statistically significant at 10% significance level, providing evidence to support hypothesis **H3.a**. Therefore, we find evidence to support that a game's WOM Volume can improve this game's game streaming. In detail, 1 percentage improvement in WOM Volume is likely to lead to a 0.1485 percentage increase in the game's game streaming while holding all other variables constant.

H3.b. A game's WOM Valence will improve this game's game streaming.

VAR Result: We find statistically significant evidence from 7 games which support **H3.b** out of 227 games.

Results: The coefficient for the cross effect of WOM Valence on game's popularity is -0.3499, which is not statistically significant at 10% significance level, which does not provide sufficient evidence to support hypothesis **H3.b**. Therefore, we can not find enough evidence to support whether WOM Valence can improve this game's game streaming.

H4. One game's popularity will improve this game's game streaming.

VAR Result: We find statistically significant evidence from 34 games which support **H4** out of 227 games.

Results: The coefficient for the feedback effect of game's popularity on game streaming is 0.3072, which is statistically significant at 1% significance level, providing strong evidence to support hypothesis **H4**. Therefore, we find sufficient evidence to support that a game's popularity will improve this game's game streaming. In detail, the coefficient of 0.3072 indicates that 1 percentage increase in game's popularity is expected to lead to a 0.3061 percentage increase in the game's game streaming while holding all other variables constant.

4.2.4.3. Results of WOM Volume and WOM Valence Model

Same as above, we will summarize the model results for the WOM Volume and WOM Valence models respectively. And then we will discuss the results of both the fixed-effects, and the random-effects for the purposes of hypothesis testing as before.

Fixed-Effects on WOM Volume

Table 18. Fixed-Effects of Volume Model

	Estimate		Std. Error
Intercept	0.3064	*	0.1037
Lagged CP	0.0995	**	0.0242
Lagged STR	0.0191	**	0.0060
Lagged WOM Volume	0.7508	***	0.0271
Lagged WOM Valence	0.4572	*	0.1739
Action	0.0455	*	0.0183
Indie	0.1151	***	0.0153
Simulation	-0.0139		0.0163
Discount	0.6509	***	0.0236
R^2	0.6068		

\#   Significant at the 10% level.
*   Significant at the 5% level.
**   Significant at the 1% level.
*** Significant at the 0.1% level.

Hypothesis Results

H5.a. One game's game streaming will improve this game's WOM Volume.

VAR Result: We find statistically significant evidence from 7 games which support **H5.a** out of 227 games.

Results: The coefficient for the cross effect of game streaming on WOM Volume is 0.0191, which is not statistically significant at 1% significance level, providing sufficient evidence to support hypothesis **H5.a**. Therefore, we find strong evidence from the model results to support that a game's game streaming will improve this game's WOM Volume. In detail, a 1 percentage increase in game's game streaming level is likely to lead to a 0.0190 percentage increase in the WOM Volume while holding all other variables constant.

H6.a. One game's popularity will improve this game's WOM Volume.

VAR Result: We find statistically significant evidence from 1 game which supports **H6.a** out of 227 games.

Results: The coefficient for the feedback effect of the game's popularity on WOM Volume is 0.0995. This coefficient is statistically significant at 1% significance level, which provides strong evidence to support hypothesis **H6.a**. Therefore, we have strong evidence to support that high game's popularity tends to encourage more reviews and comments from the players. The coefficient also suggests that 1 percentage increase in game's popularity is likely to lead to a 0.0991 percentage increase in the WOM Volume.

Fixed-Effects on WOM Valence

Table 19. Fixed-Effects of Valence Model

	Estimate	Std. Error
Intercept	0.1731 **	0.0398
Lagged CP	0.0026 #	0.0006
Lagged STR	-0.0010 *	0.0003
Lagged WOM Volume	0.0001	0.0015
Lagged WOM Valence	0.6994 ***	0.0633
Action	-0.0041 ***	0.0012
Indie	0.0064 ***	0.0010
Simulation	-0.0027 *	0.0011
Discount	0.0044 **	0.0016
R^2	0.5091	

\# Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Hypothesis Results

H5.b. One game's game streaming will improve this game's WOM Valence.

