

**NETWORK BASED INTERPERSONAL INFLUENCES
ON ONLINE CASUAL GAME CHOICES**

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Media and Information Studies – Doctor of Philosophy

2014

ABSTRACT

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Using empirical data on players' game choices and gaming behaviors and their relationships and interactions with other players on an online casual games portal site, Kongregate, I conduct three separate but complementary studies of ways in which other players may influence a player's game choices and gaming behavior.

First, I examine whether a game player's game choice is influenced by other players with whom the player has direct connections and interacts on Kongregate. On Kongregate, a player is said to have a direct connection with another player if she forms a connection with the other player by clicking the 'friend' button linked to the latter. Once a player has established a direct connection with a second Kongregate player, then the first player can initiate a chat with the second player via a dedicated communication channel between them and the first player receives information such as what games the other player is playing and has played.

I also study how the influence of other players with whom a player has direct connections on Kongregate on the player's game choices varies with the closeness of the connections between the player and those other players. In this dissertation, the closeness of the connection between two people refers to the strength of the tie (relationship) between them. The strength of a tie between two people is a function of the amount of time, the emotional intensity, the intimacy, and the reciprocal services that characterize the tie between those two people (Granovetter, 1973, p1361). According to the theory of planned behavior and several studies of peer influence (e.g., Garnier & Stein, 2002; Maxwell, 2002; Thornberry & Krohn, 1997), an individual's behavior is more likely to be influenced by someone close than others.

Second, I examine the importance of certain the homophily and social influence processes in the formation of relationships among friends on Kongregate and changes in their gaming behaviors, focusing on game genre preferences and gaming frequency. The homophily principle says that a person is more likely to be friends with others who are similar to herself than others who are dissimilar (Steglich et al., 2006). This suggests that a game player is more likely to be friends with other players who have similar gaming characteristics than others who do not. On the other hand, social influence process refers to a phenomenon in which an individual's behavior is likely to become more similar to that of her friends over time (Steglich et al., 2006), which suggests that a game player's gaming behavior will become similar to that of her friends over time.

Third, I examine players' game choices to see if they exhibit patterns consistent with a choice bandwagon and the influence traditionally ascribed to word-of-mouth. This study looks for evidence that the number of times a game is consumed on a day is influenced by the number of times the game has been consumed previously and by what game players say about the game in posts on Kongregate. In addition, I also examine how the location where information about a game is displayed on the portal site influences the number of times the game is consumed on a given day, and how the effects of word-of-mouth information and the number of times a game has been consumed previously on the number of times the game is consumed on a day vary with where information about the game is displayed on the site

This dissertation consists of five separate chapters including this introductory chapter. Each of the three studies described above is examined in a separate chapter, from Chapter 2 through 4. The last chapter concludes the dissertation by discussing how the present study can be improved or extended and by identifying important questions, which have not been addressed in this study, that might be examined in the future studies.

This dissertation is dedicated to my wife, Min Jung, and son, Ethan,
for all of their support, inspiration, and love.

ACKNOWLEDGEMENTS

I would never have been able to finish my dissertation without the guidance of my committee members, and support from my family and wife.

I would like to express my deepest gratitude to my advisor, Prof. Steve Wildman, for his excellent guidance, caring, patience, and providing me with an excellent atmosphere for doing research. I would like to thank my committee members, Prof. Johannes Bauer, Prof. Stephen Lacy, and Prof. Rick Wash, for their encouraging words, thoughtful criticism, and time and attention during busy semesters.

I would also like to thank my parents and younger brother. They were always supporting me and encouraging me with their best wishes. Finally, I would like to thank my wife, Min Jung. She was always there cheering me up and stood by me through the good times and bad times.

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CHAPTER 1 INTRODUCTION

As information and communication technologies (ICTs) develop and become more affordable, more individuals get connected to the Internet and use the Internet for their everyday lives. According to a report by Pew Internet (2013), about 85% of the U.S. adults used the Internet in 2013, whereas 79% used the Internet in 2012. The report says that a large percentage of Internet users in the U.S. interact or communicate with others and consume various products and services online. For example, about 71% of the U.S. adult internet users buy products on the Web, 71% of them watch videos on video sharing sites like Youtube, and 67% of them use a social networking site like Facebook and Twitter on the Internet.

There exist several theories which say that an individual's behavior, especially product adoption and consumption behavior, is influenced by the person's personal relationships and interpersonal interactions, because interpersonal interactions can be a source of information about a product or service and an individual's attitudes toward a product or service can be influenced by personal relationships. For example, the diffusion of innovations theory (Rogers, 2003) and the two step flow model (Katz, 1957) recognize an individual's personal relationships as an important source of information about new products, and say that an individual's interactions with others with respect to a product or service can influence the person's attitudes toward the product or service. On the other hand, other theories like the theory of planned behavior (Azjen, 1991) and peer influence theory (Deutsch & Gerard, 1955) say that others exert influence on an individual's behavior so that the individual is more likely to behave in a way that meets others' expectations to be accepted or liked by them.

While these theories emphasize the important influence on an individual's product choices and adoptions of others with whom they have direct personal connections (e.g., friendship, kinship, and co-worker), information cascades theory (Bikhchandani et al., 1992, 1998), studies of bandwagon effects (e.g., Fu & Sim, 2011), and studies of word-of-mouth (WOM) communication (e.g., Mahajan, Muller, and Kerin

1984; Mizerski 1982; Liu, 2006) stress the influence of others who are not necessarily directly connected to an individual on the person's product choices and adoptions. Information cascades theory and studies of bandwagon effects stress the influence of the number of times a product has been consumed previously on an individual's decision to consume the product. Information cascades theory says that as more consumers have chosen a particular product or brand and if their choices are observed, it is more likely that other potential consumers will choose the same product or brand, because the choices of the consumers who have already made a purchase serve as information cues for the consumers who have not made a purchase yet. 'Bandwagon effect' refers to the phenomenon of an individual's likelihood of adopting a product increasing with the number of times the product was adopted previously (e.g., Bass, 1969, Simon, 1954, Fu & Sim, 2011). Word-of-mouth interaction refers to informal communications among consumers about a product or service (Liu, 2006). Studies of the effects of WOM on a person's product choice suggest that the WOM may convey information about a product's quality that can inform product selection.

The fact that many people interact with others and consume various products and services on the Web, and the existence of several theories emphasizing the important influence of others on a person's product choices suggest that a person's choices among online products or services may be significantly influenced by others.

The empirical studies that examined interpersonal influence on an individual's product choices or adoptions in online settings mainly focused on the influence of others who were not directly connected to the decision maker. Examples of these studies are those of the effects of word-of-mouth information on a consumer's product choices (e.g., Mizerski 1982; Liu, 2006), those of information cascades (e.g., De Vany & Walls, 1996; Walls, 1997), and those of bandwagon effects (e.g., Fu & Sim, 2011). But, little research has looked at how others who are directly connected to an individual in online environments affect the person's online product adoptions or choices. Prior studies that examined the influence of others

who have direct relationships with an individual on the individual's product adoptions and choices were carried out in offline settings (e.g., Azjen & Driver, 1992; Bearden & Etzel, 1982). This small amount of research about interpersonal influence on product choices in online environments is mainly due to the difficulty of acquiring necessary data.

The literature on the effects of word-of-mouth information and the effects of the number of times a product has been consumed previously on individuals' product adoptions and choices has limitations. Few studies have examined the simultaneous effects of word-of-mouth information and the number of times a product has been consumed previously, although it is likely that the effect of one variable on an individual's product choices is influenced by the effect of the other variable. Another major limitation is that prior studies that examined the effects of word-of-mouth information and the number of times a product has been consumed previously on online product choices by employing regression models did not include some control variables whose omission can cause bias in statistical estimation of those regression models. An example is the location where information about a product is displayed on a website. Because the location where information about a product is displayed on a website can influence the extent to which consumers become aware of the product (Granka et al., 2006) and becoming aware of a product is a necessary first step in the process of product adoption (Rogers, 2003), the location of information about a product on a website can influence a consumer's product choice (Granka et al., 2006) and the effects of word-of-mouth information and the number of times a product has been consumed previously may vary with where information about the product is displayed on the site. Thus, the omission of an information location variable can lead to bias in statistical estimates of the effects of word-of-mouth information or the number of times a product has been consumed previously.

In this dissertation, I attempt to fill gaps in the literature identified above by studying interactions among game players on an online casual games service. For this, I examine how others who have direct relationships with an individual through the service's site can influence that individual's choices of online

casual games and the ways the person plays games on the service's site. I also include a variable for where information about a product is displayed on a website, and allow for the number of times a product has been consumed previously and word-of-mouth to jointly influence product choice in the empirical model.

Online casual games are online video games developed for mass consumption, even for those who would not normally regard themselves as a 'gamer'" (International Game Developers Association, 2009). Online casual games possess certain characteristics in common: they are easy to learn; they require a small amount of time to be played; and online casual game players play casual games mainly for fun and relaxation (IGDA, 2009). Online casual games are offered to game players through several different types of platforms such as web browsers on PCs (e.g., via online casual games portal sites and social networking sites), consoles, smartphones, and tablet PCs. I focus on online casual games portal sites because they constitute one of the most commonly used platforms for accessing online casual games (Liew, 2013) and it is easier to collect the data required for this dissertation from online casual games portal sites than from other platforms that host online casual games.

A typical online casual game portal site has several social features. On an online casual games portal site, game players can be friends with other players. In this study, a game player's friends on a game portal site are defined as other players whom the player is directly connected to on the portal site. Game players are motivated to become friends with other game players and interact with them, because there are many games that encourage collaboration among game players and competing (or playing) with others can be more fun, and becoming friends with other players makes it easy for a player to collaborate and interact with them. Once a game player has become friends with another player, the player can have chats with the friend via a dedicated communication channel between them. Furthermore, the player can observe what her friends have done and are doing on the site. Thus, it is possible that a player's gaming behavior is influenced by her friends on an online casual games portal site.

In addition to a game player's communications with her friends or observation of her friends' gaming behavior, on an online casual games portal site, a game player can easily observe how many times a game has been played. Because a game's popularity is likely to be a reflection of how much players enjoy playing it and more popular games will be played more often, a game player's decision whether or not to play a game is likely to be influenced by the number of times the game has been previously played, as would be predicted by the information cascade theory and studies of bandwagon effects.

Furthermore, a game player can observe how other players have rated a game. It has been found that users' ratings of a product well reflect the valence of the word-of-mouth information about the product (e.g., Dellarocas et al., 2007; Godes & Mayzlin, 2004; Liu, 2006). Because the valence of WOM reflects the quality of a product and a player might want to play a high quality game rather than a low quality game, a player's decision whether or not to play a game can be influenced by the user ratings of the game. A player can also observe how many other players have reviewed a game. The number of user reviews is a good measure of the volume of WOM and the volume of WOM of a product is likely to influence a consumer's awareness of the product (Godes & Mayzlin, 2004). This suggests that a player's game choice can be influenced by the number of people who have reviewed the game.

These social features of online casual games portal sites, the ways those sites are organized, and the accessibility on these portal sites of critical data on game players' relationships and interactions with others, their game choices, and their gaming behaviors make it possible to examine the influence of social interaction on game players' choices among a casual game service's games. The findings of this study may also shed light on the extent to which claims regarding bandwagon effects and word-of-mouth processes in offline settings generalize to online environments.

On the other hand, we should note the context that online casual games provide is somewhat different from the offline contexts to which existing theories of interpersonal influence (e.g., diffusion of innovations, theory of planned behavior, and peer influence) have been applied. First, influence of offline

friends on a person's product choices might be different from that of online friends on a person's online product choices. Second, the characteristics of online casual game players, which are they play games for a short amount of time and play mainly for fun and relaxation, suggest that an online casual game player is not likely to interact with other Kongregate players often and she is not likely to care a lot about what games other Kongregate players play. These differences suggest that the existing theories might not effectively predict interpersonal influences among online casual game players on their game choices. Thus, it is interesting to empirically study how well existing theories can be applied to online casual game players.

In addition to constituting a suitable context for examining the influence of personal relationships and interpersonal interactions on choices among online alternatives, the fact that the industry has been understudied relative to its popularity is another reason to study online casual games. The online casual games industry is one of the fastest growing new media industries. For example, more than 200 million people worldwide played casual games on the Web and the revenue of the industry was about \$6 billion in 2010, which was nearly twice larger than the revenue of the industry in 2009 (Casual Games Association, 2012), and the revenue of the industry is expected to grow up to \$46 billion by 2016 (Roland Berger, 2012). Despite the popularity of the industry, only a small number of studies have examined online casual games and those studies only looked at particular subsets of online casual games, especially those hosted on social network sites. For example, Wohn et al. (2010) studied motivations for playing games hosted on social networking sites, especially Facebook, and game players' gaming patterns. Wohn et al. (2011) examined how playing games on Facebook can influence the formation and maintenance of relationships among Facebook users. Furthermore, no prior studies of online games have examined research questions related to how a game player's game choices and gaming behavior is influenced by others and what factors influence a game's financial success. Thus, by studying how a game player's gaming behavior is influenced by her friends and by examining factors that can influence a game's

financial success, this dissertation will help us better understand the social and economic aspects of the industry.

Studies that have examined how people interact with others on the Web and how their behavior is influenced by those relationships and interactions only looked at the topic in the context of online social network sites, especially on Facebook (e.g., Bakshy et al., 2009; Wei et al., 2010). The main purpose of using social network sites is to be connected with others and interact with them, for example, by sending messages to friends and reading postings written by friends. Furthermore, many services provided on social network sites are based on interpersonal interactions among the users. But there are many other online services that people visit for other purposes than for the purpose of interacting with others.

Nevertheless, social components are being built into many of those online websites, even though the main services offered on those sites can be and perhaps often are consumed without making use of their social components.

There are many examples of such services. Hulu.com, which is a website that provides streaming video services, is an example. The main purpose of people visiting Hulu.com is to watch TV episodes or movies. Nevertheless, the site also has social components. On the site, users can be connected with other users and learn what their friends have watched and are watching currently. IMDb.com, a website that provides information on movies and TV shows, is another example. The main purpose of people visiting the site is to acquire information of movies or TV shows that she is interested in. When using the site, however, you can make connections with other users, exchange messages with them, and see their reviews of movies and what movies they like.

An online casual games portal site is another example of such an online service. The main purpose of people visiting the site is to play games, even though the users can make connections with other casual game players and are motivated to do so on the site. The existence of this difference between online casual games portal sites and social network sites suggests that the extent or the ways that a person's

behavior is influenced by others can be different between on online casual games portal sites and on social network sites. Thus, by examining interpersonal relationships and interactions in online casual games, we can extend our understanding on how the social features of an online service that people visit for other main purposes than interacting with others affect the ways that people use the service¹.

I use empirical data on players' game choices and gaming behaviors and their relationships and interactions with other players on an online casual games portal site, Kongregate, to conduct three separate but complementary studies of ways in which other players may influence a player's game choices and gaming behavior.

First, I examine whether a game player's game choice is influenced by other players with whom the player has direct connections and interacts on Kongregate. On Kongregate, a player is said to have a direct connection with another player if she forms a connection with the other player by clicking the 'friend' button linked to the latter. Once a player has established a direct connection with a second Kongregate player, then the first player can initiate a chat with the second player via a dedicated communication channel between them and the first player receives information such as what games the other player is playing and has played. A connection between two game players on Kongregate is directional. That one player has a direct connection with another Kongregate player by clicking the 'friend' button linked to the latter does not mean that the latter also has a direct connection with the former.

I also study how the influence of other players with whom a player has direct connections on Kongregate on the player's game choices varies with the closeness of the connections between the player and those other players. In this dissertation, the closeness of the connection between two people refers to the

¹ I also acknowledge that the features of online casual games that make them different from other online services may limit the degree to which the results of this study can be generalized to other online environments. But, we also should note that unless we do the individual studies, we can hardly determine what, if anything, might be common to many types of online services with social network features.

strength of the tie (relationship) between them. The strength of a tie between two people is a function of the amount of time, the emotional intensity, the intimacy, and the reciprocal services that characterize the tie between those two people (Granovetter, 1973, p1361). According to the theory of planned behavior and several studies of peer influence (e.g., Garnier & Stein, 2002; Maxwell, 2002; Thornberry & Krohn, 1997), an individual's behavior is more likely to be influenced by someone close than others.

Second, I examine the importance of certain the homophily and social influence processes in the formation of relationships among friends on Kongregate and changes in their gaming behaviors, focusing on game genre preferences and gaming frequency. The homophily principle says that a person is more likely to be friends with others who are similar to herself than others who are dissimilar (Steglich et al., 2006). This suggests that a game player is more likely to be friends with other players who have similar gaming characteristics than others who do not. On the other hand, social influence process refers to a phenomenon in which an individual's behavior is likely to become more similar to that of her friends over time (Steglich et al., 2006), which suggests that a game player's gaming behavior will become similar to that of her friends over time.

Third, I examine players' game choices to see if they exhibit patterns consistent with a choice bandwagon and the influence traditionally ascribed to word-of-mouth. This study looks for evidence that the number of times a game is consumed on a day is influenced by the number of times the game has been consumed previously and by what game players say about the game in posts on Kongregate. In addition, I also examine how the location where information about a game is displayed on the portal site influences the number of times the game is consumed on a given day, and how the effects of word-of-mouth information and the number of times a game has been consumed previously on the number of times the game is consumed on a day vary with where information about the game is displayed on the site.

By examining these three questions together, we can better understand how a game player's game choices and gaming behavior are influenced by other game players using Kongregate in a systematic and comprehensive way.

This dissertation consists of five separate chapters including this introductory chapter. Each of the three studies described above is examined in a separate chapter, from Chapter 2 through 4. The last chapter concludes the dissertation by discussing how the present study can be improved or extended and by identifying important questions, which have not been addressed in this study, that might be examined in the future studies.

With regard to data used in this dissertation, I drew 3 separate samples from Kongregate, each with variables and other features appropriate to the design of the study reported in each chapter.

In Chapter 2, I study how other game players with whom a player has direct relationships and interacts on Kongregate influence the player's game choices. As mentioned previously, a direct relationship between two players is said to be present on Kongregate if one player establishes a connection with the other player by clicking a 'friend' button linked to the latter. In this dissertation, other players with who a player has direct relationships on Kongregate are referred to as the player's Kongregate friends. I examine whether a player's adoption of a specific game is influenced by the number of the player's Kongregate friends who adopted the game earlier.

According to Rogers' (2003) diffusion of innovations theory, the number of friends or acquaintances who adopted a product earlier exerts an important influence on an individual's adoption of the product. This is because, first, an individual may become aware of the existence of a particular product through interpersonal interactions. Thus, when many of a player's Kongregate friends play a particular game, the player is more likely to become aware of the game through those friends than when only a small number of her friends play the game. Second, because the information about a product obtained via personal

relationships may be considered more reliable than information from other information sources (e.g., mass media), information about a product obtained from personal relationships can be more effective in reducing the uncertainty or risk involved in the choice of the new product than information from other sources (Rogers, 2003). This reasoning can also be applied to online casual games. Deciding what games to play involves uncertainty, because games are experience goods. Thus, the opinions of Kongregate friends who have adopted a game can influence a game player's decision whether or not to adopt that game.