VAR Result: We find statistically significant evidence from 7 games which support **H5.b** out of 227 games.

Results: The coefficient for the cross effect of the game streaming on WOM Valence is -0.0010, which is statistically significant at 5% significance level, providing sufficient evidence to deny hypothesis **H5.b**. Therefore, we find strong evidence to reject that a game's game streaming will improve this game's WOM Valence, because the model result shows strong support for the opposite of the hypothesis that game streaming will decrease this game's WOM Valence.

H6.b. One game's popularity will improve this game's WOM Valence.

VAR Result: We find statistically significant evidence from 4 games which support **H6.b** out of 227 games.

Results: The coefficient for the feedback effect of the game's popularity on WOM Valence is 0.0026, which is statistically significant at 10% significance level. As a result, we have enough evidence to support hypothesis **H6.b** that the game's popularity will improve this game's WOM Valence. In short, 1 percentage increase in game's popularity is likely to lead to a 0.0026 percentage increase in the WOM Valence.

Summary of Hypotheses Testing Results

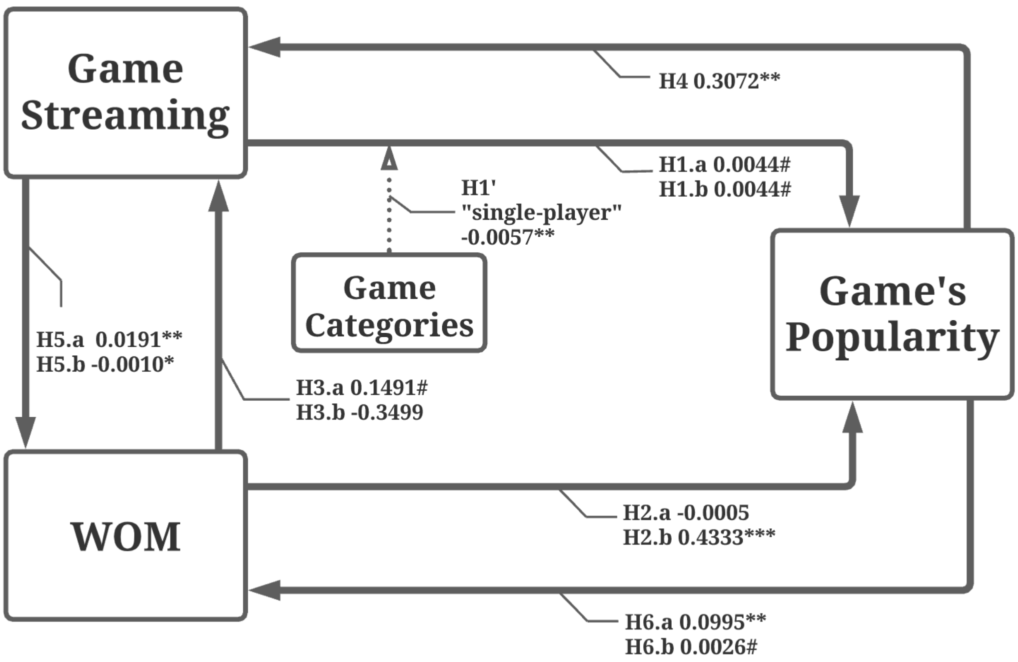
Although some of the LMER model results are different from the results that VAR suggests in terms of the hypotheses testing, we will summarize the hypotheses results in the table as below derived from the LMER model (*Table 20.*).