As the theories of planned behavior (Ajzen, 1991) and peer influence (Deutsch & Gerard, 1955) suggest, people tend to behave in ways similar to others with whom they have personal relationships (e.g., friends, family members, and colleagues), because by doing so they can be more liked and desirable in their social networks. This also suggests that a player is likely to play games that her Kongregate friends play.

In addition to the number of Kongregate friends who adopted a game earlier, I also consider the closeness of the relationships between a player and her Kongregate friends who adopted the game earlier. This is because the influence of a player's Kongregate friends on her decision to adopt the game can vary depending on how closely the player is connected to the adopters. For example, the theory of planned behavior and several studies of peer influence (e.g., Garnier & Stein, 2002; Maxwell, 2002; Thornberry & Krohn, 1997) argue that an individual's behavior is more likely to be influenced by someone close than more distant associates, because an individual is likely to behave in a way that meets expectations of someone with a close relationship than those of more distant associates. Furthermore, it is also likely that an individual communicates (or interacts) with close friends more frequently than with other friends, which suggests that an individual is more likely to become aware of games that her close friends play than the games that other friends play.

Other variables that might influence a player's game adoption decisions are also taken into account. Those variables include 1) the frequency with which a player tries new games, 2) how often a player plays games on Kongregate, and 3) whether the game's genre is the player's favorite genre.

For analysis, I used two different models, a discrete choice model and a hazard model. With the discrete choice model, I examine the effect of the number of a player's Kongregate friends who adopted a game earlier on the likelihood that the player adopts the game later. With the hazard model, I study how the number of a player's Kongregate friends who adopted a game before time t influences the likelihood that the player adopts the game at time t . I constructed measures for the dependent and independent variables from data collected from Kongregate on game players' gaming behavior (game adoption, gaming frequency, and game genre preference) and their relationships with other game players on Kongregate. The number of game players in the sample for this study was 1,668.

In Chapter 3, I examine how the formation of a relationship between two players on Kongregate is affected by their similarities in gaming behavior and whether a player's gaming behavior becomes more similar to that of her online friends over time. A relationship between any two game players on Kongregate is said to be formed if one player makes a connection with the other player by clicking a 'friend' button linked to the latter. In this study, for gaming behavior, I focus on game genre preference and gaming frequency.

A number of studies have found that relational ties are more likely to develop among people who have similar socio-demographic and/or behavioral characteristics than among people who are dissimilar and that the behaviors of the people who have relational ties (e.g., friends) tend to be similar (e.g., Easley & Kleinberg, 2010; Monge & Contractor, 2003; Valente, 2010). The 'birds of a feather flock together' tendency observed among people who drink alcohol and smoke, and similarity in smoking and alcohol use among friends are examples.

These phenomena might be observed in any part of our lives that are related to behavior or decision making in social contexts. Throughout our lives, we are more likely to be friends with people who are similar to ourselves than with others who are dissimilar, and our decisions and behavior are likely to be influenced by our friends so that we become more similar to our friends (Monge & Contractor, 2003). These processes can lead to network autocorrelation, which is said to be present in a social network if there are more relational ties among a network's members who possess similar socio-demographic or behavioral characteristics than among members who do not (Steglich et al., 2006; Goodreau et al., 2009).

There are two underlying reasons for the presence of such network autocorrelation: homophily and social influence (Crandall et al., 2008). First, people are more likely to form relational ties with others who are similar to themselves, because they feel more comfortable interacting with people who are like themselves and feel more justified in their beliefs or opinions when being with others who are similar to themselves than when interacting or being with others who are dissimilar (Centola et al., 2007). Another distinct reason for autocorrelation in a social network is social influence among people who have relationships. That is, an individual's behavior is likely to become more similar to that of her friends over time because people want to be like their friends to be liked and accepted by them (Friedkin, 1998; Monge & Contractor, 2003). For example, the phenomenon that smokers are more likely to become friends with others who also smoke can be explained by homophily, whereas a smoker with non-smoker friends becoming a non-smoker over time (the converse is also plausible) can be explained by social influence.

Studying whether a social network is characterized by homophily or as the outcome of social influence, or both of them is important. This is mainly because homophily and social influence processes can lead to very distinctive structural consequences for a social network (Crandall et al., 2008; Holme & Newman, 2006). Homophily can lead to separation among the members of a social network because members

interact with other members who have similar characteristics, whereas social influence can lead to network-wide uniformity of a network (Crandall et al., 2008).

Furthermore, if how members of a network form relationships and influence each other is understood, then more tailored tools can be devised to manage the network in a way that can generate more benefits to its members and the network sponsor. For example, if we could understand the homophily and social influence processes among adolescent substance abusers, then we might be able to develop more effective tools to help reduce their substance abuse (Pearson et al., 2006; Steglich et al., 2010).

The number of studies that have tried to distinguish between the effects of homophily and social influence processes in the same social network is small. This scarcity in the literature is mainly due to the difficulty of collecting the types of data required and the relatively recent development of suitable empirical methods. Moreover, those studies have mainly focused on homophily and social influence in social networks that develop offline (e.g., Pearson et al., 2006; Steglich et al., 2006; Friemel, 2012).

In this chapter, using panel data on game players' relationships and gaming behaviors on Kongregate, I examine homophily and social influence processes among online casual game players. Specifically, I study how the formation of a relationship between two game players is influenced by similarities in their game genre preferences, and how a player's game genre preference and gaming frequency change over time due to the influence of her Kongregate friends.

It is plausible that a player becomes friends with other players who like similar game genres, and a player's gaming behavior is influenced by her friends so that she plays similar game genres as her friends do.

It is also possible that a player's gaming frequency is affected by her friends so that it becomes similar to those of her friends over time. This is because according to the peer influence theory (Deutsch & Gerard,

1955), if a player wants to be liked or accepted by her friends, then she tries to become similar to her friends.

For this study, data on the demographic attributes (age and gender), game genre preferences, gaming frequencies, and relational ties of randomly sampled game players were collected at two separate periods from Kongregate (in May and in August, 2013). The number of game players in this sample was 2,488. The panel data were analyzed using RSiena, a social network analysis program used for social network panel data.

In Chapter 4, I study how the number of times that an online casual game is consumed on a particular day is influenced by the number of times that the game has been consumed previously, by WOM on the game, by where information about the game is displayed on the Kongregate site, and by the interactions of these three factors.

Several studies have found that an individual's adoption of a media product is influenced by the number of times the product has been consumed previously (e.g., De Vany & Walls, 1996; Fu & Sim, 2011). Because media products are experience goods, consumers cannot accurately estimate how much they will like a media product before consuming it. Therefore it is likely that an individual often faces uncertainty about the quality of a media product when she makes a decision whether to consume or acquire it. The existence of uncertainty suggests that an individual's decision whether to consume or purchase a media product may be influenced by how many times the media product has been previously consumed, because the volume of prior consumption might reflect the quality of the product (De Vany & Walls, 1996; Fu & Sim, 2011).

Even though several scholars (e.g., Banerjee, 1992; Bass, 1969; Bikhchandani et al., 1992, 1998; Simon, 1954) have identified the number of times that a product has been consumed previously as an important factor influencing an individual's decision whether to consume it, only a few studies have empirically

examined how an individual's product choice is influenced by how many times the product has been consumed previously. Examples include Vany and Walls (1996), Walls (1997), and Fu and Sim (2011).

Furthermore, few of these prior empirical studies examined how the effect of the number of times that a product has been consumed on an individual's adoption of the product varies with other types of information about the product to which the individual has been exposed. If an individual acquires other information about a product, then the effect of the number of times a product has been consumed on an individual's product choices can be influenced by such additional information. For example, an individual can easily observe how others have evaluated a product on the Web through average user ratings and user reviews. Such additional information may alter the effect of the number of times a product has been consumed on product choices.

In the present study, using empirical data on game adoptions of Kongregate players, I examine how the effect of the number of times a game has been consumed previously on the number of times the game is played on particular day is influenced by WOM on the game.

Along with the extent to which a product has been consumed previously, WOM itself has been found to influence a person's choices among media products. WOM refers to the informal communication of evaluations of a product among consumers (Liu, 2006). Studies that have examined the effects of WOM on a person's product choice say that WOM may convey information about a product's quality so that consumers are more likely to choose a product with positive WOM than a product with negative WOM (e.g., Mahajan, Muller, and Kerin 1984; Mizerski 1982; Liu, 2006). Because for some media products like movies and books, there is a strong positive correlation between the number of people who consume a product and the number of times the product is consumed, and it is easier to collect data on the number of times a product is consumed than data on the number of people who consume the product, prior studies that have examined effects of WOM in media industries focused on how the number of times a media

product, especially movies and books, is consumed is influenced by the WOM on the product. For example, Liu (2006) studied the effects of WOM on a movie's theatrical performance and found important influence for WOM on a movie's box office revenues. Chevalier and Mayzlin (2003) examined the effects of WOM on the sales of a book on Amazon.com and found that sales were influenced significantly.

These prior studies of WOM did not take into account the possible effect of the number of times a product has been consumed previously on sales of a product and on the effect of WOM on sales of a product. If a consumer can easily observe both how many times a product has been consumed and WOM on the product, the consumer's product choices may be influenced by both the number of times a product has been consumed previously and WOM. If so, the effect of WOM on an individual's decision whether to acquire a product is likely to vary with the number of times the product has been consumed previously. Thus, it is important to study the effects of the number of times that a product has been previously consumed and WOM about the product on an individual's product choice at the same time.

The location where information about a product is displayed on a website can influence the extent to which the product is exposed to consumers, because the location of information about the product influences the extent to which people visiting the site become aware of it (Granka et al., 2006). For example, a consumer is more likely to become aware of a product whose information is displayed on the first page than a product whose information is displayed on other pages. This suggests that the number of players who play a game can be influenced by where information about the game has been displayed on the site.

Furthermore, the location of information about a game can influence the effects of the number of times a game has been consumed previously and word-of-mouth information on the number of players who play the game, which suggests that the omission of the location variable may lead to bias in statistical

estimates of the effects of the number of times a game has been consumed previously and word-of-mouth information. Thus, when studying the effects of the number of times a game has been consumed previously and word-of-mouth information on the number of players who play a game with regression models, it is important to include a variable for where information about the game is displayed on the site. Accordingly, I examine how the location where information about a game is displayed on the site influences the number of players who start to play the game on a particular day and how the effects of the number of times a game had been consumed previously and word-of-mouth information on a game on the number of players who start to play the game on a particular day vary depending on where information about the game has been displayed on the site.

For this study, I collected information for the 14 days immediately following their initial placement on the site for all the new games released on Kongregate during a 3-week period, between May 10 and May 30, 2013. For each game, the number of times the game was accessed each day, user ratings, the number of reviews, and whether the game was displayed on the opening page were recorded. For statistical analysis, I used pooled ordinary least squares (POLS) for estimation, and other methods such as fixed effects, random effects, and the Arellano and Bond estimation methods were also tried.

As background for the three empirical chapters that follow, in the remainder of this chapter I provide a brief introduction to the online casual games industry and to Kongregate.

1) The online casual games industry

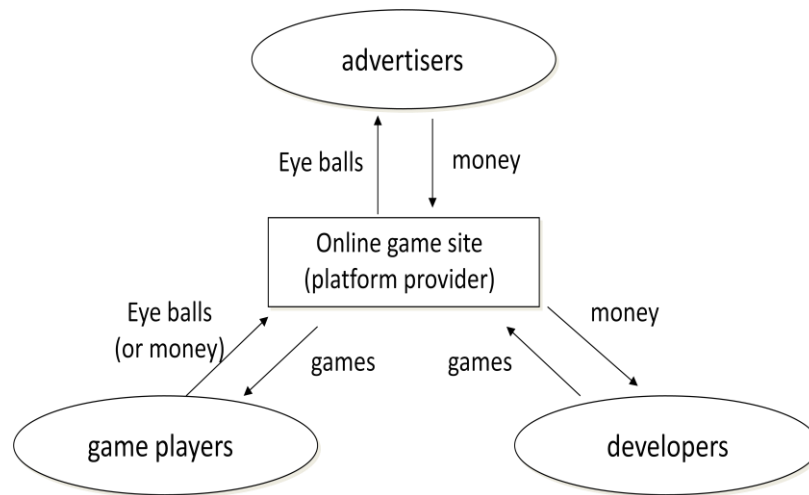
The online casual games industry is growing rapidly. More than 200 million people worldwide played casual games on the Web and the revenue of the industry was about \$6 billion in 2010, which was nearly twice the revenue of the industry in 2009 (Casual Games Association, 2012). The industry is expected to generate about 46 billion US dollars by 2016 (Roland Berger, 2012).

Despite the popularity of online casual games, the exact definition of an online casual game has not been established. But there is a general concept of what online casual games are. According to the Casual Games Association Market Report, “Online casual games are online video games developed for the mass consumer, even those who would not normally regard themselves as a ‘gamer’” (IGDA, 2009). Online casual games share some common characteristics as follows:

- online casual games are easy to learn,
- online casual games require a small amount of time to be played,
- online casual gamers play casual games mainly for fun and relaxation,
- costs of developing online casual games are relatively low compared to other online or video games (IGDA, 2009).

Online casual games are provided to game players through several different platforms. An online casual games portal site is one of those platforms (e.g., Kongregate and Armor Games). Other types of online casual game platforms include social network sites and instant messaging services. Facebook and MSN messenger are examples. With the popularity of smart phones and tablet PCs, the number of game players playing casual games on smart phones and tablet PCs has also increased.

There are four types of stakeholders in the casual game industry; platform providers, game developers, game players, and advertisers. The relationship between stakeholders can be illustrated as below:



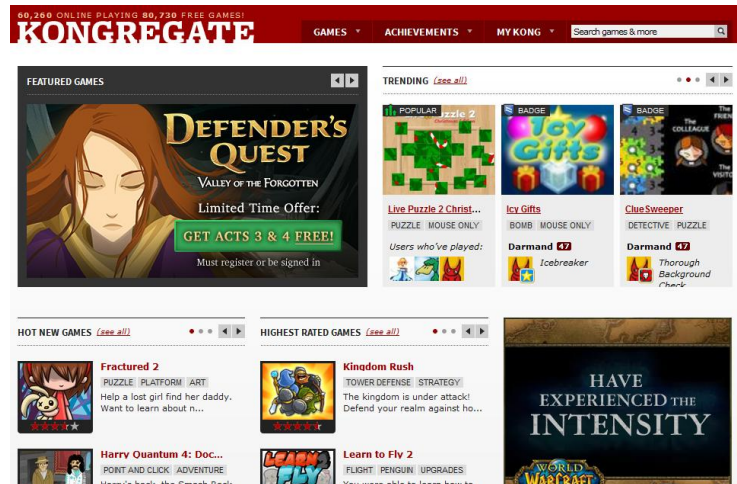
<Figure 1 Relationships among stakeholders in the online games industry>

In Figure 1, an online game portal site is a platform that links three sets of stakeholders – game players, game developers, and advertisers (that is, a portal site is a multi-sided platform). A game developer provides games to a game portal site and those games are played by game players who visit the site. Advertising is the main revenue source to game providers and the platform provider. Advertising revenues generated by a game are shared between the game developer and the game portal site according to a pre-determined contract. Game players, in general, play games on a portal site for free with the advertisements embedded in the games or displayed on the site.

2) Kongregate

Kongregate.com is an online casual games portal site, which started its service in 2006. With its growth, Kongregate was acquired by Gamestop in 2010. Kongregate provides online game players with a variety of casual games, which are developed by either professional game developers or other players who use Kongregate. As of Feb, 2014, there were 80,747 games on the site and the number of registered users on

the site was 6,970,697 as of Jan, 2012². The number of new games uploaded on the site every day ranges from 30 to 50. Figure 2 shows the main page of Kongregate.com.



<Figure 2 The front page of Kongregate.com>

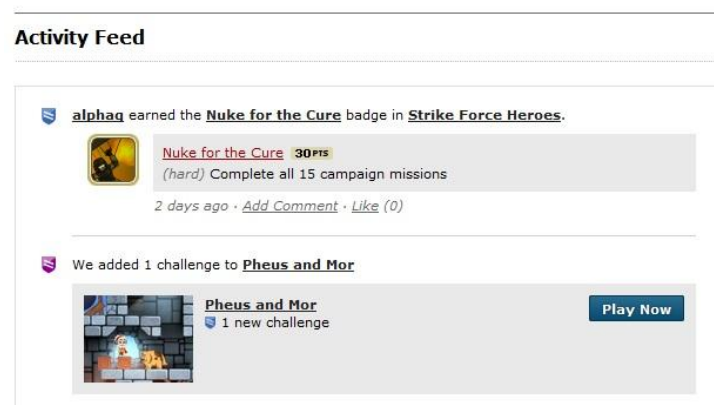
Kongregate's revenues come from either advertising or micro-transaction payments for virtual game items. The revenues that Kongregate makes from the games on its site are shared with game developers. About 70% of micro-transaction revenues are shared with developers, while Kongregate shares between 25% and 50% of the advertising revenue generated by its games with their developers. The fraction of advertising revenue shared with a developer depends on the type of contract signed with Kongregate. At minimum, developers receive 25% of the ad revenue generated from their games. Meanwhile when a game is exclusively provided to Kongregate, then the developer earns 15% more, and when a game incorporates the APIs provided by Kongregate, the developer earns another 10%.

In general, players play games on Kongregate for free with some advertisements showing up during their game plays. Players can play games without registering on the site, but with registration, players can enjoy several extra features. For example, a player can have direct relationships with other players and

² The information of the current total number of registered users is not available.

bookmark a game. Moreover, with a monthly payment, a player can become a plus member for service enhancements like no ads and exclusive username icon.

On Kongregate, a player can have a direct relationship with any other player by clicking the ‘friend’ button linked to the other player. Once a player has a direct relationship with another player, she can check on the player’s profile for information such as the games that the player has recently played, the game that the player is currently playing, and the player’s favorite games. Kongregate also lists the games a player’s Kongregate friends recently have played and what they have accomplished in games on ‘Activity Feed’, which is automatically displayed on the front page when a player is logged onto the site. Figure 3 shows an example of ‘Activity Feed’. With this feature, a game player can easily find what her Kongregate friends are doing and have done recently on the site. In addition, a player can communicate with her friends by sending messages and chatting with them.



<Figure 3 Example of an Activity Feed>

CHAPTER 2

Abstract

Several theories stress the importance of interpersonal influence on an individual's adoption of a product or service. Especially, the diffusion of innovation theory emphasizes the important influence of friends or acquaintances who adopt a particular product earlier on a person's decision whether or not to adopt the product. In this chapter, I study the effect of the number of a player's Kongregate friends who adopted a particular game earlier on the likelihood that the player will adopt the game. I also consider the strength of ties between the player and the player's Kongregate friends who adopted the game earlier as another main explanatory variable. Other variables representing player and game specific characteristics that can influence a player's game adoption are also taken into account. Using a discrete choice model and a hazard model with data on 1,668 game players' gaming activities and relational connections on Kongregate with other players, I find that Kongregate friends who adopted a game earlier do not have much statistically significant effect on a player's game adoption.

1. Introduction

Several theories stress the importance of interpersonal influence on a person's behavior, including the adoption of a product. Examples include diffusion of innovations theory (Rogers, 2003), theory of planned behavior (Ajzen, 1991), two-step flow theory (Lazarsfeld et al., 1944; Katz, 1957), and peer influence theory (Deutsch & Gerard, 1955).

A large number of studies have empirically examined interpersonal influence on adoption behavior and found an important role for interpersonal influence. For example, Childers and Rao (1992) found that the influence of family and friends on a consumer's product choice was significant and the extent to which a consumer's product choice was influenced by others varied with the person's susceptibility to interpersonal influence. Mangleburg et al. (2004) found that an adolescent's shopping behavior and

attitude towards a brand was influenced by friends shopping with her, because an adolescent tried to create images favorable to her friends by buying what they liked. Lu et al. (2005) found an important role for interpersonal influence in a person's adoption of new mobile Internet services. Harrison et al. (1997) examined small business executives' decisions to adopt information technology using the theory of planned behavior. They found that the expectations of others close to an executive had a statistically significant influence on the executive's decision on information technology adoption.

Even though there are many studies of interpersonal influence on product adoption, most of them have examined the topic in offline settings. The Internet has become a popular place where people go to buy products and consume media services. Furthermore, many of the Internet sites where people purchase products and consume media services provide their users with social features that enable them to connect with other users and share information about their activities. Examples include Facebook.com, YouTube.com, eBay.com, IMDb.com, SecondLife.com, and Kongregate.com. These sites have their own social features that enable a user to interact with other users on their sites. In addition to these sites, there are many other sites offering social features through social network sites such as Facebook and Twitter so that their users can share information about their activities on the sites with their friends. Examples are Hulu.com, NYTimes.com, ABC.com, and Amazon.com.

The existence of these information sharing behaviors and interactions with other online friends³ on websites with social features suggests that an individual's online product choices may be influenced by her online friends. First, an individual using a website with social features may become aware of what her online friends have purchased or have consumed on the site through information they share about their consumption activities. According to the diffusion of innovations theory (Rogers, 2003), becoming aware of a product is a necessary first step in the process of product adoption. Thus, an individual's online product adoptions can be influenced by the person's online friends if the person can observe information

³ In this study, an individual's online friends are defined as people with whom the individual interacts on the Web whether or not the individual interacts with them offline as well.

about her online friends' consumption activities. Second, the theory of planned behavior and peer influence theory suggest that an individual is likely to behave similarly to others close to her in order to create a favorable image with them. If these theories apply to online friends, a person's online product choices are likely to be influenced by them. However, there is little research that has examined how online friends influence an individual's online product choices.

Many studies have examined other people's online influences on an individual's product choices and the ways that an individual consumes products and media services. But most of those studies have looked at the impact of online word-of-mouth information, such as product recommendations and product reviews (e.g., Chevalier & Mayzlin, 2006; Duan et al., 2008; Huang & Chen, 2006; Senecal & Nantel, 2004; and Steffes & Burgee, 2009). The foci of these studies were on product reviews or comments generated by other consumers with no direct connections to the consumer making a product choice and none of those studies asked how online friends affect a person's choices among online services.

On the other hand, there are several studies that have examined information diffusion processes within social networks in online settings, although those studies did not focus on interpersonal influence on an individual's online product choices. For example, Bakshy et al. (2009) studied information spread among users of Second Life and found that an individual's social networks on Second Life play an important role in spreading information among individuals on Second Life. Bakshy et al. (2012) examined information diffusion among users of Twitter and found that interpersonal interactions are an important route through which information spreads among Twitter users. Ugander et al. (2012) examined how the probability of an individual joining Facebook after receiving invitations from her friends who were already Facebook users to join Facebook varies with the number of Facebook friends who invited the person to join Facebook and the structural diversity of her personal social network consisting of those friends, which was measured as the number of connected clusters within the social network in that study. They found that the probability of an individual joining Facebook was influenced more by the number of connected

clusters among Facebook users who invited the person than the number of friends. Although these studies did not examine interpersonal influence on an individual's online product choices and were implemented in specific contexts, the strong influence of interpersonal interactions on information diffusion within online settings suggests that an individual's online product choices may also be influenced by her online friends.

In this chapter I study whether players with whom a player interacts on Kongregate influence her game choices. On Kongregate, a player can directly connect with another player by clicking a 'friend' button linked to that person. In this chapter, game players with whom a player has direct connections on Kongregate are referred to as the player's Kongregate friends.

As described in Chapter 1, I specifically examine the effect of the number of a player's Kongregate friends who adopted a particular game earlier on the likelihood that the player will adopt⁴ the game. According to Rogers' diffusion of innovations theory (2003), the number of an individual's friends who adopted a product or service earlier can influence the person's decision whether or not to adopt the product or service, because interpersonal interactions can be an important source of information about a product and a person's attitude towards a product may be influenced by interpersonal interactions. But only few studies have examined this topic (e.g., Bandiera & Rasul, 2006). Even among those studies that have examined interpersonal influence on an individual's product adoption in offline settings, few looked at how the number of friends or acquaintances who adopted a product earlier influenced a person's decision to adopt it. This is mainly because, in offline settings, it is difficult to collect data on how many of a person's friends or acquaintances have adopted a particular product and when they adopted the

⁴ On Kongregate, if a player has acquired points in a game, then the number of the game points and the name of the game in which the player acquired the points is recorded on the page that lists the player's game accomplishments, which also can be observed by her Kongregate friends. In this study, a game player is considered to have adopted a game if she has acquired any game points in the game. This means that not every player who has tried a game is identified as an adopter of the game for this study.

product⁵. However, individual level data on game adoption can be collected on Kongregate, which makes it possible to examine whether a player's adoption of a game can be predicted by the number of the player's Kongregate friends who adopted the game earlier.

In addition to the number of Kongregate friends who adopted a game earlier, I also consider the closeness of the relationships on Kongregate between a player and her Kongregate friends who adopted the game earlier, because it is possible that the influence of a Kongregate friend on a player's game adoption decision can vary with the relational closeness between the player and her friend. In other studies (e.g., Bakshy et al., 2011; Christakis & Fowler, 2007) it was found that the extent to which an individual's behavior is influenced by others varies with the person's relational closeness with those others. In this study, the closeness of a relationship between two players is referred to the strength of the tie between them. The strength of a tie between two people is a function of the amount of time, the emotional intensity, the intimacy, and the reciprocal services which characterize the tie between those two people (Granovetter, 1973, p1361). In the social network literature, the strength of a tie between two people is usually measured by degree of communication reciprocity, the number of mutual friends, and interaction frequency (Gilbert & Karahalios, 2009). For this study, the strength of a tie between two players is measured by whether the tie is reciprocal.

A tie between two game players on Kongregate is directional. Consider two players, A and B, on Kongregate. That player A has established a direct connection to player B by clicking the 'friend' button linked to B does not mean that B also has a direct connection with A. In order for B to have a direct connection to A, B must click the 'friend' button linked to A. On Kongregate, only a player who has a direct connection to another player automatically receives information about the latter's game activities, such as what games the latter has played and is playing at the moment. That is, if player A has a direct

⁵ There is an empirical study that examined how the extent to which an individual's behavior is influenced by her friends varies with the number of friends who have a particular behavior, though it is not about product choices. Christakis and Fowler (2007) found that an individual is more likely to become obese when the number of her friends or acquaintances who are obese is large.

connection to B, but not vice versa, then A automatically receives information about what games player B is playing and has played on Kongregate, while B receives no information about A's game activities. When A and B have directional connections to each other, then the tie between A and B is said to be reciprocal.

Other control variables include; 1) the frequency with which a player tries new games, 2) how often a player plays games on the site, and 3) whether the game's genre is the player's favorite genre. The frequency with which a player tries new games was included because when other things are equal, a player who tries new games more often is more likely to adopt any game than a player who tries new games less often. We would also expect that the likelihood that a player adopts a game is likely to be influenced by how often the player plays games. Whether a game's genre is a player's favorite genre can also be a factor that influences her adoption decision.

In this study, I focus on game players who have registered on Kongregate, because only for registered players can information about gaming behavior, game adoptions, and Kongregate friends be collected. Furthermore, because only a registered player can make connections with other Kongregate players, unregistered players are not suitable for studying influences of Kongregate friends on game choices. That registered players are examined in this study also means that the results of this study cannot be generalized to game players who are not registered on Kongregate because there may be differences between registered and unregistered game players. For example, registered players may be more serious about their casual games and play more games more frequently than unregistered players.

2. Statistical models and data

In this section, I describe the regression models used to address the research questions introduced in the preceding section and describe how the data used in this study were collected.

2.1 Regression models

In order to more thoroughly study whether the number of a player's Kongregate friends who adopted a game earlier can predict the player's adoption of the game, I develop two separate models. First, using a discrete choice model, I examine the effect of the number of a player's Kongregate friends who adopted a game before the player's first visit to Kongregate after the game was released on the site on the likelihood the player adopts the game within 7 days after this visit. Second, using a hazard model, I study how the number of Kongregate friends who adopted a game before a particular day, say day t , influences the likelihood that the player adopts the game on day t .

2.1.1 Discrete choice model

With this model, I study how the number of a player's Kongregate friends who adopted a game before the player's first visit to Kongregate after the game was released on the site is associated with the likelihood that the player will adopt the game within 7 days of her first visit to the site after the game's release. In addition, I also ask how the effect of a player's prior adopter friend on the likelihood of adoption varies with the strength of the tie between the player and the player's prior adopter friend. For this, I include the number of a player's prior adopter friends who have a reciprocal tie with the player and the number of the player's prior adopter friends who do not have reciprocal ties as the main independent variables. Because a player who first visited the site relatively late after a game's release is likely to have more Kongregate friends who adopted the game before her first visit to the site than a player who first visited the site shortly after the game's release, the number of days between a game's release and a player's first visit to the site is included as well.

Furthermore, because a player's adoption of a game can also be influenced by her Kongregate friends who adopted the game between her first visit to the site and her adoption of the game, the number of Kongregate friends who adopted the game between a player's first visit and her adoption of the game and

those friends' tie strengths with the player are also considered. For those who did not adopt the game during the 7 days following their first visits to the site, the number of Kongregate friends who adopted the game during the 7 days was counted. A player is likely to have more Kongregate friends who adopted a game between the player's first visit and the time of adoption, the longer the time between the first post-release visit and the time of adoption. Thus, a variable for when a player adopts a game after her first visit should be included in the model as a control variable. But, there is a problem. That is, there would be a high correlation between the variable for when a player adopts a game and the dependent variable because those who did not adopt a game during the 7 days would have a value of '7' for the variable representing when they adopted the game. Thus, it is not statistically appropriate to include a variable for when a player adopts a game during the 7 days in this model. Accordingly, when interpreting the results of the variables for the number of a player's Kongregate friends who adopted a game between the player's first visit and her adoption of the game, this limitation should be considered. This limitation can be addressed in a hazard model.

I also include as independent variables the frequency with which the player adopts new games, how often the player plays games on Kongregate, and whether the genre of the game is the player's favorite genre. Finally, in order to control for factors unique to a game that can influence its adoption, I include a game fixed effect variable, which might reflect the game's genre, popularity, quality, and difficulty. The regression model is presented in Equation (1).

$$\begin{aligned}
Adoption_{jg7} = & \beta_0 + \beta_1 \#prior_adopters_w/_reciprocal_tie1_{jg} + \beta_2 \#prior_adopters_w/o_reciprocal_tie1_{jg} \\
& + \beta_3 \#days_btw_1^{st}_visit_game_release_{jg} + \beta_4 \#prior_adopters_w/_reciprocal_tie2_{jg} + \\
& \beta_5 \#prior_adopters_w/o_reciprocal_tie2_{jg} + \beta_6 \#fre_new_games_j + \beta_7 \#gaming_frequency_j \\
& + \beta_8 \#genre_match_{jg} + \beta_9 \#total_Kong_friends_j + \beta_{10} \#fixed_effects_g + e_{jg},
\end{aligned} \tag{1}$$

The variables in (1) are defined and measured as follows.

Adoption_{jg7}

This is a dummy variable for whether player j adopted game g within 7 days after her first visit to Kongregate since game g 's release. This variable takes value of 1 if player j adopted game g within 7 days after her first visit to Kongregate since game g 's release and 0 otherwise. As mentioned before, the 7-day period was chosen because the number of players who adopted the games examined in this study after the 7 days passed was small. In this study, a game player is considered to have adopted a game if she has acquired points in the game. This operational definition has been made because whether a player has played a game on Kongregate can only be observed if she has earned any points from the game. On Kongregate, a player earns game points by accomplishing tasks provided in games. It is possible that even if a player played a game she is not considered to have adopted the game unless she earned game points from the game. But, because the tasks provided in the games examined in this chapter were relatively easy to accomplish and they were provided at the beginning of the games, it is not likely that there are a large number of players who quit playing the games examined in this chapter before accomplishing at least one task.

Game players who adopted game g on the day when the game was released and those who visited the site on game g 's release day were excluded from this study as subjects for the dependent variable because the number of Kongregate friends who adopted game g before the player's first visit to the site since the game's release cannot be measured for these players.

#prior_adopters_w/_reciprocal_tie1_{jg}

This variable represents the number of player j 's Kongregate friends who have a reciprocal tie with her and adopted game g before her first visit to Kongregate after game g was released on the site.

#prior_adopters_w/o_reciprocal_tie1_{jg}

This variable represents the number of player j 's Kongregate friends who have a nonreciprocal tie with her and adopted game g before her first visit to Kongregate after game g was released on the site.

#days_btw_1st_visit_game_release_{jg}

This is the number of days between the day when player j first visited Kongregate and game g 's release date.

#prior_adopters_w/_reciprocal_tie2_{jg}

This variable is the number of player j 's Kongregate friends who have a reciprocal tie with her and adopted game g between her first visit and her adoption of game g .

#prior_adopters_w/o_reciprocal_tie2_{jg}

This variable is the number of player j 's Kongregate friends who have a nonreciprocal tie with her and adopted game g between her first visit and her adoption of game g .

fre_new_games_j

This variable represents the frequency with which game player j adopts new games, which was measured as the number of games the player adopted during the 14 days before game g was released on the site.

This 14-day period was chosen arbitrarily.

gaming_frequency_j

This variable represents player j 's general gaming frequency. This variable was measured as the number of days that j played games during the 14 days before game g was released.

genre_match_{jg}

This is a dummy variable for whether game g 's genre is player j 's favorite genre. A player's favorite genre was assumed to be the genre that the player played most frequently during the 14 days before game g 's release on Kongregate. This variable takes value 1 if the game's genre is the player's favorite genre, and 0 otherwise.

#total_Kong_friends_j

This is the total number of player j 's Kongregate friends.

fixed_effects_g

This a binary variable that reflects factors unique to game g . For the two games examined in this study ('Live Puzzle' and 'Mystery IQ Test'), the variable takes value 1 for 'Live Puzzle' and 2 for 'Mystery IQ Test'.

2.1.2 The hazard model

In this study, I use the proportional hazard model introduced by Cox in 1972 to study the effect of the number of a player's Kongregate friends who adopted a game before day t on the likelihood that the player adopts the game on that day. I also ask how the effect of a Kongregate friend who adopted a game earlier on the likelihood that the player adopts the game varies with the strength of the tie between the player and that friend. In this model, the strength of a tie between two players is measured by whether the tie is reciprocal. Similar to the previous model, a player's Kongregate friends who adopted a game before her first visit to the site since the game's release were distinguished from the player's Kongregate friends who adopted the game between the player's first visit and day t .

Game adoptions by the players in the sample during the 5 days following their first visits to the site since a game's release were observed. The 5-days period was chosen because the number of players who adopted the games examined in this study after 5 days passed since their first visits was negligible⁶. The data used in this study is right censored because we do not have information about the adoption decisions of players who did not adopt a game within the 5 days following their first visits to the site after its release.

⁶ Only 3 players in the sample adopted the games after 5 days passed.

Our model includes both fixed and time-varying independent variables. Fixed variables are those whose values do not change during the 5 days following a player's first visit to the site since a game's release, whereas time-varying variables are those whose values change during these 5 days.

Following are the fixed independent variables. The descriptions of these variables are omitted, because they are the same as those in the previous model.

- *#prior_adopters_w/_reciprocal_tie1_{jg}*
- *#prior_adopters_w/o_reciprocal_tie1_{jg}*:
- *#days_btw_1st_visit_game_release_{jg}*
- *fre_new_games_j*
- *gaming_frequency_j*
- *genre_match_{jg}*
- *#total_Kong_friends_j*
- *fixed_effects_g*

Time-varying independent variables are

- *#prior_adopters_w/_reciprocal_tie2_{jg}*

This variable is the number of player *j*'s Kongregate friends with a reciprocal tie with player *j* who adopted game *g* between player *j*'s first visit and day *t*.

- *#prior_adopters_w/o_reciprocal_tie2_{jg}*

This variable is the number of player *j*'s Kongregate friends with a nonreciprocal tie with player *j* who adopted game *g* between player *j*'s first visit and day *t*.

Following Mills (2011), we have the following Cox hazard function

$$h_{jg}(t) = h_0(t) \{ \exp(\lambda_1 \cdot \#prior_adopters_w/_reciprocal_tie1_{jg} + \lambda_2 \cdot \#prior_adopters_w/o_reciprocal_tie1_{jg} + \lambda_3 \cdot \#days_btw_1^{st}_visit_game_release_{jg} + \lambda_4 \cdot \#prior_adopters_w/_reciprocal_tie2_{jg}(t) +$$

$$\lambda_5 \cdot \#prior_adopters_w/o_reciprocal_ties2_{jg}(t) + \lambda_6 \cdot fre_new_games_j + \lambda_7 \cdot gaming_frequency_j + \lambda_8 \cdot genre_match_{jg} + \lambda_9 \cdot \#total_Kong_friends_j + \lambda_{10} \cdot fixed_effects_g\} \}. \quad (2)$$

$h_{jg}(t)$, the hazard rate for player j on day t (the likelihood that player j adopts game g on day t), is the product of two terms: 1) $h_0(t)$ – unspecified baseline hazard function, which can be regarded as the hazard rate when all the independent variables are zero; 2) an exponential function of fixed and time-varying independent variables. Because the baseline hazard is left unspecified, there is no intercept term in the exponential function (Mills, 2011). To test whether the effect of prior adopter Kongregate friends on the likelihood that a player adopts a game varies with a game's unique factors, I also include interactions terms for $fixed_effects_g$ and variables for prior adopter Kongregate friends ($prior_adopters_w/_reciprocal_tie1_{jg}$, $\#prior_adopters_w/o_reciprocal_tie1_{jg}$, $prior_adopters_w/_reciprocal_tie2_{jg}$, and $\#prior_adopters_w/o_reciprocal_tie2_{jg}$).

2.2 Data

For this study, I used data for randomly selected registered game players on Kongregate because information such as games played and listings of Kongregate friends can only be collected for registered players. I downloaded a list of registered game players who were playing games on Kongregate at least twice a day during the week of 3/24 (Sun) to 3/30 (Mon), 2013. The original dataset had 17,858 game players. Because this size of dataset is too big to be handled by social network analysis statistical packages in a timely manner and collecting data on the gaming behavior and game adoptions of all the 17,858 players and their Kongregate friends (the average number of Kongregate friends for the players in sample was about 60) would have been extremely time-consuming, I randomly chose 2,000 players from the 17,858 using a random number generator. Among those 2,000 players, only the 1,668 who made their personal information publicly available and who had at least one friend were selected for the study. The average number of Kongregate friends for the players in the final sample was 61.6.