Table 20. Summary of Hypotheses tested by LMER Model

Hypothesis	Path	Coefficient	*p*	Conclusion
H1.a	Streaming → Popularity	0.0044	0.0865	Confirmed
H1.b	Streaming → Popularity	0.0044	0.0865	Opposite
H1’	single-player Categories → (Streaming ↓ Popularity)	-0.0057	0.0052	Confirmed
H2.a	Volume → Popularity	-0.0005	0.9430	Not Significant
H2.b	Valence → Popularity	0.4333	<0.001	Confirmed
H3.a	Volume → Streaming	0.1491	0.0917	Confirmed
H3.b	Valence → Streaming	-0.3499	0.5436	Not Significant
H4	Popularity → Streaming	0.3072	0.0013	Confirmed
H5.a	Streaming → Volume	0.0191	0.0073	Confirmed
H5.b	Streaming → Valence	-0.0010	0.0110	Opposite
H6.a	Popularity → Volume	0.0995	0.0027	Confirmed
H6.b	Popularity → Valence	0.0026	0.0504	Confirmed

Finally, when it comes to the theoretical framework, we are able to use the estimated coefficients as well as corresponding significance levels to represent the relationships between different areas of interest. And we will summarize and highlight the statistics in the framework as below (*Figure 3.*).

Figure 3. The Tested Model



\# Significant at the 10% level.

* Significant at the 5% level.

** Significant at the 1% level.

*** Significant at the 0.1% level.

4.2.5. Model Validation with F-test for LMER

We can observe a relatively good fit through the R^2 of each mode. However, R^2 is only one of the comparable criteria that indicate model fit, and we need further evidence to prove that the mixed-effect model is the right choice compared to the null model which only contains the fixed-effects. Therefore, this research will also implement a F-test for each equation between the proposed mixed-effects model and the null model which only contains the fixed-effects while holding all the other variables the same (Kuznetsova., Brockhoff & Christensen, 2017). In detail, we will build the null model for each equation by excluding the random-effects, and then we will compare the results of the null model to the mixed-effects model through F-test, whose test results indicate the credibility of the mixed-effects this research used. In essence, if the p-value of the F-test is significant at 5% significance level, then we can prove the credibility of the random-effects included by this research, proving the validity of the mixed-effects model (Halekoh & Højsgaard, 2011).

After implementing the F-test for the four pairs of mixed-effects models with the relevant null models, we can summarize the results as below (*Table 21.*).

Table 21. Results of F-test for All Models With Null Models

	AIC	logLik	Chisq	Df	Pr(>Chisq)	
Null - CP	4113.5044	-2044.7522	-	-	-	
CP	4054.4211	-2000.2106	89.0833	15	1.47E-12	***
Null - STR	48466.6317	-24221.3159	-	-	-	
STR	48342.8727	-24144.4363	153.7591	15	4.32E-25	***
Null - Volume	19915.6741	-9945.8371	-	-	-	
Volume	19678.7771	-9821.3886	248.8970	6	7.06E-51	***
Null - Valence	-40180.5027	20102.2514	-	-	-	
Valence	-40342.6199	20198.3099	192.1172	15	8.45E-33	***

\# Significant at the 10% level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Therefore, we can conclude that all the four mixed-effects models are significantly accurate in explaining the random-effects. In other words, the four F-tests all provide strong evidence for this research to confirm a significant difference between the fixed-effects model and the mixed-effects model. As a result, this research is able to prove that the linear mixed-effects model fits the data better than the models with only fixed-effects, indicating the credibility of the random-effects across different game genres groups.

5. Implications

Based on the tested hypotheses and model results, our finding indicates that game streaming helps game companies boost game's popularity in general but hurts game's popularity for single-player games. Meanwhile, our result found strong evidence of the existence of interactions between game streaming and WOM Volume. Hence, we will summarize our results and discuss both the academic implications and managerial implications.

5.1. Implications for Theory

Our study contributes to the academy by investigating the cannibalization effect of the game streaming on the game's popularity in a quantitative way. At the same time, in contrast with the current literature, we not only study both the positive and negative effects of game streaming on the game's popularity, but also divide WOM into WOM Volume and WOM Valence and test how these two variables affect game's popularity. This method also differentiates with other literatures in the way that we try to investigate altogether the interactions among game streaming, game's popularity, WOM Volume, and WOM Valence instead of a one-way relationship. For example, we test the effects of game streaming on the game's popularity as well as the game's popularity's feedback effect on game streaming. After testing twelve hypotheses regarding the interactions among game streaming, game's popularity, WOM Volume, and WOM Valence, our models and findings have several implications for theory.