I collected data on game adoptions for those 1,668 game players and their Kongregate friends for two games, 1) Mystery IQ Test, and 2) Live Puzzle as in Table 1. The genre of ‘Live Puzzle’ is puzzle and that of ‘Mystery IQ Test’ is brain. A puzzle game is a game that requires a player to put pieces together in a way that meets the goal of the game. A brain game is a game in which a player uses logic to accomplish the tasks. A puzzle game can be a sort of a brain game. ‘Mystery IQ Test’ incorporates several other types of tasks in addition to puzzle type tasks including verbal quizzes and math questions.

Game title	Kongregate release date	Genre	Rating
Live Puzzle	4/29/2013	Puzzle	3.9/5
Mystery IQ Test	5/5/2013	Brain	3.7/5

<Table 1 Information about games examined in this study >

For a game to be included in this study, the game had to provide at least one task right after its release so that players could earn points by accomplishing the task. Among all the games released on Kongregate during a month-period, from 4/9/2013 to 5/8/2013, only the two games above met this requirement.

For players in the sample, I first checked whether a game player played any games on Kongregate during the 7 days after each game’s release. For those who played games during the 7 days, I collected information about whether and when they adopted each of the games in Table 1. Then, I collected the data on game adoptions for their Kongregate friends.

3. Results

3.1 Descriptive results

Brief descriptive information about the dataset is provided in Table 2. Among the game players in the sample, 362 players played games on Kongregate during the 7 days after ‘Live Puzzle’ had been released on the site. Among those 362 players, 45 players adopted ‘Live Puzzle’ during the 7 days. In the case of

‘Mystery IQ Test,’ there were 366 players who played games on the site during the 7 days after it had been released and among those 366 players, 103 players adopted the game during the 7 days.

game	release date	# gamers who played games on the site during the 7 days	# gamers who adopted the game during the 7 days
Live Puzzle	4/29/2013	362	45
Mystery IQ Test	5/5/2013	366	103

<Table 2 Descriptive information about the sampled data>

3.2 Regression results

3.2.1 Results for the discrete choice model

I used two different estimation methods, probit and logit, to estimate the parameters of the discrete choice model in Equation (1). Before estimating the model in Equation (1), several diagnoses were carried out to check whether the assumptions of each estimation method were satisfied. Because there was a high correlation (0.91) between the ‘number of days that player j played games on the site during the 14 days before game g ’s release’ variable and ‘number of new games that player j adopted during the 14 days before game g ’s release’ variable, estimating Equation (1) with both variables included might cause a multicollinearity problem. Thus, Equation (1) was estimated twice, once with each of the variables.

The probit and logit estimates for model (1) are reported in Table 3. Along with the coefficient values of the parameters, each variable’s average partial effect (APE) is also reported. Due to the similarity between the results of probit and those of logit estimation method, I only present the results for the probit model. When interpreting the results in Table 3, it should be noted that the coefficients were obtained from estimating the model in Equation (1) without a variable for when a player adopted the game.

Dependent variable: likelihood that player j adopts game g within the 7 days following her first visit to the site since game g 's release

Variables	Probit			Logit		
	Coef	APE	p	Coef	APE	p
$\#prior_adopters_w/_reciprocal_tie1_{jg}$	0.076	0.017	0.010	0.130	0.017	0.013
$\#prior_adopters_w/o_reciprocal_tie1_{jg}$	- 0.046	- 0.011	0.106	- 0.085	- 0.011	0.125
$\#days_upto_1^{st}_visit_{jg}$	- 0.168	- 0.038	0.000	- 0.303	- 0.039	0.000
$\#prior_adopters_w/_reciprocal_tie2_{jg}$	- 0.141	- 0.032	0.007	- 0.245	- 0.032	0.007
$\#prior_adopters_w/o_reciprocal_tie2_{jg}$	- 0.028	- 0.007	0.530	- 0.047	- 0.006	0.575
$\#newgames_{jg}$	0.024	0.006	0.074	0.043	0.005	0.060
$(\#gamingdays_{jg})$	(0.035)	(0.008)	(0.122)	(0.064)	(0.008)	0.096
$genre_match_{jg}$	0.492	0.113	0.001	0.817	0.107	0.001
$\#total_Kong_friends_j$	0.005	0.0001	0.751	0.001	0.0001	0.647
$fixed_effects_g$	0.646	0.148	0.000	1.129	0.148	0.000
constant	- 1.325	-	0.000	- 2.259	-	0.000
Model fit	Pseudo $R^2 = 0.18$			Pseudo $R^2 = 0.18$		
	LR $\chi^2(9) = 133.94, p < 0.001$			LR $\chi^2(9) = 132.84, p < 0.001$		

$N=725$, $\#prior_adopters_w/_reciprocal_tie1_{jg}$: Among player j 's Kongregate friends who adopted game g before player j 's first visit to Kongregate since game g was released on the site, the number of friends who have a reciprocal tie with player j , $\#prior_adopters_w/o_reciprocal_tie1_{jg}$: Among player j 's Kongregate friends who adopted game g before player j 's first visit to Kongregate since game g was released on the site, the number of friends who have a nonreciprocal tie with player j , $\#days_upto_1^{st}_visit_{jg}$: the number of days between the day when player j first visited Kongregate and game g 's release day, $\#prior_adopters_w/_reciprocal_tie2_{jg}$: Among player j 's Kongregate friends who adopted game g between player j 's first visit and her adoption of game g , the number of friends who have a reciprocal tie with player j , $\#prior_adopters_w/o_reciprocal_tie2_{jg}$: Among player j 's Kongregate friends who adopted game g between player j 's first visit and her adoption of game g , the number of friends who have a nonreciprocal tie with player j , $\#newgames_{jg}$: the number of new games player j adopted during the 14 days before game g 's release, $\#gamingdays_{jg}$: the number of days player j played games on Kongregate during the 14 days before game g 's release, $genre_match_{jg}$: dummy variable for whether game g 's genre is player j 's favorite genre, $\#total_Kong_friends_j$: total number of player j 's Kongregate friends, $fixed_effects_g$: fixed effect for game g

<Table 3 Statistical estimation results of the model in Equation (1)>

First of all, it turns out that among a player's Kongregate friends who adopted a game before the player's first visit to the site since the game's release, the number of Kongregate friends who have a reciprocal tie with the player is positively associated with the likelihood that the player adopts the game within 7 days following her first visit (the coefficient of $\#prior_adopters_w/_reciprocal_tie1_{jg} = 0.0759$). On the other hand, the number of a player's prior adopter Kongregate friends who do not have a reciprocal tie with the

player is negatively associated with the likelihood that the player adopts the game within 7 days following her first visit (the coefficient of $\#prior_adopters_w/o_reciprocal_tie1_{jg} = -0.046$). The negative coefficient of $\#days_upto_1^{st}_visit_{jg}$ indicates that the earlier the first visit to the site after a game's release day, the higher the probability of adopting that game.

The number of a player's Kongregate friends with a reciprocal tie who adopted game g between player j 's first visit to the site and her adoption of game g was negatively associated with the likelihood that player j adopted the game (the coefficient of $\#prior_adopters_w/_reciprocal_tie2_{jg} = -0.141$). This negative coefficient is understandable because a player would have fewer Kongregate friends who adopted a game before her the earlier she adopted the game and when player j adopted game g was not controlled for in the model.

The number of games that a player adopted during the 14 days before game g 's release had a positive association with the likelihood that the player adopted game g (the coefficient of $\#newgames_{jg} = 0.024$). But it was only marginally significant ($p = 0.074$). The effect of the number of days that player j played games on the site during the 14 days before game g 's release was similar to that of $\#newgames_{jg}$ (the coefficient of $\#gamingdays_{jg} = 0.035$, $p = 0.122$).

Whether the genre of a game is a player's favorite genre was also positively associated with the likelihood that the player adopts game g and statistically significant (the coefficient value of $genre_match_{jg} = 0.492$, $p = 0.001$).

Finally, it turns out that the factors unique to a game also played an important role in predicting the likelihood that a player adopts the game. That is, the coefficient value of the game fixed effect variable is statistically significant and its average partial effect (APE) is relatively large as well (APE of $fixed_effects_g = 0.148$, $p < 0.001$). These game unique factors might include genre, difficulty, and quality. Because 'Mystery IQ Test' was coded as 2 and 'Live Puzzle' was coded 1, the positive APE value of

fixed_effects_g means that the contribution of unmeasured attributes of ‘Mystery IQ Test’ to the probability of adopting the game is higher than that of unmeasured attributes of ‘Live Puzzle’.

Because a variable for when a player adopted game *g* was not included in Equation (1), the coefficients of *#prior_adopters_w/_reciprocal_tie2_{jg}* and *#prior_adopters_w/o_reciprocal_tie2_{jg}* in Table 3 do not provide valid information about the effects of a player’s Kongregate friends who adopted game *g* between her first visit and her adoption of the game. Furthermore, the inclusion of *#prior_adopters_w/_reciprocal_tie2_{jg}* and *#prior_adopters_w/o_reciprocal_tie2_{jg}* may influence the coefficient estimates for other variables in Equation (1). Thus, I estimated the model in Equation (1) without *#prior_adopters_w/_reciprocal_tie2_{jg}* and *#prior_adopters_w/o_reciprocal_tie2_{jg}*. The corresponding results are reported in Table 3-1.

Variables	Probit			Logit		
	Coef	APE	<i>p</i>	Coef	APE	<i>p</i>
<i>#prior_adopters_w/_reciprocal_tie1_{jg}</i>	0.041	0.009	0.109	0.065	0.008	0.163
<i>#prior_adopters_w/o_reciprocal_tie1_{jg}</i>	− 0.042	− 0.009	0.127	− 0.076	− 0.010	0.146
<i>#days_upto_1st_visit_{jg}</i>	− 0.146	− 0.034	0.000	− 0.265	− 0.035	0.000
<i>#newgames_{jg}</i>	0.016	0.004	0.209	0.029	0.004	0.176
<i>genre_match_{jg}</i>	0.447	0.104	0.002	0.742	0.099	0.002
<i>#total_Kong_friends_j</i>	− 0.0009	− 0.0002	0.503	− 0.001	− 0.0002	0.587
<i>fixed_effects_g</i>	0.597	0.139	0.000	0.216	0.027	0.000
constant	− 1.289	−	0.000	− 2.175	−	0.000
Model fit	Pseudo R ² = 0.17			Pseudo R ² = 0.17		
	LR chi2(9) = 124.06, <i>p</i> < 0.001			LR chi2(9) = 123.22, <i>p</i> < 0.001		

<Table 3-1 Statistical estimation results of the model in Equation (1) without *#prior_adopters_w/_reciprocal_tie2_{jg}* and *#prior_adopters_w/o_reciprocal_tie2_{jg}* >

The estimates in Table 3-1 differ little from their counterparts in Table 3; there are only small differences in the coefficients and *p*-values between in Table 3 and Table 3-1. For example, the coefficient for *#prior_adopters_w/_reciprocal_tie1_{jg}* in Table 3-1 is smaller than that in Table 3 and its *p*-value is larger than that in Table 3. The coefficient of *#prior_adopters_w/o_reciprocal_tie1_{jg}* and its *p*-value in Table 3-

1are slightly larger than their counterparts in Table 3. The coefficients for $\#newgames_{jg}$, $genre_match_{jg}$, and $fixed_effects_g$ are a little bit smaller than their counterparts in Table 3, while their p -values are slightly larger than those in Table 3. The coefficient for $\#total_Kong_friends_j$ changed to negative in Table 3-1 from positive in Table 3, but neither is statistically distinguishable from zero. The results in Table 3-1 show that dropping $\#prior_adopters_w/_reciprocal_tie2_{jg}$ and $\#prior_adopters_w/o_reciprocal_tie2_{jg}$ from Equation (1) does not much influence the coefficients of other variables.

3.2.2 Results for the hazard model

The statistical estimation results for the Cox hazard model in Equation (2) are reported in Table 4.

Variable	β	$\exp(\beta)$	p
$\#prior_adopters_w/_reciprocal_tie1_{jg}$	0.205	1.227	0.227
$\#prior_adopters_w/o_reciprocal_tie1_{jg}$	- 0.451	0.636	0.107
$\#prior_adopters_w/_reciprocal_tie1_{jg} * fixed_effects_q$	- 0.079	0.923	0.384
$\#prior_adopters_w/o_reciprocal_tie1_{jg} * fixed_effects_q$	0.207	1.230	0.152
$\#days_upto_1^{st}_visit_{jg}$	- 0.241	0.785	0.000
$\#prior_adopters_w/_reciprocal_tie2_{jg}$	0.549	1.732	0.195
$\#prior_adopters_w/o_reciprocal_tie2_{jg}$	0.336	1.399	0.221
$\#prior_adopters_w/_reciprocal_tie2_{jg} * fixed_effects_q$	- 0.283	0.753	0.196
$\#prior_adopters_w/o_reciprocal_tie2_{jg} * fixed_effects_q$	- 0.140	0.868	0.320
$\#newgames_{jg}$	0.013	1.013	0.420
$(\#gamingdays_{jg})$	(0.027)	(1.027)	(0.361)
$genre_match_{jg}$	0.571	1.770	0.003
$\#total_Kong_friends_j$	- 0.002	0.997	0.346
$fixed_effects_g$	0.838	2.313	0.000
Model fit	Log Likelihood test = 120.3, $p = 0.000$		

<Table 4 Statistical estimation results of the Cox hazard model in Equation (2)>

Let us first see the effect of a player's Kongregate friends with a reciprocal tie who adopted a game before the player's first visit after the game's release ($\#prior_adopters_w/_reciprocal_tie1_{jg}$) on the likelihood that the player adopted the game on day t . Because the model has an interaction term for $\#prior_adopters_w/_reciprocal_tie1_{jg}$ and $fixed_effects_g$, the marginal effect of $prior_adopters_w/_reciprocal_tie1_{jg}$ is ' $0.205 - 0.079 \cdot fixed_effects_g$ '. This result suggests that the effect of Kongregate friend with a reciprocal tie who adopts a game before the player's first visit after the game's release ($\#prior_adopters_w/_reciprocal_tie1_{jg}$) on the likelihood that the player adopted the game on day t was larger for 'Live Puzzle' than for 'Mystery IQ Test' because the value of $fixed_effects_g$ is 1 for 'Live Puzzle' and 2 for 'Mystery IQ Test'. For example, the marginal effect of $\#prior_adopters_w/_reciprocal_tie1_{jg}$ on the dependent variable, the hazard rate, for 'Live Puzzle' is 0.205. Because a Cox hazard function is expressed as

$$h_j(t) = h_0(t) \exp(\beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \dots + \beta_m x_m), \quad (5)$$

a natural log transformation of (5) gives

$$\ln(h_j(t)) = \ln(h_0(t)) + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \dots + \beta_m x_m \quad (5-1)$$

Because the right side of (5-1) has a log form and the x_k do not, the value of β_k indicates by how many percents the hazard rate, $h_j(t)$, changes when there is an increase in the value of x_k . Accordingly, the marginal effect of $\#prior_adopters_w/_reciprocal_tie1_{jg}$ on the dependent variable, the hazard rate, for 'Live Puzzle' is 0.205, says that when the value of $\#prior_adopters_w/_reciprocal_tie1_{jg}$ increases by 1, then the likelihood that the player adopts 'Live Puzzle' on day t increases about 21%.

Similarly, the marginal effect of a player's Kongregate friends with a nonreciprocal tie who adopted a game before the player's first visit to the site after the game's release on the likelihood that the player adopted the game on day t is ' $-0.451 + 0.207 \cdot fixed_effects_g$ '. This result shows that the effect of

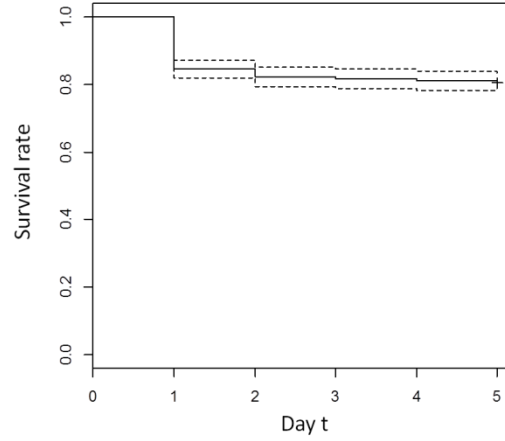
$prior_adopters_w/o_reciprocal_tie1_{jg}$ on the dependent variable is negative, but by a smaller amount for ‘Mystery IQ Test’ than for ‘Live Puzzle’.

The marginal effect of the number of a player’s Kongregate friends who adopted a game between the player’s first visit to the site and day t on the likelihood that the player adopted the game on day t is ‘ $0.549 - 0.283 \cdot fixed_effects_g$ ’. That is, the effect of an increase in the value of $\#prior_adopters_w/o_reciprocal_tie2_{jg}$ on the dependent variable is positive but it is larger for ‘Live Puzzle’ than for ‘Mystery IQ Test’.

The result for $\#prior_adopters_w/o_reciprocal_tie2_{jg}$ is similar to that for $\#prior_adopters_w/o_reciprocal_tie1_{jg}$. The marginal effect of $\#prior_adopters_w/o_reciprocal_tie2_{jg}$ is $0.336 - 0.140 \cdot fixed_effects_g$, which is positive.

The results for other variables in Table 4 are similar to their counterparts in Table 3. Increasing the number of days between player j ’s first visit to the site and game g ’s release date has a negative effect on the likelihood that player j adopted the game on a particular day after her first visit (the coefficient of $\#days_upto_1^{st}_visit_{jg} = -0.241$, $p = 0.000$). The coefficient value for $genre_match_{jg}$, 0.571, indicates that the likelihood that j adopts game g on day t is 57% higher when the genre of game g is player j ’s favorite genre than when it is not. The likelihood that a player adopts ‘Mystery IQ Test’ is 84% higher than the likelihood that she adopts ‘Live Puzzle’.

Figure 4 presents the survival function for the equation (2) model.



<Figure 4 Survival rate>

According to Figure 4, the fraction of game players who adopted game g decreased as more days passed after a player's first visit following the game's release. For example, on day 1, about 18% of the game players in the sample adopted game g whereas only a few percent of them adopted the game on day 2, and the percentage fell as days passed.

4. Discussion

To study whether a Kongregate game player's adoption of a game can be predicted by the number of her Kongregate friends who adopted the game earlier, I developed two different models. First, a discrete choice model was used to examine how the likelihood that a player adopts a game within the 7 days following her first visit to Kongregate after the game's release varies with the number of her Kongregate friends who adopted the game before her first visit to the site. Second, with a hazard model, I studied how the number of a player's Kongregate friends who adopted a game before day t contributes to the likelihood that the player adopts the game on day t . In addition to the number of Kongregate friends who adopted the game earlier, I also considered impact of the strength of the ties between the player and her prior adopter Kongregate friends.

I found that the number of a player's Kongregate friends with a reciprocal tie who adopted a game before the player's first visit was positively associated with the likelihood that the player adopted the game during the 7 days following her first visit after its release. This positive association can mean that a player's adoption likelihood a game might be positively influenced by the number of prior adopter friends with a reciprocal tie. In contrast, the number of a player's Kongregate friends without a reciprocal tie who adopted the game before her first visit was negatively associated with her likelihood of adoption. It is unlikely that this negative association means that a player's Kongregate friends with a nonreciprocal tie who adopted a game earlier negatively influenced the likelihood that the player would adopt the game. The negative association might just reflect the fact that for players in the sample who did not adopt the games examined in this study, the number of prior adopter friends with a nonreciprocal tie was larger than the number of prior adopter friends with a reciprocal tie (Average number of prior adopter friends with a reciprocal tie was 1.24 and that of prior adopter friends with a nonreciprocal tie was 1.81).

This model also suggests that players who visited early after a game's release were more likely to adopt the game. How early a player visited the site after a game's release might be associated with other factors which were not taken into account in this study that can influence the likelihood that the player adopts the game on a day after her first visit to the site. One example of those factors is the frequency with which a player plays games on the site after a game is released. In this study, I used the number of days that a player played games on the site during the 14 days before a game's release as a measure of the frequency with which a player plays games on the site in general, rather than the number of days that a player games on the site after a game's release, because the latter is influenced by the dependent variable. But they may be different. That is, the number of days that a player played games during the 14 days before a game's release might not represent well the frequency with which the player plays games after the game's release. That a player first visited the site early after a game's release might indicate only that the player played games more frequently after the game's release than a player who first visited the site late after the game's release.

Another example would be whether a player is exposed to a game when information about the game is displayed on the first page of the site, because information about a game is more likely to be displayed on the first page in the days immediately after its release than after more days have passed. Thus, a player who visited the site soon after a game's release is more likely to see information about the game displayed on the first page.

The unique characteristics of a game were also found to play an important role in explaining a player's adoption of the game. This finding could have resulted from several different things. First, for example, it is possible that the first task in 'Mystery IQ Test' was easier than that in 'Live Puzzle', so there were more players who accomplished the task in 'Mystery IQ Test' than the task in 'Live Puzzle'. It is also plausible that 'Mystery IQ Test' might have been advertised where more game players could become aware of the game than 'Live Puzzle'. As can be seen in Table 1, the user ratings of 'Live Puzzle' were higher than those for 'Mystery IQ Test'. This suggests that user ratings of a game might not much influence how many game players play the game, at least when the user ratings of a game are larger than a certain value.

With the Cox hazard model, I studied the effects of the number of a player's Kongregate friends who adopted a game prior to the player's first visit after the game's release on the site and the effects of the number of the player's Kongregate friends who adopted the game between the player's first visit to the site and the t^{th} day following her first visit on the likelihood that the player would adopt the game on the t^{th} day. The effect of the strength of the ties between the player and her prior adopter Kongregate friends was also considered. Because the results for the variable for when a player first visited after a game's release ($\#days_upto_1^{st_visit}_{jg}$) and for the dummy variable representing the unmeasured factors unique to each game ($fixed_effects_g$) in the Cox model are similar to their counterparts in the discrete choice model, here I just focus on the estimates of prior adopter Kongregate friends-related variables in the Cox model..

The estimates of the Cox model show that the effect of a player's prior adopter Kongregate friends with a reciprocal tie on the likelihood that the player adopted the game on a particular day was positive. But the size of the effect was larger for 'Live Puzzle' than for 'Mystery IQ Test'. This finding suggests that a player's decision whether to play 'Live Puzzle' was more influenced by her prior adopter Kongregate friends who have a reciprocal tie than her decision to play 'Mystery IQ Test'.

Different from the effects of a player's prior adopter Kongregate friends with a reciprocal tie, the effects of prior adopter Kongregate friends with a nonreciprocal tie varies with when those friends adopted the game. The effect of a player's Kongregate friends with a nonreciprocal tie who adopted a game before the player's first visit to the site after the game's release was negative, whereas the effect of the player's Kongregate friends with a nonreciprocal tie who adopted the game between the player's first visit and day t was positive. Similar to the results of the discrete choice model, the negative effect might be just due to the fact that for players in the sample who did not adopt the games examined in this study, the number of prior adopter friends with a nonreciprocal tie was larger than the number of prior adopter friends with a reciprocal tie. On the other hand, the positive effect can mean that a player's adoption decision is positively influenced not only by prior adopter friends with a reciprocal tie but also by prior adopter friends with a nonreciprocal tie.

It turns out that the effects of a player's prior adopter Kongregate friends with a reciprocal tie on the likelihood that the player adopted a game were larger than the effects of the player's prior adopter Kongregate friends with a nonreciprocal tie. If it is true that a player has a closer relationship with her Kongregate friend with reciprocal ties than her other Kongregate friends, then this finding is consistent with the predictions of the theory of planned behavior (Ajzen, 1991) and peer influence theory (Deutsch & Gerard, 1955) that an individual's product choices are more influenced by her close friends than by distant ones.

However, the effects of the ‘prior adopter Kongregate friends’ variables were not statistically robust. This statistical imprecision means that the findings in this study cannot be generalized to all the registered players on Kongregate. The statistical imprecision might be interpreted in two ways. First, it might be because of the small sample size of 735. So when a larger sample is used, the statistical significance may increase. Second, the coefficients for the ‘prior adopter Kongregate friends’ variables may be statistically insignificant because a player’s game choice is not much influenced by her prior adopter friends regardless of the strength of her ties with them. If the second reason is true, then it suggests either or both of two things: 1) a casual game player on Kongregate is not much motivated to play a game because her Kongregate friends also play it and 2) interpersonal communications among Kongregate friends are not an important source of information about new games to casual game players on Kongregate. On the other hand, the weak influence of a player’s prior adopter Kongregate friends might be because the two games examined in this study are single player games. It is possible that the influence of prior adopter friends on a player’s adoption decision of a game varies with whether the game is a single player game or a multiplayer game.

In this study, I used two different models; a discrete choice model and a hazard model. The dependent variables of those models are slightly different. The dependent variable of the discrete choice model is the likelihood that a player would adopt a game during the 7 days following her first visit to the site after the game’s release, whereas that of the hazard model is the likelihood that a player would adopt the game on a particular day after her first visit to the site after the game’s release. The hazard model would be more appropriate to study both the effects of prior adopter friends who adopted a game before a player’s first visit to the site after the game’s release and the effects of prior adopter friends who adopted the game after her first visit and before the player adopted the game.

The results of those two models were quite similar. The coefficient signs of the variables in the discrete choice models were the same as their counterparts in the hazard model. Their p-values were also similar. These similarities support the validity of the results of both models.

5. Summary and conclusion

In this chapter, I examined the effect of the number of a player's Kongregate friends who adopted a game earlier on the likelihood that the player adopts the game. In addition to the effect of the number of a player's Kongregate friends who adopted a game earlier, I also asked how the strength of the ties between a player and her Kongregate friends who adopted a game earlier was associated with the likelihood that the player adopts the game.

I found that the effect of the number of Kongregate friends who adopted a game earlier on a player's adoption of the game was statistically insignificant whether those prior adopter friends had a reciprocal tie with the player. In this study, I only considered the effect of the number of Kongregate friends who adopted a game earlier on a player's game adoption. As found in other studies (e.g., Ugander et al., 2012), however, other characteristics of a player's personal network composed of her prior adopter Kongregate friends such as the number of clusters, may exert more influences on the player's game adoption than the number of the player's friends. Thus, in the future studies, other characteristics of a player's personal network than the number of friends should be examined. I also found that other factors such as genre preference, when a player first visited the site after a game's release, and unique characteristics of a game played important roles in predicting a player's adoption of the game.

This study has some limitations. First, genres of the games examined in this study were brain and puzzle. It is possible that the influence of Kongregate friends on a player's adoption of a game varies with the genre of the game. Second, the two games examined in this study were both single player games. The statistically insignificant influences of Kongregate friends on a player's adoption of those two games

might be because those games are single player games. Thus, in the future studies, it is recommended that multiplayer games be examined.

The research questions were examined in the context of online casual games. But it is likely that interpersonal influence on an individual's game adoption decision is different from interpersonal influence on an individual's adoption decisions for other online products. Thus, in future studies, in order to extend our understandings about how an individual's online product choices or adoptions are influenced by her online friends, the research questions asked in this study should also be examined in other online contexts.

CHAPTER 3

Abstract

Homophily and social influence are the main explanations for why there are more ties among people who have similar socio-demographic or behavioral characteristics. Homophily refers to the phenomenon that people are more likely to make relational ties with others who are similar to themselves than those who are not, whereas social influence refers to the phenomenon that an individual's behavior is likely to become more similar to that of her friends over time. It is important to study both homophily and social influence processes of a social network because each process can lead to different structural characteristics for a social network; homophily can lead to separation among the members of a network, whereas social influence can lead to network-wide uniformity. In this study, I examine homophily and social influence processes among online casual game players. Specifically, I ask whether an online casual game player tends to be friends with other online casual game players who have similar game genre preferences and whether a player's genre preferences and gaming frequencies become more similar to those of her Kongregate friends over time. For this study, demographic attributes, game genre preferences, gaming frequencies, and relational ties for 2,488 game players were collected for two time periods from Kongregate. The coefficient values for the variables for homophily and social influence processes were found to be statistically insignificant, which suggests that there might not be homophily and social influence processes may not influence gaming frequencies and genre preferences for players in the sample.

1. Introduction

A number of studies have found that relational ties are more likely to form between individuals who have similar socio-demographic and/or behavioral characteristics than between individuals who are dissimilar and that behaviors and attitudes of people who have relational ties tend to be similar (e.g., Easley &

Kleinberg, 2010; Monge & Contractor, 2003; Valente, 2010). The ‘birds of a feather flock together’ tendency observed among people who drink alcohol and smoke, and similarity in smoking and alcohol use among friends are examples. That is, a smoker (or drinker) tends to be friends with other smokers (or drinkers) and an individual is more likely to smoke (or drink) if many of his friends also smoke (or drink) (Alexander et al., 2001; Christakis & Fowler, 2008; Urberg et al., 1997).

These phenomena can be observed in many parts of our lives that are related to behavior or decision making in social contexts. Throughout our lives, we are more likely to be friends and interact with people who are similar to ourselves than with others who are dissimilar, and our behavior or attitude toward an issue is likely to be influenced by our friends so that we become similar to our friends (Monge & Contractor, 2003). These processes can lead to network autocorrelation, which is said to be present in a social network if there are more relational ties among a network’s members who possess similar socio-demographic or behavioral characteristics than among members who do not (Steglich et al., 2006; Goodreau et al., 2009).

There are two underlying reasons for the presence of network autocorrelation: homophily and social influence (Crandall et al., 2008). First, people are more likely to form relational ties with others who are similar to themselves than with those who are not, because they feel more comfortable interacting with people like themselves and feel more justified in their beliefs or opinions when with others who are similar to them than when interacting or being with people who are dissimilar (Centola et al., 2007). Another distinct reason for autocorrelation in a social network is social influence. That is, an individual’s behavior is likely to become more similar to that of her friends in a network over time, because people want to be like their friends to be liked and accepted by them (Friedkin, 1998; Monge & Contractor, 2003). For example, the phenomenon that smokers are more likely to become friends with others who also smoke can be explained by homophily, whereas a smoker with non-smoker friends becoming a non-smoker over time (the converse is also plausible) can be explained by social influence.

Studying whether a social network possesses the homophily characteristic or the social influence characteristic, or both of them is important. This is mainly because homophily and social influence processes can lead to very distinctive structural consequences of a social network (Crandall et al., 2008; Holme & Newman, 2006). Homophily can lead to separation among the members of a social network because members interact with other members who have similar characteristics, whereas social influence can lead to network-wide uniformity (Crandall et al., 2008).

Furthermore, if how members of a network form relationships and influence each other is understood, then more tailored tools can be devised to manage the network in ways that can generate more benefits for its members and the network sponsor. For example, if we could understand the homophily and social influence processes among adolescent substance abusers, then we might be able to develop more effective tools to help reduce their substance abuse (Pearson et al., 2006; Steglich et al., 2010).

Although it is important to distinguish between the effects of homophily and social influence processes in a social network, the number of studies that have attempted to do so is small. This scarcity is mainly due to the late development of statistical methods that can separate the effects of homophily and social influence and to the difficulty of collecting the panel data needed to do this (Steglich et al., 2010). Moreover, most of the studies that have attempted to separate homophily from social influence process have studied adolescents. For example, Pearson et al. (2006) studied homophily and social influence among adolescents with regard to substance abuse. Steglich et al. (2006) examined homophily and social influence processes in adolescents' friendship networks with respect to music tastes (techno, rock, and classical music). Friemel (2012) examined homophily and social influence in a social network composed of adolescents with regard to TV viewing behavior (frequency and genres viewed). The extent to which the findings of these studies of adolescents generalize to other demographic groups is not known. On the other hand, researchers have examined how an individual's behavior changes over time due to social

influence from a social network perspective (e.g., Christakis & Fowler, 2007; 2008), but these studies did not consider the influence of homophily process.

A couple of studies have attempted to separate homophily from social influence in interpersonal interactions on the Web. Crandall et al. (2008) studied homophily and social influence among Wikipedia editors. Aral et al. (2009) proposed a new statistical method to separate homophily from social influence and applied the method to a social network composed of a large number of individuals connected through instant messaging. They specifically examined the extent to which the diffusion of a mobile service application in the network could be explained by homophily and social influence. Although several studies have examined social influence processes from social network perspectives in online settings (e.g., Bakshy et al., 2009; Bakshy et al., 2011), they did not try to separate the effects of homophily and social influence.

In this study, I investigate both homophily and social influence processes among online casual game players. I focus on online casual games portal sites because they are one of the most commonly used platforms for accessing online casual games (Liew, 2013) and it is easier to collect the data required for this dissertation from online casual games portal sites than from other platforms that host online casual games. Specifically, using panel data on the formation of relationships among game players and changes in their gaming behaviors over time collected from the online casual game aggregator, Kongregate, I examine whether a player tends to form connections⁷ with other game players who have similar gaming characteristics to herself and whether a player's gaming behavior tends to become more similar to those of her Kongregate friends⁸. In this Chapter's study, I focus on game genre preferences and gaming frequency as traits and behaviors that might be affected by homophily and social influence processes.

⁷ As described in the preceding chapters, a player can form a connection with another player on Kongregate by clicking the 'friend' button linked to the latter. Once a player connects to another player, then she has access to the information about that player.

⁸ A player's Kongregate friend is referred to another Kongregate player to whom the player has a connection.

Despite the popularity and rapid revenue growth of the online casual games industry, only a few scholars have studied the industry, and no prior studies have examined research questions related to the operation of homophily and social influence processes among online casual game players. By studying the extent to which homophily and social influence processes are manifest in the online interactions of online casual game players, this research will help us better understand certain social and economic aspects of the industry.

If homophily is present, it might be reflected in game players connecting to other players who like similar game genres on Kongregate. On the other hand, a player's game genre preferences might become more similar to those of her Kongregate friends over time, because a player wants to play the game genres that her Kongregate friends play to be better liked by her friends or to have more fun playing games with her Kongregate friends. It is also possible that a player's gaming frequency is affected by her Kongregate friends so that it becomes more similar to those of her Kongregate friends over time. Similar to the possible social influence process of game genre preference among friends on Kongregate, if a player wants to be liked or accepted by her friends, then she might try to become more similar to her friends by playing games as frequently as her friends do.

In order to study homophily and social influence processes among online casual game players, I use panel data on what games players played, how often they played, and their connections with other Kongregate players that have been collected from Kongregate. The panel data were collected in May and again in August, 2013. The panel data are analyzed with RSiena, the R version of SIENA (Simulation Investigation for Empirical Network Analysis), a social network analysis program used for social network panel data. Using RSiena, we can find whether or not a game player in the sampled network tends to form new connections with other game players who have similar game genre preferences to herself and whether a game player's game genre preferences and gaming frequency become similar to those of her friends over time. In the following section, the details of the statistical analysis are explained.

2. Statistical model and data

2.1 Model specification

In this subsection, I describe the statistical model used to test whether ‘game genre preference’ homophily, and ‘game genre preference’ and ‘gaming frequency’ social influence processes are found among game players in the sample and how the model is specified for this study. To address the questions of whether a game player tends to form new connections with other players who have similar game genre preference and a game player’s genre preferences and gaming frequency become more similar to those of her Kongregate friends over time, I use the actor-driven model developed by Snijders (1996, 2001)⁹.

The actor-driven model is based on the premise that an actor is a decision maker who decides whether to form new ties or terminate existing ties with other actors in the network and whether to make changes in her behavior.

For statistical analysis, the actor-driven model uses panel data on the ties and behaviors of the members of a network that are collected over time. The actor-driven model assumes that the differences in ties and behavioral characteristics of the members of a network observed in the panel data are results of small changes that each member of the network made between observation periods. In this regard, the actor-driven model estimates those small changes assuming the process of change is a Markov chain, which means that changes in an actor’s ties or behaviors are influenced only by the current ties and behaviors of all the members of the network to which the actor belongs, but not by their past ties and behaviors.

The actor-driven model assumes that when an actor has a chance to make a change in her ties, the actor’s decision whether to establish a new tie with another actor in the network or whether to terminate an existing tie depends on her objective function, which is a random utility function (Steglich et al., 2006).

⁹ Due to the space constraint, the actor-driven model used in this study is only briefly explained in this section. For more details of the model, please see Snijders (2009), Snijders et al. (2007), and Snijders et al. (2010).

More precisely, it is assumed that an actor chooses the alternative among all the possible alternatives from which she can choose that generates the highest value for her objective function (Snijders, 2009). The term ‘objective function’ was chosen, because it represents an actor’s short term objectives (Snijders et al., 2010).

In the actor-driven model, an objective function for an actor, say j , is expressed as

$$f_j(X, Z),$$

where X is a matrix representing the structural characteristics of the network that actor j belongs to and Z is a matrix representing behaviors of the members of the network. Thus, actor j ’s objective function consists of factors that she can control (her ties and behaviors) and factors that she cannot control (other members’ ties and behaviors).

For the actor-driven model, an objective function is expressed as

$$f_j(X, Z) = \sum_k \beta_k s_{k,j}(X, Z) + e, \quad (3)$$

where the $s_{k,j}$ are variables, whose values are determined by X and Z , that represent states of j ’s ties and behaviors and those of other members in the network. Examples of $s_{k,j}$ are ‘outdegree’ and ‘reciprocity’. The outdegree of an actor is the number of ties directed from the actor to other actors in the social network. The reciprocity variable is the number of reciprocated ties between actor j and other members in the network. The β_k are parameters for the variables that measure the contribution of each variable to predicting changes in actors’ ties and behavioral characteristics. The β_k are estimated using empirical panel data. The estimates for the β_k are chosen to make the observed changes in the panel data the ones most likely to have occurred. e is an error term.

In the actor-driven model, the probability that actor j forms a tie with another actor in the network, say actor h , is

$$\Pr(X_{j,h} = 0 \rightarrow 1) = \exp[\sum_k \beta_k s_{k,j}(X, Z)] / \sum_{X' \in C(X)} \exp(\sum_k \beta_k s_{k,j}(X', Z)), \quad (4)$$

where $x_{j,h}$ is the element of X that contains information about the tie between actor j and h , and $C(X)$ is the set of all the possible tie structures that can be reached from the current ties in the network.

I will explain how the probability in (4) is derived, which is similar to the logic of discrete choice models (Train, 2009). Suppose that there are 2 possible alternatives that actor j can choose for her ties at a given moment. The probability that actor j chooses a specific alternative, say p , rather than another alternative, say q , is

$$\Pr_{jp} = \text{Prob}[\sum_k \beta_k s_{k,j}(X_p, Z) + e_p > \sum_k \beta_k s_{k,j}(X_q, Z) + e_q],$$

where X_p is the matrix that results from choosing alternative p . That is, when the value of actor j 's objective function from choosing alternative p is larger than that of her objective function with alternative q , the actor chooses alternative p over q . In the actor driven model, the error term, e , is assumed to follow a logistic distribution.