5.1.1. Game streaming helps game companies boost game's popularity in general but may hurt the game's popularity for single-player games

The Positive impact from game streaming on game's popularity from **H1.a** is consistent with the result of Kaytoue et al. (2012), which shows that streaming platforms can attract more game players. However, we also find an opposite impact of game streaming among single-player games. In detail, 1% increase in the game streaming may result in around 0.129% decrease in game's popularity for single-player games. This finding provides quantitative evidence for the hypothesis in (Smith, Obrist & Wright, 2013) work when prior work was not able to quantify the cannibalization effect of the streaming platforms. This cannibalization effect echoes the hypothesis **H1'**.

5.1.2. The existence of interplay between game streaming and word-of-mouth volume

Although we found little literature testing the interplay between game streaming and WOM Volume, much literature acknowledged the game streaming has a positive correlation with WOM in general (Feng, 2006). Our hypotheses **H3.a** and **H5.a** confirmed the positive impact existing in between. In short, game streaming is able to generate more game reviews on different streaming platforms and the number of game reviews are also likely to strengthen game streaming.

5.1.3. Different random-effects across different game genres groups

Apart from the fixed effects, another key contribution of this research is that we took game genres into consideration by allowing the random-effects across different game genres groups. Take the random-effects of the game's popularity equation as an example (*Table 16.*), the model results implied different random-effects that are additional to the fixed-effect incurred by the game streaming on the game's popularity across different game genres groups. Of all the random-effects of game streaming on game's popularity across different groups, we were able to observe five game genres where the random-effects are negative. The five game genres are "RPG", "Racing", "Early Access", "Animation & Modelling", and "Adventure". As a result, with the negative additional random-effect of game streaming on game's popularity, games from these game genres may experience a less beneficial effect of game streaming on game's popularity. Similarly, this research is also able to derive the random-effects of other variables such as WOM Volume and WOM Valence on the game's popularity, as well as the random-effects from other equations as shown in the Appendix (*Appendix 1 2 3.*).

5.2 Implication for Game companies

Our approach and empirical results also offer several new implications for game companies. We provided quantitative support for managers in game companies to decide whether they should rely on cooperation with streaming platforms or not, which is largely dependent on the types of the games.

5.2.1. More collaboration between game companies and streaming platforms

Since our finding indicated a positive effect of game streaming on the game's popularity in general, closer collaboration between game companies and streaming platforms is likely to be crucial and profitable for the game companies when trying to increase game's popularity. Game companies can jointly develop a game with streaming platforms and engage potential gamers in the game development via the streaming platforms. For instance, the game companies can broadcast the development process of the games, and broadcast the procedures of testing game functions, and thereby showing viewers the process of developing, refining, testing, and iterating on the code of a game or other piece of software. (Johnson & Woodcock, 2019). As a result, this partnership is likely to lead to a higher game's popularity before launching, which is expected to bring more players and profit for the game companies. Apart from that, tournaments held by game developers and streaming platforms can also strengthen this partnership. Streaming platforms can preserve iconic and memorable moments in the tournaments and keep streaming these moments to attract potential customers. From this perspective, an increased game streaming level is likely to help game companies increase the game's popularity, which in turn generates more profit.

5.2.2. Less game streaming for single-player games

Prior literature could not manage to conduct the empirical analysis on the cannibalization effect of game streaming, but we address this issue. Our finding signals the negative impact of game streaming on game's popularity in single-player games based on the empirical results. As mentioned above, although in general game streaming increases game's popularity, a 1 percent increase in game streaming level in fact decreases the game's popularity for single-player games by 0.0013 percent. Therefore, we do not recommend the game companies who are going to release single-player games to facilitate game streaming. That is because game companies are more likely to observe a cannibalization effect that game streaming will hurt game's popularity. As a result, we would recommend the game companies to depend more on other advertising methods other than game streaming to try increasing game's popularity. For instance, they can still encourage positive reviews from the players, because this research expects a significant benefit that WOM Valence can bring to the game's popularity. In conclusion, single-player game companies had better limit the streamed contents on the streaming platforms.

5.2.3. Encourage positive reviews

Moreover, this research found strong evidence to support hypothesis **H2.b**, which means that WOM Valence is very likely to boost the game's popularity. As a result, our finding indicates that the positive reviews of games are likely to increase the game's popularity. Therefore, we recommend game companies to put more effort into encouraging the players to leave positive reviews. For instance, the game companies can offer positive incentives for the gamers to encourage their positive reviews. Game companies can provide some free gifts or presents in the game to motivate the players to leave more positive reviews.

Most importantly, we also want to highlight one example for the game companies based on the random-effects results regarding the game's popularity model (*Table 16.*). We observe a positive random-effect of WOM Valence on the game's popularity within the "Racing" game genre, whose estimated coefficient is 0.134. In other words, the ultimate coefficient of effect that WOM Valence has on game's popularity for the games from the "Racing" genre is 0.567, meaning that a 1 percent increase in the WOM Valence is likely to result in a 0.566 percent increase in the game's popularity. From this perspective, we highly recommend the game companies, especially the game companies that have released the games under the "Racing" genre, to make appropriate use of WOM Valence and encourage more positive reviews from the players, which is likely to increase their game's popularity.

5.2.4. Properly use game discounts tend to increase game's popularity

Our model results also reveal a positive effect that game discounts have on the game's popularity. In detail, a 1 percent increase in the game discounts is likely to lead to a 0.252 percent increase in the game's popularity. As expected, game companies can consider offering certain discounts to attract more players and increase game's popularity. However, it is also worth mentioning that game companies should not continuously increase the discounts, because the game discounts also reduce the price which decreases the profit that a company can generate. Therefore, we also recommend the game companies to appropriately adjust the game discounts to increase game's popularity rationally.

5.2.4. Game tags of Action, Indie, and Simulation

As mentioned above, we also included three of the most popular game tags that various games have in the game's popularity model (*Table 15.*). Despite the fact that the estimated coefficients for "Action" and "Indie" are not significant, the coefficient for "Simulation" game tag is significant, which is equal to 0.0148. Such a positive coefficient means that if the game companies or the game players attach the game tag "Simulation" to the game, then it is more likely for the games to have a higher popularity level. In other words, our research also discovered the benefits of game tag "Simulation" may bring to the game companies. Therefore, we may encourage the game companies to more often use the "Simulation" tag to describe their games on the gaming platform. However, we only recommend the game companies to do that when the games are related to "Simulation" as well.

6. Future Research

Future researchers can extend this research in several ways. Firstly, we can expect an improved dataset with more precise relationships between the game streaming and game's popularity. Secondly, future studies can also focus on whether game companies hurt streaming platforms. Finally, it may also be of value to further research on how to alleviate the cannibalization effect of game streaming on the game's popularity, especially for single-player games.

6.1. Improve the dataset

Although the current dataset comprises the number of streamers on the streaming platform as well as the number of concurrent players, the current dataset is not able to tell whether the game player is also aware of the game streaming. In other words, future research may present a clearer picture of the impact of game streaming on game's popularity if it manages to find the exact number of game players who were motivated purely by game streaming. To illustrate, not every single game player is aware of the streaming platforms. However, if the future research can better and more accurately quantify the number of game players who purchase games merely because of game streaming, then the effects of game streaming on game's popularity will be more accurate as well. As a result, improved dataset can provide a stricter causality between game streaming and game's popularity.

6.2. Focus on the reciprocal effect from game's popularity on game streaming

Future research can also focus on the effects that the game companies have on the streaming platforms, which is, whether game companies hurt streaming platforms. This research has actually already included such a feedback effect of game's popularity on game streaming, however, a specific research focusing more on this link may help to extract more insights out of this feedback effect. For example, game companies tend to collaborate with the most popular streaming platforms, while possibly underestimating the collaboration with small streaming platforms. Then it might be of value and interest to research on how game companies affect the game streaming platforms.