Similarly, when there are N different possible alternatives from which actor j can choose, the probability that actor j chooses a specific alternative, say p , among those N possible alternatives is

$$\begin{aligned} \Pr_{jp} &= \text{Prob}(\sum_k \beta_k s_{k,j}(X_p, Z) + e_p > \sum_k \beta_k s_{k,j}(X_m, Z) + e_m \forall m \neq p) \\ &= \text{Prob}(e_m < e_p + \sum_k \beta_k s_{k,j}(X_p, Z) - \sum_k \beta_k s_{k,j}(X_m, Z) \forall m \neq p) \end{aligned} \quad (5-1)$$

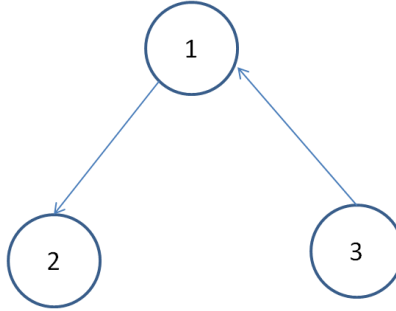
Because e_q has a logistic distribution, (5-1) becomes

$$\Pr_{jp} = \prod_{p \neq q} e^{-e^{-[\varepsilon_p + \sum_k \beta_k s_{k,j}(X_p, Z) - \sum_k \beta_k s_{k,j}(X_q, Z)]}} \quad (5-2)$$

After some algebraic manipulation, (5-2) becomes¹⁰

$$\Pr_{jp} = \frac{e^{\sum_k \beta_k s_{kj}(X_p, Z)}}{\sum_{m=1}^N e^{\sum_k \beta_k s_{kj}(X_m, Z)}} \quad (5-3)$$

The probability in (5-3) is the operationalization of that in (4). As an example, consider a network composed of three actors, 1, 2, and 3. The ties among those actors are directional. Currently, the ties among the three actors are as in Figure 5. That is, Actor 1 has a tie to Actor 2 (but Actor 2 does not have a tie to Actor 1), and Actor 3 has a tie to Actor 1.



<Figure 5 Example ties of a network>

Now, let us calculate the probability that Actor 1 forms a tie to Actor 3. For this case, I assume that the objective function for Actor 1 only consists of an outdegree variable and a reciprocity variable. Then, Actor 1's objective function is expressed as

$$f_1(X) = \beta_1 \cdot \text{outdegree}(X) + \beta_2 \cdot \text{reciprocity}(X) + e,$$

where e has a logistic distribution.

From Equation (5-3), the probability that Actor 1 forms a tie with Actor 3 is

¹⁰ For more details on this statistical process, please see Train (2009).

$$\Pr(X(x_{1,3} = 0 \rightarrow 1)) = \exp[\beta_1 \cdot \text{outdegree}(X(x_{1,3} = 0 \rightarrow 1)) + \beta_2 \cdot \text{reciprocity}(X(x_{1,3} = 0 \rightarrow 1))] / \sum_{X' \in C(X)} \exp(\beta_1 \cdot \text{outdegree}(X') + \beta_2 \cdot \text{reciprocity}(X')). \quad (6)$$

Because the actor-driven model assumes that an actor makes only one change in her ties at a time, the possible changes that Actor 1 can make are: 1) no changes, 2) terminate her tie to Actor 2, and 3) form a tie to Actor 3. Therefore, the probability in Equation (6) becomes

$$\Pr(X(x_{1,3} = 0 \rightarrow 1)) = \exp[\beta_1 \cdot \text{outdegree}(X(x_{1,3} = 0 \rightarrow 1)) + \beta_2 \cdot \text{reciprocity}(X(x_{1,3} = 0 \rightarrow 1))] / \{ \exp[\beta_1 \cdot \text{outdegree}(X(\text{no change})) + \beta_2 \cdot \text{reciprocity}(X(\text{no change}))] + \exp[\beta_1 \cdot \text{outdegree}(X(x_{1,2} = 1 \rightarrow 0)) + \beta_2 \cdot \text{reciprocity}(X(x_{1,2} = 1 \rightarrow 0))] + \exp[\beta_1 \cdot \text{outdegree}(X(x_{1,3} = 0 \rightarrow 1)) + \beta_2 \cdot \text{reciprocity}(X(x_{1,3} = 0 \rightarrow 1))] \} \quad (6-1).$$

When $x_{1,3}$ becomes 1, the size of the outdegree of Actor 1 is equal to 2 ($x_{1,2} = 1$ and $x_{1,3}=1$) and the number of reciprocated ties that Actor 1 has with other actors is 1 ($x_{1,3}=1$ and $x_{3,1}=1$). Similarly, when $x_{1,2}$ changes from 1 to 0, the size of the outdegree for Actor 1 is 0 ($x_{1,2} = 0$ and $x_{1,3}=0$) and the number of reciprocated ties that Actor 1 has with other actors becomes 0. Finally, when Actor 1 does not make any change, the size of her outdegree is 1 and the number of her reciprocated ties is 0. Thus, the probability in Equation (6-1) becomes

$$\Pr(X(x_{1,3} = 0 \rightarrow 1)) = \exp(\beta_1 \cdot 2 + \beta_2 \cdot 1) / [\exp(\beta_1 \cdot 0 + \beta_2 \cdot 0) + \exp(\beta_1 \cdot 1 + \beta_2 \cdot 0) + \exp(\beta_1 \cdot 2 + \beta_2 \cdot 1)].$$

Similar to the log-odds ratio used in a multinomial logit model (see Train, 2009), the log-odds ratio of two probabilities for choosing certain alternatives, say p and q , becomes

$$\log(\Pr_{jp} / \Pr_{jq}) = \sum_k \beta_k s_{k,j}(X_p, Z) - \sum_k \beta_k s_{k,j}(X_q, Z), \quad (6-2)$$

which is obtained using Equation (5-3). □

Variables included in an objective function are determined by researchers based on related theories and prior studies (Snijders, 2009; Snijders et al., 2010). Because the objective of this study is to test whether ‘game genre preference’ homophily and ‘game genre preference’ and ‘gaming frequency’ social influence processes operate among casual game players in the sample, variables representing those homophily and social influence processes are included in the model. In addition, other variables that have been recommended by prior studies of homophily and social influence (e.g., Pearson et al., 2006; Snijders, 2009; Steglich et al., 2010) are included. Those variables are outdegree, reciprocity, and gender homophily. The objective function used in this study is

$$f_j(X, Z) = \beta_1 \cdot \text{Outdegree}_j + \beta_2 \cdot \text{Reci}_j + \beta_3 \cdot \text{gender_hp}_j + \beta_4 \cdot \text{Genre_hp}_j + \beta_5 \cdot \text{Fre_assi}_j + \beta_6 \cdot \text{Genre_assi}_j + \text{error}. \quad (7)$$

The variables in (7) are described in Table 5.

Variable	Functional form [$x(z)$ is an element of $X(Z)$, a matrix representing the new structure of the network (the members’ behaviors) that will be resulted from a change that actor j makes]	What to test
Outdegree [†] (<i>Outdegree_j</i>)	$\sum_h x_{j,h}$	Extent to which game players in the sampled network make connections with other Kongregate players in the network
Reciprocity ^{††} (<i>Reci_j</i>)	$\sum_h x_{j,h} \cdot x_{h,j}$	Extent to which the ties between game players in the sampled network are reciprocated
Gender homophily (<i>Gender_hp_j</i>)	$\sum_h \left\{ x_{j,h} \left(1 - \frac{ z_{js} - z_{hs} }{2} \right) \right\}$, where z_{js} is a variable representing actor j ’s gender	Extent to which game players in the sampled network tend to make more connections with other players of the same gender than with the opposite gender

[†] Outdegree of an actor is the number of ties directed from the actor to other actors in the social network.

^{††} When actor 1 has a tie to actor 2 and vice versa, the tie between actor 1 and 2 is said to be reciprocal.

<Table 5 Variables included in the actor-driven model of this study>

Table 5 (cont'd)

Game genre homophily (<i>Genre_hpj</i>)	$\sum_h \left\{ x_{j,h} \left(1 - \frac{ z_{jp} - z_{hp} }{2} \right) \right\}$, where z_{jp} is a variable representing actor j 's genre preference	Extent to which game players in the sampled network tend to make more connections with other players who like the same game genre than with those who like different game genres
Gaming frequency social influence (<i>Fre_assij</i>)	$\sum_h \left\{ x_{j,h} \left(1 - \frac{ z_{jf} - z_{hf} }{Fre_max} \right) \right\}$, where z_{jf} is a variable representing actor j 's gaming frequency and Fre_max is the maximum number of that the frequency variable can take	Extent to which the gaming frequencies of game players in the sampled network tend to become more similar to those of their Kongregate friends in the network over time
Game genre social influence (<i>Genre_assij</i>)	$\sum_h \left\{ x_{j,h} \left(1 - \frac{ z_{jp} - z_{hp} }{2} \right) \right\}$, where z_{jp} is a variable representing actor j 's genre preference	Extent to which game players in the sampled network more frequently play the game genres that their Kongregate friends play over time

2.2 Data collection

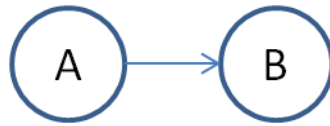
Panel data on relational ties among randomly selected 2,488 game players on Kongregate and their gaming behaviors were collected over two time periods (May and August, 2012). The original sample was composed of 15,627 players who were playing games on Kongregate at the time of data collection in May, 2012. But I decided to study a subset of the sample, which was composed of game players who had at least one tie with other game players in the sample because it is more appropriate for studying how a game player's gaming behavior changes over time due to the influence of her friends¹¹. There were 2,488 players who had at least one friend in the original sample. This does not mean that other players who are not included in this study did not have any Kongregate friends. That they were excluded from the dataset only means that they did not have any Kongregate friends in the sample.

The following data were collected in each time period for the same individuals.

¹¹ It is possible that a player's gaming behavior is influenced by other Kongregate friends who are not included in the sampled dataset or others who are not Kongregate game players. As recognized by a number of scholars (e.g., Steglich et al., 2006; Kadushin, 2010), however, this is one of limitations of social network analysis resulted from the infeasibility of studying the influence of all the people connected to an individual on the person's behavior.

- *list of each game player's Kongregate friends*
- *each game player's game genre preference*
- *each game player's gaming frequency*

On Kongregate, a player can connect to another player by clicking a 'friend' button linked to the player. The player who is connected with another player is called a friend of the latter on Kongregate, which is referred to as 'Kongregate friend' in this study. Thus, the list of a player's Kongregate friends only includes those players the player made connections to, not those who made a connection to the player. For example, in Figure 6, player B is a Kongregate friend of player A, but not vice versa.



<Figure 6 A is connected to B, but B is not connected to A>

A game player's game genre preference at a given time period was measured by determining the game genre that the game player played most frequently during the one week before the data collection time. In this study, I only looked at the four game genres that were most popular among the casual gamers on Kongregate¹² during the data collection period. They are 'Multiplayer,' 'Defense,' 'Puzzle,' and 'Shooter.'

As a proxy of gaming frequency, the number of days a game player played games on Kongregate during the week before the data collection time was counted. Here, whether a player played games on Kongregate on a given day is determined by whether the player obtained any game points on that day by playing games. Because it is possible that a game player obtains no points even if she plays a game, the measure of whether a player obtained any points by playing games on a given day is a proxy for whether the player played a game on that day.

¹² These four genres were identified examining the genres of all the games released on Kongregate during one week time period in May, 2012 and their popularities.

3. Results

3.1 Descriptive results

I first start with the cross-sectional structural characteristics of the players in the sample in May and August. Table 6 shows the number of game players and the number of ties among the game players in May and August. As can be seen in Table 6, the numbers of game players are the same over time, because I studied the same players in the two time periods. The number of ties among the players in the sample increased from 7,386 in May to 8,194 in August. This implies that the number of newly formed ties among the 2,488 players in the sample was larger than the number of severed ties during this interval.

	# of nodes	# of ties
May	2488	7386
August	2488	8194

<Table 6 Structural characteristics of the sample in May and August>

Table 7 shows the number of male and female game players among those in the sampled dataset who reported their gender. 892 players out of 2,488 did not disclose their gender. Among the 1,596 game players who disclosed their gender information, 1,327 were male (83%) and 269 were female (17%) game players.

male (%)	female (%)	No gender info (%)
1327 (53.3)	269 (10.8)	892 (35.9)

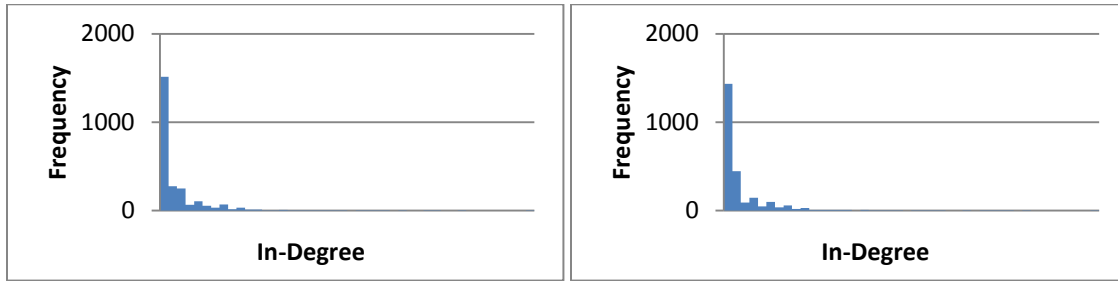
<Table 7 Numbers of male and female players reporting their gender>

Table 8 shows indegree¹³ information for the players in the sample in May and August, and Figure 7 shows the corresponding distributions of indegrees.

¹³ In social network analysis, indegree of a person refers to the number of ties directed to the person from others.

	min indegree	max indegree	mean indgree	median indegree
May	0	61	2.97	1
August	0	66	3.29	1

<Table 8 Information about indegrees in May and August>



<Figure 7 Distribution of indegrees in May (left) and August (right)>

Table 8-1 shows outdegree¹⁴ information for the players in the dataset in May and August. Because the values for the outdegree and indegree of a network are the same, their mean values are also the same. The distribution of outdegrees is omitted here due to its similarity to that of indegrees.

	min outdegree	max outdegree	mean outdgree	median outdegree
May	0	37	2.97	1
August	0	37	3.29	1

<Table 8-1 Information about outdegrees in May and August>

Table 9 presents descriptive statistics for players' gaming behaviors on Kongregate in May and August, 2013. Among the 2,488 sampled players, 1,547 game players (62.1%) acquired game points by playing games on Kongregate during the week before the data collection time in May, while 961 game players (38.6%) acquired game points during the week before the data collection time in August.

¹⁴ In social network analysis, the outdegree of a person refers to the number of ties directed from the person to others.

	# of players who acquired game points (%)	# of players who acquired game points from <i>multiplayer</i> games	# of players who acquired game points from <i>defense</i> games	# of players who acquired game points from <i>puzzle</i> games	# of players who acquired game points from <i>shooter</i> games
5/19 ~ 5/25	1547 (62.1)	614	457	507	882
8/11 ~ 8/17	961 (38.6)	323	297	554	305

<Table 9 Descriptive results of gaming behavior>

3.2 Findings for homophily and social influence processes

The estimates for the Equation (7) parameters are reported in Table 10.

Variable		Coefficient	SE	p-value
Outdegree		-4.0051	0.1600	0.000
Reciprocity		4.2674	0.1077	0.000
Homophily	Gender	0.1418	0.2963	0.632
	Frequency	-0.3927	0.2839	0.167
	Multiplayer	0.2750	0.7861	0.726
	Defense	-0.1015	0.5784	0.861
	Puzzle	0.0273	0.3093	0.930
	Shooter	-0.0566	0.4244	0.894
Social influence	Gaming frequency	0.1426	0.0928	0.124
	Multiplayer	0.0746	0.2501	0.765
	Defense	0.1706	0.1718	0.321
	Puzzle	0.1514	0.1183	0.201
	Shooter	0.1235	0.2584	0.633

<Table 10 Statistical estimates for Equation (7)>

The negative coefficient value for the ‘outdegree’ variable and its statistical significance implies that a relational connection between game players in the dataset tends to be avoided unless there are other desirable properties to the connection such as reciprocity and gender homophily. For the example presented in Figure 5, the negative coefficient value of the ‘outdegree’ variable means that the value of the objective function of an actor of the network, say j , in Figure 5 is larger when she terminates an existing tie with another actor than when she forms a new tie. But this does not mean that all the existing

ties in the sampled network will be terminated over time because the coefficient value of a parameter in an actor-driven model represents the marginal effect of the corresponding variable holding the effects of other variables fixed. The coefficient values in Table 10 are used to calculate the log-odds ratio of the probabilities of choosing different alternatives, which is similar to that in multinomial response models. To illustrate, I apply the estimates for the outdegree and reciprocity variable coefficients in Table 10 to the example described by Figure 5. When the value for the coefficient for the ‘outdegree’ variable (β_1 in Equation (4)) is ‘- 4.0051’ and that of the parameter for the ‘reciprocity’ variable (β_2 in Equation (4)) is 4.2674, the ratio of the probability of Actor 1 in Figure 5 forming a new tie with Actor 3 and the probability of Actor 1 terminating her tie with Actor 2 is

$$\begin{aligned} & \Pr(X(x_{1,3} = 0 \rightarrow 1)) / \Pr(X(x_{1,2} = 1 \rightarrow 0)) = \\ & \exp[\beta_1 \cdot \text{outdegree}(X(x_{1,3} = 0 \rightarrow 1)) + \beta_2 \cdot \text{reciprocity}(X(x_{1,3} = 0 \rightarrow 1))] / \exp[\beta_1 \cdot \text{outdegree}(X(x_{1,2} = 1 \rightarrow 0)) + \\ & \beta_2 \cdot \text{reciprocity}(X(x_{1,2} = 1 \rightarrow 0))], \end{aligned}$$

which is obtained from Equation (4).

Then, the log-odds ratio of $\Pr(X(x_{1,3} = 0 \rightarrow 1)) / \Pr(X(x_{1,2} = 1 \rightarrow 0))$ becomes

$$\begin{aligned} & [\beta_1 \cdot \text{outdegree}(X(x_{1,3} = 0 \rightarrow 1)) + \beta_2 \cdot \text{reciprocity}(X(x_{1,3} = 0 \rightarrow 1))] - [\beta_1 \cdot \text{outdegree}(X(x_{1,2} = 1 \rightarrow 0)) + \\ & \beta_2 \cdot \text{reciprocity}(X(x_{1,2} = 1 \rightarrow 0))] = (\beta_1 \cdot 2 + \beta_2 \cdot 1) - (\beta_1 \cdot 0 + \beta_2 \cdot 0) = \beta_1 \cdot 2 + \beta_2 \cdot 1 = -3.7428. \end{aligned}$$

Thus, we have

$$\Pr(X(x_{1,3} = 0 \rightarrow 1)) / \Pr(X(x_{1,2} = 1 \rightarrow 0)) = \exp(-3.7428) = 0.0237.$$

This means that when Actor 1 in Figure 5 has an opportunity to make a change in her ties, the probability of terminating her tie with Actor 2 is higher than that of forming a new tie with Actor 3. The value of the log-odds ratio of two probabilities varies with the current state of the network that the actor faces.

The positive coefficient for the ‘reciprocity’ variable with its statistical significance indicates that game players in the sampled network tend to have reciprocated ties with other game players in the dataset. In other words, if another player is connected to a player, then the player is also likely to make a connection to the one connected to her, which leads to a reciprocal tie between the two players. Similar to the case of the outdegree variable explained above, the value of an actor’s objective function is larger when she has one more reciprocal tie than when she terminates an existing reciprocal tie. The effect of the positive coefficient value for the ‘reciprocity’ variable on the log-odds ratio of the probabilities of choosing different alternatives can be calculated in an analogous way to that for the ‘outdegree’ variable described above.

The absolute values for the coefficients of outdegree and reciprocity variables in Table 10 are similar. But this does not mean that the numbers of outdegree ties and reciprocal ties created were also similar. 808 new outdegree ties and 410 reciprocal ties were created between observation periods. We can also find that the magnitudes of the coefficients for outdegree and reciprocity variables are larger than those of the coefficients of other variables in the table. This relationship is similar to what has been found in previous studies (e.g., Pearson et al., 2006; Steglich et al., 2006).

The coefficient values for the variables related to homophily processes are not statistically significant. This suggests that there were no homophily tendencies for any of the homophily variables examined with the possible exception of frequency, for which the *p*-value is small enough that it cannot be dismissed out of hand.

Table 10 also presents the statistical estimates for the social influence variables for gaming frequency and genre preferences. The coefficient value for the ‘gaming frequency social influence’ variable is only marginally significant, but its positive sign means that a player’s gaming frequency becomes more similar to that of her friends over time. With respect to genre preference social influence, the coefficients for all

genre preference social influence variables are positive, although their statistical significances vary. The coefficient values for the ‘Defense’ and ‘Puzzle’ social influence variables are larger than those of the other social influence variables and their p -values are relatively small.

4. Discussion

In this section, I discuss the main results presented in the preceding section.

It was found that game players in the sample tend to have reciprocal ties, which means that once a player is friended by another player, then the former is also likely to make a connection to the latter. This finding along with the negative ‘outdegree’ variable coefficient suggests that even though casual game players are not likely to initiate connections to other game players unless there other desirable properties to those new connections such as homophily, once they have been connected by other players, they are likely to make connections to those players who first made connections to themselves as well.

The coefficient values for most of the variables for homophily process among game players in the sampled network with regard to gaming frequencies and genre preferences were not statistically significant except for that of the ‘frequency’ homophily variable. The ‘frequency’ homophily variable has a negative coefficient, which means that a player is more likely to form a tie with another player when the other player’s gaming frequency is different from hers than when it is similar. Players who play more frequently also tend to have more points and possibly more advanced skills. If a large portion of the new ties created between the data observation periods were created by game players with low point counts, less skilled players seeking tips from more skilled players could explain the negative coefficient.

I found that a player’s gaming frequency tends to become similar to that of her friends over time, which suggests that social influence affects gaming frequency. Genre preference social influence processes were found to vary with the kind of game genre. There were more statistically significant and stronger genre

preference social influence processes for ‘defense’ and ‘puzzle’ games than for ‘multiplayer’ and ‘shooter’ games.

5. Conclusion

In this study, I examined homophily and social influence processes with respect to game genre preferences and gaming frequencies among online casual game players. The results suggest that there might not be strong homophily and social influence processes operating among the game players in the sampled network.

In this study, panel data on game players’ relational ties with other game players and their gaming characteristics were collected during two different time periods with a 3-month interval. But it is possible that the 3-month interval is too short or too long for the homophily and social influence processes examined in this study to be observed among online casual game players. Thus, in the future research, different time intervals should be tried.

One of the limitations of this study, which is also one of the common shortcomings of social network analysis is that it is possible that a game player in the sampled network might be influenced by players outside of the sampled network. As recognized in other social network research (e.g., Steglich et al., 2006; Kadushin, 2010), the changes in the behaviors of a member who belongs to a particular network cannot be entirely explained by the influence of the other members in the same network, because the changes in their behaviors must have been caused by the influence of others outside of the network to some extent if they have friends outside the network. But this limitation is an inevitable in social network analysis because the scope of a social network study is confined to a specific social network that is a subset of its members’ social connections.

CHAPTER 4

Abstract

Although many studies point out the important influence of the number of times a product has been consumed previously on an individual's adoption of the product, how the effect of the number of times a product has been consumed previously on adoption is influenced by other types of information about the product has not been much studied. This study examines how the effect of the number of times a game has been consumed previously on the number of times the game is consumed on a particular day is influenced by word-of-mouth on the game. In addition, I also consider the possible effect of the location where information about a game is displayed. For this, I use panel data on 83 online casual games that have been collected from an online casual games portal site, Kongregate.com. With regression analyses, I find the effect of the number of times a game has been consumed previously on the number of times a game is consumed on a particular day varies with WOM on the game. Average user ratings of a game and where information about a game is displayed on the website are also found to play important roles in predicting the number of times a game is consumed.

1. Introduction

Several studies have found that an individual's adoption of a media product is influenced by the number of times the product has been consumed previously (e.g., De Vany & Walls, 1996; Fu & Sim, 2011).

Because media products are experience goods, consumers cannot accurately estimate how much they will like a media product before consuming it. Therefore it is likely that an individual often faces uncertainty about the quality of a media product when she makes a decision whether to consume or acquire it. This existence of uncertainty suggests that an individual's decision whether to consume or purchase a media product may be influenced by how many times the media product has been previously consumed, because the volume of prior consumption might reflect the quality of the product (De Vany & Walls, 1996; Fu & Sim, 2011).

For many web services, an individual can easily find how many times a media product has been consumed. For example, Youtube displays the number of times a video has been viewed and on Kongregate, the number of times a game has been played is displayed next to the game. Conspicuous information about how many times a product has been consumed makes it possible for an individual's online media product choices to be influenced by the number of times products have been consumed previously (Metzger et al., 2010).

This possibility has been examined by researchers from several different disciplines, sometimes using different terms. For example, economists studied the phenomenon by developing economic models. Banerjee (1992) proposed a model of herd behavior for which “everyone does what everyone else is doing, even when their private information suggests doing something quite different” (p. 798). Similar to the herd behavior model, Bikhchandani et al. (1992, 1998) developed a model of information cascades. According to the authors, an information cascade occurs when “it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information” (Bikhchandani et al., 1992 p. 994). But the models of herd behavior and information cascade are based on strong assumptions, which make it difficult for those models to be employed in reality without relaxing those assumptions. For example, both models assume that a decision maker only observes the actions of preceding consumers, but s/he learns nothing directly about the quality of the product/service from them. But this assumption is unlikely to hold in reality. An individual can often easily learn about how other consumers who have already consumed a product evaluated the product through word-of-mouth (WOM).

Some scholars used the term ‘bandwagon effect’ to describe the phenomenon of an individual's likelihood of adopting a product increasing with the number of times the product was adopted previously (e.g., Bass, 1969, Simon, 1954, Fu & Sim, 2011). Similar to herd behavior and information cascade, a

bandwagon is more likely to occur when an individual has little information about a product, and thus faces uncertainty about the quality of a product (Simon, 1954, Fu & Sim, 2011).

Even though several scholars have identified the number of times that a product has been consumed as an important factor that influences an individual's decision whether to consume it, only a small number of studies have empirically examined whether an individual's product choice is influenced by how many times the product has been consumed previously. Examples include Vany and Walls (1996), Walls (1997), and Fu and Sim (2011).

Furthermore, few of these prior empirical studies examined how the effect of the number of times that a product has been consumed on an individual's adoption of the product varies with other types of information about the product to which the individual has been exposed. If an individual acquires other information about a product, then the effect of the number of times a product has been consumed on an individual's product choices can be influenced by such additional information. For example, an individual can easily observe how others have evaluated a product on the Web through average user ratings and user reviews. Such additional information may alter the effect of the number of times a product has been consumed on product choices may be influenced by such additional information.

Fu and Sim (2011)'s study is an example of those studies that have examined how the effect of the number of times a product has been consumed on an individual's adoption of the product may be moderated by other types of information. The authors examined how the effect of the number of times a video has been viewed on Youtube on an individual's decision whether to watch the video is influenced by pictorial previews and textual descriptions of the video.

In the present study, using empirical data on game adoptions of Kongregate players, I examine how the effect of the number of times a game has been consumed previously on the number of times the game is played on particular day is influenced by WOM on the game.

Along with the extent to which a product has been consumed previously, WOM itself has been found to influence a person's choice of media products. Word-of-mouth information refers to informal communications among consumers about a product or service (Liu, 2006). Studies that have examined the effects of WOM on a person's product choice say that WOM may convey information about a product's quality so that consumers are more likely to choose a product with positive WOM than a product with negative WOM (e.g., Mahajan, Muller, and Kerin 1984; Mizerski 1982; Liu, 2006). Because for some media products like movies and books, there is a strong positive correlation between the number of people who consume a product and the number of times the product is consumed, and it is easier to collect data on the number of times a product is consumed than data on the number of people who consume the product, prior studies that have examined effects of WOM in media industries focused on how the number of times a media product, especially movies and books, is consumed is influenced by the WOM on the product. For example, Liu (2006) studied the effects of WOM on a movie's theatrical performance and found important influence for WOM on a movie's box office revenues. Chevalier and Mayzlin (2003) examined the effects of WOM on the sales of a book on Amazon.com and found that sales were influenced significantly.

These studies of WOM did not take into account the possible effect of the number of times a product has been consumed previously on sales of the product and on the effect of WOM on sales of the product. If a consumer can easily observe both how many times a product has been consumed and WOM on the product, the consumer's product choices may be influenced by both the number of times the product has been consumed and WOM. If so, the effect of WOM about a product on an individual's product choices is likely to vary with the number of times the product has been consumed previously. Thus, it is important to study how the effect of WOM on individual's product choices varies with the number of times a product has been previously consumed.

Another factor that should be considered when studying the effects of the number of times a product has been consumed and WOM on an individual's online product choices is the location where information about a product is displayed on a website. This is because the location where information about a product is displayed on a website can influence the extent to which consumers become aware of the product (Granka et al., 2006) and becoming aware of a product is a necessary first step in the process of product adoption (Rogers, 2003). Thus, the number of people who consume a media product is likely to vary depending on where information about the product is displayed on a website, and this might alter the effects of WOM and the number of times a product has been consumed previously on an individual's product choices.

In this chapter, I examine how the number of times an online casual game is consumed on a particular day is influenced by the number of times the game has been consumed previously, by WOM on the game, and by where information about the game is displayed on the Kongregate site.

As a measure for the number of times an online casual game is consumed by game players on Kongregate, I use the number of times a game is accessed by players. That a game is accessed by a game player means that the game player connects to the game in order to play it. Once a player has connected to a game, a dedicated network connection between the player's device such as a PC and smartphone, and the computer server that hosts the game is established. Furthermore, the number of times a game has been accessed previously by game players can be observed by game players on Kongregate's site. Thus, a game player's decision whether or not to play a game on Kongregate can be influenced by how many times a game has been previously accessed by game players. It is highly likely that the number of times a game has been accessed by game players is not equal to the number of game players who have accessed the game, because it is possible that a game player has accessed the game more than once to play it. Nonetheless, the correlation between the number of times a game has been accessed by game players on a particular day and the number of game players who have accessed the game on that day might be strong

and positive in online casual games unless there is a high variation among players in how frequently they play the same game during a day.

As measures of word-of-mouth information, I use average user ratings and the number of user reviews. Several scholars have argued that average user ratings are good reflections of the valence of the word-of-mouth information about the product, and the number of user reviews is a good measure of the volume of word-of-mouth information (e.g., Dellarocas et al., 2007; Godes & Mayzlin, 2004; Liu, 2006).

Furthermore, prior studies of WOM found that average user ratings and the number of user reviews are important influences on how many times a product is consumed or purchased, because the average user ratings for a product reflect its quality (Liu, 2006) and the number of user reviews is likely to influence a consumer's awareness of the product (Godes & Mayzlin, 2004). Thus, it is also likely that a game player's game choice will be influenced by both average user ratings and the number of user reviews.

As found by Granka et al. (2006), the location where information about a product is displayed on a website can influence the extent to which the product is exposed to consumers who visit the site. For example, a product whose information is displayed on the first page of a website is more likely to be exposed to consumers who visit the website than a product whose information is displayed on other pages of the site, because it takes more effort to find information about a product whose information is displayed on the second or third page of the site. Thus, it is expected that a game whose information or image is displayed on the first page of the site is more likely to be exposed to game players who visit the site than a game whose information is displayed on other pages of the site. This suggests that a game whose information is displayed on the first page is likely to be played by more game players than a game whose information is displayed on other pages.

For this study, I only focus on games whose average user ratings are greater than or equal to 3.0 (out of 5.0), because games with average user ratings below 3.0 attract few players. I collected information about

all the new games whose average user ratings were greater than or equal to 3.0 that were released on Kongregate during a 3-week period, between May 10 and May 30, 2013 for the 14 days immediately following their initial placement on the site. For each game, the number of times the game was accessed by game players, average user ratings, the number of reviews, and whether information about the game was displayed on the first page of the site were recorded each day. For statistical analysis, I used pooled ordinary least squares (POLS) as a primary estimation method, and other methods such as fixed effects, random effects, and Arellano and Bond estimation methods were also tried.

2 Regression model and data

2.1 The regression model

The dependent variable for this regression model is the number of times a game is accessed by players on a particular day, say day t . To test whether the dependent is influenced by the number of times the game has been consumed previously, I include the number of times the game has been accessed by game players before day t as an independent variable. In addition, I include average user ratings of a game for the valence of WOM about the game and the number of user reviews on the game for the volume of WOM. I also include a variable indicating whether or not information about a game is displayed on the front page of the site on day t .

Other independent variables that can influence the dependent variable are also incorporated. Those variables are the genre of the game, whether or not rewards for completing game tasks are offered in the game, the day of the week of day t , and the number of days that have passed by day t since the game was released on the site. The genre of a game might influence the number of players who play the game, because some genres may attract more players than others. A binary variable representing whether or not rewards for completing game tasks are offered in the game is included, because game players' motivations to play a game may depend on whether rewards are offered in the game. The day of the week

of day t is included because the number of players playing games on the site may vary with the day of the week of a day. It is also possible that the number of games that are newly released on the site varies with the day of the week. For example, there might be more games released on Sundays than on other days. Finally, the number of days since the game was released is included because it is possible that a game's popularity increases or falls over time.

The basic regression model is specified as in Equation (1).

$$\begin{aligned} \#accesses_{g,t} = & \beta_0 + \beta_1 \cdot cum_ \#accesses_{g,t-1} + \beta_2 \cdot UR_g + \beta_3 \cdot cum_ \#reviews_{g,t-1} + \beta_4 \cdot FP_{g,t} + \beta_5 \cdot genre_g + \\ & \beta_6 \cdot reward_g + \beta_7 \cdot weekday_t + \beta_8 \cdot \#dayspassed_t + error_{g,t} \end{aligned} \quad (8)$$

The variables are defined blow.

- $\#accesses_{g,t}$: the number of times game g is accessed on day t .
- $cum_ \#accesses_{g,t-1}$: the cumulative number of times game g has been accessed up to day $t-1$.
- UR_g : the average user ratings of game g .
- $cum_ \#reviews_{g,t-1}$: the number of user reviews on game g up to day $t-1$.
- $FP_{g,t}$: A dummy variable for whether information about game g is displayed on the first page of the site on day t .
- $genre_g$: the genre of game g .
- $reward_g$: a dummy variable representing whether rewards are offered in game g .
- $weekday_t$: the day of the week for day t .
- $\#dayspassed_{g,t}$: the number of days that have passed by day t since game g was released.

Extension of the basic model

The basic regression model in (8) is extended in several ways. First, to test for possible non-linear relationships between the dependent variable and $cum_#accesses_{g,t-1}$, a model with squared and cubed terms for $cum_#accesses_{g,t-1}$ added is also estimated. To test whether the effect of $cum_#accesses_{g,t-1}$ on the dependent variable varies with UR_g , $cum_#reviews_{g,t-1}$, and $FP_{g,t}$, regression models containing corresponding interaction terms are estimated as well. Finally, I also include an interaction term for $cum_#accesses_{g,t-1}$ and $#dayspassed_{g,t}$ to test how the effect of $cum_#accesses_{g,t-1}$ on the dependent variable changes over time.

2.2 Data

For this study, I identified all the new games that were released on Kongregate during a 3-week period between May 10 (Friday) and May 30 (Thursday), 2013. As mentioned previously, among those new games, I focused on games whose average user ratings were greater than or equal to 3.0 (out of 5.0), because for games whose average user ratings were smaller than 3.0, the number of new game players who start to play them over time is very small. This also means that the statistical results obtained using the data on these games cannot be generalized to games whose average user ratings are smaller than 3.0. The number of games examined in this study is 83. Data for all variables were recorded every day for 14 days after each game's release on Kongregate.

Descriptive data for the variables are reported in Table 11.

Avg. # of times a game was accessed per day during the first 14 days	Avg. # of times a game was accessed during the first 14 days	Avg. user ratings (out of 5.0)	Avg. # of user reviews per day during the first 14 days	Avg. # of user reviews during the first 14 days
2,019.8 (4802.7)*	28,481.4 (54,978.4)	3.43 (0.28)	5.1 (14.3)	77.0 (144.9)

* The numbers in the parentheses are standard deviations.

<Table 11 Descriptive data for the games examined in this study>

2.3 Statistical estimations

In this chapter, I estimate the model in Equation (8) using a pooled ordinary least squares (POLS) estimation method. Because the model in Equation (8) is a panel model, other estimation methods such as fixed effects (FE), the Arellano and Bond method (1991), and random effects (RE) were considered as well. None of these methods are without liabilities. POLS provide consistent estimates if there is no omitted variable problem, while the others pose clear consistency problems for this model because it is evident that the consistency assumptions of those methods are violated by this model. POLS is used as a primary estimation method, but the model in Equation (8) is also estimated with FE and RE robustness checks. The Arellano and Bond method is not used for reasons explained below. Below, I explain in model detail why I chose POLS over the other two methods to estimate the model in Equation (8) and used the others to check robustness.

1) Pooled ordinary least squares (POLS) estimation

With POLS we can generate consistent estimates for the model in Equation (8), unless there is an omitted variables problem. An omitted variables problem arises when there is an explanatory variable(s) which is omitted in the model that is correlated with one or more other explanatory variables. This causes bias in statistical estimation of the model, because the error term in time t is correlated with explanatory variables in time t . For Equation (8), it is possible that there are some time-invariant omitted variables that are correlated with both some of the independent variables, especially those of particular interest ($cum_#accesses_{g,t-1}$, UR_g , and $cum_#reviews_{g,t-1}$), and with the dependent variable. An example is the difficulty level of a game. It is likely that the difficulty level of a game influences both the number of times a game player plays the game and user ratings of the game. But, it is not clear that the difficulty level of a game is correlated with the number of players who access the game. Furthermore, the fact that most of online casual games offer different difficulty levels that a player can choose (e.g., easy, medium,

and hard) would make it more difficult to evaluate the correlation between the difficulty level of a game and the number of people who access the game to play it. At any rate, because difficulty cannot be measured, it cannot be included in the model.