6.3. Research on how to alleviate the cannibalization effect of game streaming on the single-player games

Our model results pointed out the cannibalization effect driven by the streaming platforms, especially on the single-player games. In other words, streaming single-player games may reduce the game's popularity. However, it is not of central interest to our research regarding how to alleviate such cannibalization effects. Therefore, how to reduce or even eliminate the cannibalization effect of the streaming effects on game companies may be of interest to the game companies, which is likely to enable the game companies to stream more game contents to the audiences without worrying about the decrease in profit.

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Appendix

Appendix 1. Random-Effects of STR Model

Game Genres	Intercept	CP	STR	Volume	Valance
Action	1.2151	-0.0203	-0.0059	0.0165	-1.7129
Adventure	0.4993	-0.1683	0.0888	-0.0010	0.8932
Animation & Modeling	0.9164	-0.0831	0.0763	-0.0951	0.2635
Early Access	-1.8443	0.1161	-0.2286	0.4031	-1.4062
Free to Play	0.9596	-0.0547	0.1166	-0.2007	0.4944
Indie	0.7402	0.0108	0.0603	-0.1840	0.4163
Massively Multiplayer	2.3113	-0.1195	0.0989	-0.1930	0.0177
Racing	-3.1693	0.3223	-0.2248	0.2230	-0.7320
RPG	-0.3635	-0.0399	-0.0402	0.1039	0.5958
Simulation	-0.0761	-0.0576	0.0445	-0.0149	0.6399
Sports	0.4813	-0.1569	0.0662	0.0378	0.5016
Strategy	-1.6700	0.2512	-0.0521	-0.0955	0.0288

Appendix 2. Random-Effects of Volume Model

Game Genre	Intercept	CP	STR	Volume	Valence
Action	-0.0143	0.0401	-0.0022	-0.0595	0.3483
Adventure	-0.0104	0.0325	-0.0019	-0.0432	0.3663
Animation & Modeling	-0.1467	0.0345	-0.0002	-0.0587	-0.5741
Early Access	-0.1091	0.0455	0.0090	-0.0148	-0.0445
Free to Play	-0.1981	-0.0005	-0.0151	0.1027	-0.4445
Indie	-0.2539	0.1211	-0.0055	-0.1153	0.3734
Massively Multiplayer	0.1778	-0.0633	-0.0156	0.0887	-0.2647
Racing	0.2060	-0.0569	-0.0073	0.0194	0.0059
RPG	0.0612	0.0011	0.0070	-0.0101	0.0095
Simulation	0.1229	-0.0741	0.0070	0.0153	0.5539
Sports	0.1368	-0.1142	0.0155	0.1458	-0.4065
Strategy	0.0278	0.0342	0.0093	-0.0704	0.0771

Appendix 3. Random-Effects of Valence Model

Game Genre	Intercept	CP	STR	Volume	Valence
Action	-0.0592	-0.0011	0.0000	-0.0029	0.1367
Adventure	-0.0357	-0.0007	0.0000	-0.0020	0.0860
Animation & Modeling	0.4115	-0.0018	-0.0011	0.0152	-0.6549
Early Access	-0.0250	0.0000	0.0001	-0.0014	0.0437
Free to Play	-0.0829	0.0014	0.0004	-0.0005	0.0943
Indie	0.0235	0.0003	0.0000	0.0002	-0.0398
Massively Multiplayer	-0.0214	0.0009	0.0002	-0.0013	0.0101
Racing	0.0124	0.0004	0.0000	-0.0008	-0.0260
RPG	-0.0180	-0.0004	0.0000	-0.0020	0.0480
Simulation	-0.0657	0.0003	0.0002	0.0001	0.0912
Sports	-0.1156	0.0011	0.0004	-0.0021	0.1562
Strategy	-0.0239	-0.0004	0.0000	-0.0025	0.0545