There may be other such omitted variables. The choice to use POLS as the primary estimation method was a choice of a method with unknown consistency problems over methods with known consistency problems.

When there are time-invariant omitted variables that influence the dependent variable, it is possible that error terms in different times are correlated. For this reason, I use the heteroskedasticity robust version of standard errors for statistical estimates.

2) Other possible estimation methods

Here, I discuss fixed effects (FE), random effects (RE), and Arellano and Bond estimation methods.

2-1) Fixed effects (FE)

If there are unobserved time-invariant explanatory variables in a panel model whose omission makes the error term correlated with one or more explanatory variables in the model and leads to bias in POLS estimation of the model, then FE estimation might be a good way to address possible correlation between the error term and explanatory variables by eliminating the effects of the unobserved time-invariant explanatory variables in the model. But, the presence of $cum_#accesses_{g,t-1}$ in the model in Equation (8) is a problem for FE estimation because the dependent variable in time t influences $cum_#accesses_{g,s}$, for $s > t$. This causes the error term in time t to be correlated with an explanatory variable in time s . This violates the strict exogeneity assumption required for FE estimation to have consistent estimates.

2-2) The Arellano and Bond estimation method

For a panel model with an explanatory variable whose future values are influenced by the dependent variable today, as in Equation (8), the Arellano and Bond estimation method can be used to eliminate the effects of unobserved time-invariant explanatory variables whose omission creates correlation between explanatory variables and the error term. Even when the future values of an explanatory are influenced by the dependent variable today, the Arellano and Bond estimation method can generate consistent estimates if a sequential exogeneity assumption is satisfied. This requires that explanatory variables in the past be uncorrelated with the current error term. But because of certain characteristics of the estimation method, it cannot generate consistent estimates of Equation (8).

First, because the method employs first-differencing to eliminate the effects of unobserved time-invariant variables, explanatory variables representing time effects, such as the number of days that have passed since game g was released on the site, cannot be included in the model. This omission of the ‘number of days that have passed since game g was released on the site’ variable will create a serious endogeneity problem that leads to inconsistent estimates of the main explanatory variables, $\ln_cum_accesses_{g,t-1}$ and $cum_reviews_{t-1}$, because the ‘number of days that have passed’ variable is highly correlated with both $\ln_cum_accesses_{g,t-1}$, $cum_reviews_{t-1}$, and the dependent variable.

Second, the Arellano and Bond method can be used for a model that has an explanatory variable whose future values are influenced only by limited past values of the dependent variable so that it can find proper instrument variables. In model (8), however, the sum of all the times a game was accessed in the past is used as an explanatory variable, which means the value of $cum_accesses_g$ in time t is influenced by all the values of the dependent variable between time 1 and time $t-1$. This makes it difficult to find proper instruments for the Arellano and Bond estimation method.

2-3) Random effects (RE)

When it is likely that there exist time-invariant omitted variables in a panel model, and the focus of statistical estimation is on the efficiency of statistical estimates of model parameters, random effects (RE) estimation method can be used. But for consistent estimates of model parameters, the RE method requires much stronger assumptions for the correlation between independent variables and the error term than their counterparts for POLS. Those are 1) orthogonality between independent variables in the model and the time-invariant omitted variables, 2) strict exogeneity for the error term, that is, the error term in time t is not correlated with independent variables in time s , where $t \neq s$. In addition to the possibility that some omitted variables are correlated with the independent variables in the model, as explained for FE, the model in Equation (8) violates the strict exogeneity assumption of RE method because the dependent variable in time t influences $cum_#accesses_{g,s}$, when $s > t$.

3. The POLS estimates

The statistical estimation results of the model in Equation (8) are reported in Table 12. It turns out that cubic and quadratic terms of $cum_#accesses_{g,t-1}$ did not contribute much to improving the model fit (p -value for the contribution of the cubic term to improving the model fit is 0.896 and that for the contribution of the quadratic term is 0.904). Thus they were excluded from the final regression, the results for which are reported in Table 12.

DV: $\#accesses_{g,t}$: the number of times game g is accessed on day t

Variable	Coef.	Std. Err.	t	P>t
$cum_ \#accesses_{g,t-1}$	-0.411	0.077	-5.35	0.000
$cum_ \#accesses_{g,t-1} \cdot UR_g$	0.134	0.017	8.01	0.000
$cum_ \#accesses_{g,t-1} \cdot cum_ \#reviews_{g,t-1}$	0.00013	0.00005	2.91	0.004
$cum_ \#accesses_{g,t-1} \cdot FP_{g,t}$	-0.018	0.015	-1.20	0.232
$cum_ \#accesses_{g,t-1} \cdot \#dayspassed_t$	-0.009	0.002	-4.84	0.000
UR_g	1939.041	427.649	4.53	0.000
$cum_ \#reviews_{g,t-1}$	0.781	3.991	0.20	0.845
$FP_{g,t}$	6533.194	1106.787	5.90	0.000
$reward_g$	968.643	2790.287	0.35	0.726
$\#dayspassed_t$	-105.682	19.453	-5.43	0.000
cons.	-5048.919	1330.945	-3.79	0.000
Model fit	$R^2 = 0.663, F(23, 1055) = 34.65, p < 0.001$			

$N = 1079$, $\#accesses_{g,t}$: number of times game g is accessed on day t , $cum_ \#accesses_{g,t-1}$: cumulative number of times game g has been accessed up to day $t-1$, UR_g : average user ratings of game g , $cum_ \#reviews_{g,t-1}$: number of user reviews on game g up to day $t-1$, $FP_{g,t}$: whether information about game g is displayed on the first page of the site on day t , $reward_g$: whether rewards are offered in game g , $\#dayspassed_{g,t}$: number of days that have passed by day t since game g was released

<Table 12 POLS estimates for Equation (8)>

To save space, the results of genre and day of the week related variables, which are 15 in total, are not reported in the table. The contribution of genre related variables to the model fit was statistically significant ($p = 0.007$), whereas that of day of the week related variables was statistically insignificant ($p = 0.942$).

Let us first see the effect of $cum_ \#accesses_{g,t-1}$ on the dependent variable, $\#accesses_{g,t}$. Because the model in Equation (1) contains some interaction terms of $cum_ \#accesses_{g,t-1}$ and other independent variables (UR_g , $cum_ \#reviews_{g,t-1}$, $FP_{g,t}$, and $\#dayspassed_t$), the marginal effect of $cum_ \#accesses_{g,t-1}$ is a linear function of those other independent variables. Due to its statistical insignificance, the interaction term for $cum_ \#accesses_{g,t-1}$ and $FP_{g,t}$ is not included in the equation above. The marginal effect of $cum_ \#accesses_{g,t-1}$ on the dependent variable is

$$-0.411 + 0.134 \cdot UR_g + 0.00013 \cdot cum_ \#reviews_{g,t-1} - 0.009 \cdot \#dayspassed_t \quad (9)$$

Equation (9) shows that the marginal effect of $cum_#accesses_{g,t-1}$ varies with the values of UR_g , $cum_#reviews_{g,t-1}$, and $\#dayspassed_t$. In order to see the average marginal effect of $cum_#accesses_{g,t-1}$, I plug the average values of UR_g , $cum_#reviews_{g,t-1}$, and $\#dayspassed_t$, which are 3.43, 54.7, and 7 respectively, in the sample into (9), giving an average marginal effect of ‘- 0.0059’. The marginal effect of $cum_#accesses_{g,t-1}$ can be both negative and positive depending on the values of UR_g , $cum_#reviews_{g,t-1}$, and $\#dayspassed_t$.

The positive coefficient values of the interaction terms for $cum_#accesses_{g,t-1}$ and WOM related variables (UR_g and $cum_#reviews_{g,t-1}$) show that the marginal effect of $cum_#accesses_{g,t-1}$ increases as the values of UR_g and $cum_#reviews_{g,t-1}$ increase, while the negative coefficient value for $cum_#accesses_{g,t-1} \cdot \#dayspassed_t$ shows that the marginal effect of $cum_#accesses_{g,t-1}$ falls with time from the date of release.

The marginal effect of UR_g on the dependent variable is $1939.041 + 0.134 \cdot cum_#accesses_{g,t-1}$. The statistically significant coefficient value for $cum_#accesses_{g,t-1} \cdot UR_g$ indicates that the marginal effect of UR_g varies with the value for $cum_#accesses_{g,t-1}$. But, different from the case of the marginal effect of $cum_#accesses_{g,t-1}$, the direction of the marginal effect of UR_g does not change with the value of $cum_#accesses_{g,t-1}$. The marginal effect of UR_g on the dependent variable increases as the value of $cum_#accesses_{g,t-1}$ increases. On the other hand, the marginal effect of $cum_#reviews_{g,t-1}$ was found to be positive and increase with the value of $cum_#accesses_{g,t-1}$ ($cum_#accesses_{g,t-1} \cdot cum_#reviews_{g,t-1} = 0.00013$, $p = 0.004$).

Finally, the number of times a game was accessed by players on a particular day was found to be influenced by whether information about the game was displayed on the first page of the site on the day (The coefficient value of $FP_{g,t}$ is 6533.194, $p < 0.001$). A game whose information was displayed on the

first page was more likely to be accessed by players than a game whose information was displayed other pages of the site.

4. Robustness checks

As a robustness check, the model in Equation (8) was also estimated by fixed effects (FE) and random effects (RE) methods. The RE estimates are not reported here because the coefficients are the same as those in Table 12. That the RE coefficients are the same as those of POLS indicates the estimate of the standard deviation of the unobserved individual heterogeneity in the RE estimation is either zero or negative, which makes the variance matrix of the error terms diagonal. According to Wooldridge (2010), if the variance matrix of the error terms is diagonal, it is because the RE assumption that the variance of the unobserved individual heterogeneity is not correlated with independent variables has been violated. The FE estimation results are reported in Table 12-1.

Variable	Fixed effects		
	Coef.	t	p
$cum_#accesses_{g,t-1}$	-1.363	-19.24	0.000
$cum_#accesses_{g,t-1} \cdot UR_g$	0.346	18.92	0.000
$cum_#accesses_{g,t-1} \cdot cum_#reviews_{g,t-1}$	0.00009	4.38	0.000
$cum_#accesses_{g,t-1} \cdot FP_{g,t}$	-0.031	-3.79	0.000
$cum_#accesses_{g,t-1} \cdot \#dayspassed_t$	-0.003	-3.10	0.002
UR_g	dropped	-	-
$cum_#reviews_{g,t-1}$	-0.003	-0.00	0.999
$FP_{g,t}$	5774.4	11.79	0.000
$reward_g$	10236.1	9.82	0.000
$\#dayspassed_t$	36.860	1.81	0.070
cons.	2448.094	10.71	0.000
Model fit	$R^2 = 0.49$		

<Table 12-1 FE estimates for Equation (8)>

Time invariant variables (e.g., UR_g) were dropped from the model because FE eliminates all the time invariant variables. FE coefficients for $cum_#accesses_{g,t-1}$ and its interaction terms have the same signs as

those in Table 12, although their values are either larger or smaller, and the p -value of the FE estimate for $cum_#accesses_{g,t-1} \cdot FP_{g,t}$ is smaller than its counterpart in Table 12. Similar to Table 12, the FE estimate for UR_g is positive and increases with $cum_#accesses_{g,t-1}$. The FE estimate for $FP_{g,t}$ also shows that presenting information about a game on the first page significantly influences the number of times the game is accessed on the day. The FE estimate for $reward_g$ is statistically much more significant than the POLS estimate in Table 12, although they have the same sign.

Two FE estimates have opposite signs from those in Table 12. First, the FE estimate for $cum_#reviews_{g,t-1}$ is negative whereas the variable's POLS estimate is positive. But both FE and POLS estimates for the variable are statistically insignificant (p-values for the FE and POLS estimates are 0.999 and 0.845, respectively). The FE estimate for $#dayspassed_t$ is positive, different from the negative POLS estimate for the variable. Because it is common to include dummy variables for time instead of a continuous variable, I also estimated Equation (8) with FE by including time dummy variables for the number of days that passed after a game's release instead of $#dayspassed_t$. The contribution of those time dummy variables to improving the model fit was not statistically significant (p-value was 0.573). The fact that the signs and significance for time variables varied with model specification suggests either that time passed alone does not influence adoption decisions or that further work is needed to more confidently identify its effect.

5. Discussion

In this subsection, I discuss the main results reported in Section 3. First, I found that the effect of an increase in the number of times a game has been accessed previously on the number of times the game is accessed on a particular day varied with the average user ratings and the number of user reviews on the game. When a game has high average user ratings and a large number of user reviews, an increase in the number of times a game has been accessed previously positively influences the number of times the game is accessed on a particular day. But when a game has low average user ratings and a small number of user

reviews, the effect of the number of times the game has been accessed previously can be negative. This result suggests that occurrence of a choice bandwagon is influenced by WOM.

Second, average user ratings were found to play an important role in predicting the number of times a game is accessed on a particular day. An increase in the average user ratings of a game leads to more game accesses on a particular day, the larger the number of times the game has been accessed previously. This suggests that a game player may think that the average user ratings of a game better represents the game's quality when the game has been accessed by more game players.

As suggested by prior studies that have examined the effects of the location where information about a product is displayed on the product's sales (e.g., Granka et al., 2006; Resnick & Albert; 2013), whether or not information about a game is displayed on the first page was found to play a role in predicting the number of game player who start to play the game on a particular day. This suggests that game players are more likely to play a game whose information is displayed on the first page than a game whose information is displayed elsewhere, perhaps because game players more likely to become aware of a game whose information is displayed on the first page than a game whose information is displayed elsewhere and being displayed on the first page might signal the quality of a game.

6. Summary and conclusion

In this study, I first identified the main limitations of prior studies that have examined the effect of the number of times a product has been consumed previously and that of WOM on an individual's product choices, which are 1) most studies did not examine their simultaneous effects, and 2) a location variable where information about a product is displayed on the Web was not included for statistical estimation. To address these limitations, I examined the effects of the number of times a product has been consumed previously and WOM using data collected from Kongregate with a location variable taken into account.

In this study, I found that when a game has positive WOM, a choice bandwagon is more likely to occur than when a game has negative WOM. I also found that the valence of WOM (average user ratings) plays an important role in predicting the number of times the game is accessed and its role becomes more important the more the game has been accessed previously. The effect of the number of user reviews on the number of times a game is accessed was found to vary with the number of times the game had been accessed previously. Where information about a game was displayed on the website was found to play an important role in predicting the number of players who started to play the game on particular day.

Because characteristics of consumers and their consumption behaviors might vary across different online settings, for future studies, it is recommended that the same research questions addressed in this chapter be examined using data for other online services such as Amazon.com or Youtube.com where people visit to consume media products or other types of media products.

CHAPTER 5 CONCLUSION

Although many people interact with others and consume various products and services on the Web, and there are a number of theories that emphasize the importance of interpersonal influence on an individual's product choices, not many studies have examined how online friends, which are defined as people with whom an individual interacts on the Web, influence an individual's online product choices. Using data on game players' game choices, gaming behavior, and their relationships and interactions with other game players on Kongregate, I studied how a player's Kongregate friends can influence her game choices and gaming behavior.

In Chapter 2, I examined whether the number of a player's Kongregate friends who adopted a game earlier is associated with the likelihood that the player adopts the game. For this, I developed two separate models; a discrete choice model and a hazard model. With the discrete choice model, I studied how the number of a player's Kongregate friends who adopted a game before the player's first visit to Kongregate after the game's release is associated with the likelihood that the player adopts the game. With the hazard model, I examined how the number of a player's Kongregate friends who adopted a game before a particular day, say day t , is associated with the likelihood that the player adopts the game on day t .

I also considered the effect of the strength of ties between a player and her Kongregate friends who adopted a game earlier on the likelihood that she adopts the game. In this study, the strength of a tie between two players was measured by whether or not the tie was reciprocal.

I found that the number of a player's Kongregate friends who adopted a game earlier and the strength of the tie between the player and her prior adopter Kongregate friends had little impact on the likelihood that the player adopted the game and the tie.

In Chapter 3, I examined whether a player tends to form more connections with other Kongregate players who like the same game genres as herself, and whether a player's genre preferences and gaming frequencies become more similar to those of her friends over time. In order to address these research questions, I used the actor-driven model developed by Snijders (1999, 2001) with panel data on game activities for 2,488 game players on Kongregate. The results suggest that game genre preference homophily, and game genre preference and gaming frequency social influence processes might not be influencing the players in the sample.

In Chapter 4, I examined whether the number of times that a game was accessed by players on a particular day was influenced by the number of times that the game has been previously accessed by game players, by WOM on the game, and by whether information about the game was displayed on the first page of Kongregate's site. User ratings and the number of user reviews were used as measures of WOM.

I found that the effect of the number of times a game had been accessed previously on the number of times the game was accessed on a particular day varied with WOM. I also found that a game's average user ratings had a positive effect on the times the game was accessed on a day. The number of times a game was accessed by players on a particular day was found to be influenced by whether information about the game was displayed on the first page of the site on that day.

This dissertation tried to extend our understanding of interpersonal influence on individuals' online product choices by focusing on the online casual games industry. The ways in which online casual game players interact with other players and influence them may be different from the ways in which individuals interact and influence each other in other online contexts. Therefore, answers to the research questions posed in this dissertation may be different for other online contexts. It is recommended that the same research questions be addressed for other online contexts in the future.

Because this dissertation addressed three different research questions in a fixed amount of time, the size of the sample used for each research question was somewhat limited. In particular, the number of games examined in Chapter 2 was only two. Thus, in future studies, it is recommended that a larger sample be used to address each research question so that the external validity of the study can increase.

Although I attempted to address a few research questions related to online interpersonal interactions and influence, there are other important research questions that should be addressed to extend our understanding of online interpersonal interactions and influence. For example, several studies have found that the structural characteristics of a social network influence the speed with which information about a new product or issue spreads among its members and the ways in which they respond to the information in offline settings (e.g., Easley & Kleinberg, 2010; Valente, 1995, 2010; Jackson, 2010). It is also possible that the ways in which information about a product or an issue spreads in an online social network and the ways in which members of an online social network respond to the information may vary with its structural characteristics. Future studies should ask how the structural characteristics of online social networks influence the ways in which information about a new product or service spreads among their members and how they respond to the information.

One of the questions on which this dissertation focused was whether a player's Kongregate friends influence her game choices. But I did not ask why an individual's online product choices are influenced by her online friends. There may be multiple reasons why an individual's product choices are influenced by her online friends. For example, as the theory of planned behavior (Ajzen, 1991) suggests, an individual's product choices can be influenced by others because they influence the person's attitude towards a product. Or as the peer influence theory (Deutsch & Gerard, 1955) suggests, an individual's product choices can be influenced by others because a person wants to create a favorable image with others by mimicking their buying behaviors. Thus, future studies of online interpersonal influence on

product choices should also study why an individual's online product choices are influenced by her online friends.

Another important question that should be asked when studying interpersonal influence on product choices is how personal characteristics affect who is more or less likely to be influenced by others. For example, an individual's susceptibility to interpersonal influence is one of the factors that can affect the extent to which an individual's product choices are influenced by others. Bearden et al. (1989) found that product choices of a person who is more susceptible to peer influence are more likely to be influenced by her friends. It might be interesting to ask whether the extent to which a person's online product choices are influenced by her online friends varies with the person's susceptibility to interpersonal influence or other personal attributes.

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