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The effect of direct network externality on user's preference in the platform economy

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The effect of direct network externality on user's preference in the platform economy

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Abstract

The effect of direct network externality on user's preference in the platform economy

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In our society, the industrial economy has been mainstream; however, the platform economy has also started to become mainstream since the 2000s, with the development of the Internet. In the industrial economy, network externality was important only for the network's base industry. However, in the platform economy, people are connected to others—even to strangers—and, thus connectivity with others is an important aspect of the platform economy. Thus, researchers have actively conducted studies on the network externality of a platform. However, there is no unanimity on either the criteria for classifying the platform types or the definition of network externality. As it is necessary to define the network externality in a platform economy, this dissertation investigates the role of network externality in a platform economy.

The emergence of the two-sided market has created the new economy. This new

economy is called as the network economy and the digital economy. However, it is more appropriate to call it a platform economy because it is an economy that develops around platforms. A platform economy can be defined as “an economy based on network externality that connects users who do not know each other to improve users’ utility.” It can be achieved by cyclical value creation in the platform economy. Especially, the consumers motivation to use the platform is important to create cyclical value creation. In the platform economy, it is important that people obtain the use information of other users; this can meet the consumers’ desire to get more reliable information.

This dissertation suggests that the study of platform economics needs to focus on the needs of consumers. It considers the importance of network effects while emphasizing the importance of function integration; this is because the other studies on the platform economy have been focusing on the firm. Consumers' desire to eliminate information asymmetry lets them use the other users’ use information as new information. This is an extension of studies focusing on signaling theory and screening theory, as part of the effort to solve information asymmetry in information economics. Based on social learning theory, consumers are beginning to accept others’ use information as new information. Thus, the platform types could be categorized with two dimension based on the users’ needs; the degree of interaction with people, and the degree of functional integration. Then, empirical analyses are conducted on three platforms. After investigating the effects of different direct network externalities, the sellers’ efficiency is investigated when the direct network externality increases. Finally, the measured direct

network externality effect is considered as one of the product's characteristics.

The first study uses structural equation modeling (SEM) to investigate whether the number of other consumers affects consumers' utility when there is a high degree of interaction among people on the platform. It reveals not only the difference between the two types of network externalities (peers and the total number of users) on the social platform that have been studied indiscriminately, but also shows that this difference varies according to their perception of the quality of life.

The second study considers whether the increase in the sellers' efficiency is influenced by the number of consumers when there is a medium degree of interaction with people and functional integration on the platform. This study uses meta-frontier analysis (MFA) to examine the impact of the network externality on sellers' utility, taking into account the technical efficiency of sellers. When sellers use the platform, it ensures that they are exposed to a large number of consumers which makes them profitable, besides compensating for the cost and technical effort involved in using the platform.

Network externality increases not only the utility of consumers by increasing the number of consumers, but also the utility of sellers. Then, would it influence a user's preference? The final study examines whether people can be influenced by other users' use information even if they use a technology, in which there is no connectivity. Despite the importance of network externality in the platform economy, network externality has not been considered as a characteristic of a product when conducting acceptance analysis by using conjoint analysis. Therefore, the effect of network externalities on consumer

preference is examined in this study. Autonomous vehicles are a representative technology with high degree of functional integration. In this study, network externality is the most important among the various features of autonomous vehicles. In other words, it can be seen that securing the network externality is important for the autonomous vehicle enterprise. However, if there is no technical certification regulation, network externalities will be diluted. Hence, governments should set up regulations that will eliminate the risk of technology certification regulations for people. In addition, as consumers do not feel any difference between supporting autonomous driving and driving a fully autonomous car, 13% of them would buy an autonomous car within one year. Thus, the autonomous vehicle firms should implement a strategy that supports putting autonomous driving vehicles on the market as soon as possible to secure the users.

As a result, the network externality based on the number of consumers is important not only in terms of direct and indirect network externality, but also in users' preference. Owing to the emphasis on connectivity through the Internet, consumers are more likely to be affected by the network externalities of the total number of users rather than the external influences of their peers when choosing a product or service. In addition, uncertainty about the platform can be solved through network externalities. , The consumer perceives a risk owing to the absence of a technology certification standard; further, it dilutes the network external effects. This can be solved by governments setting the standards for technical certifications. Beyond eliminating uncertainty, network externality is the most important information about products that people perceive. Thus,

securing the number of consumers makes the seller more efficient on the platform as the platform becomes dominant. Therefore, it is important for platform operators to collect users to create an oligopoly. Although oligarchy is important for market stability, governments should set policies to help ensure that the oligopoly of large companies does not prevent the development of better technology.

Keywords: Platform, Social Learning Theory, Network Externality, Technology Efficiency, Structure Equation Model, Meta-frontier Analysis, mixed logit model

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Chapter 1. Introduction

1.1 Research motivation

Because of the information revolution, the traditional economy has begun to change. The new economy is assuming a prominent position in the economy and it differs from the industrial economy in having network externality. The network externality creates value by not following the rules that apply to the industrial economy; this is because the network externality resolves the problem of information asymmetry.

Since the Industrial Revolution, our economy has been an industrial economy; thus, economists' studies of the economy reflect its industrial characteristics. Achieving economies of scale was important in the industrial economy, which is populated with oligopolies, that is, a few large firms in the industry dominated their market (Shapiro & Varian, 1999). However, we have now entered the era of the network economy. In this economy, network externality is important and there is a temporary monopoly. The network economy is the emerging economic order within the information society. The name stems from a key attribute—products and services are created and value is added through social networks operating on large or global scales. (Shapiro & Varian, 1999) In a network economy, network externality is an important factor for products to survive in society (Figure 1-1). In industrial economies, value creation is linear, but in a platform economy, value creation is two-way and recursive.

Network externality was important only in a few industries, such as telecommunication, where the network was based in the industrial economy. However, now everyone and everything is moving toward connectivity based on the Internet. This is why many scholars are trying to understand this phenomenon. Most markets with network externalities are characterized by the presence of two distinct sides whose ultimate benefit stems from the interaction through a common platform (Rochet & Tirole, 2003). Usually, this economy is populated by temporary monopolies (Shapiro & Varian, 1999).

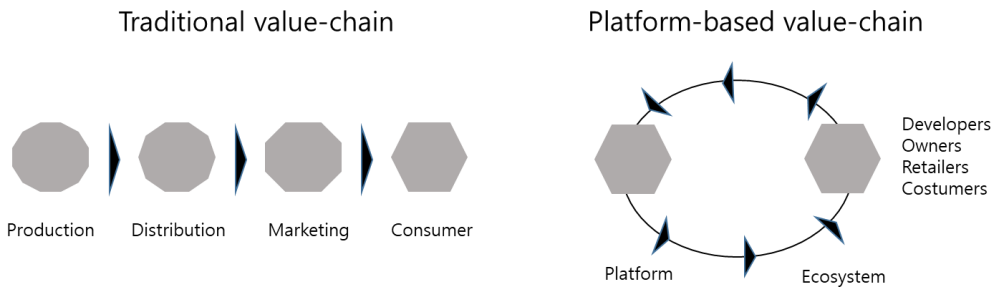


Figure 1-1 the different value creation

Platform-based economies that depend on network externality are called platform economies. The term platform economy was first used in the Harvard Business Review in April 2015, and is an extension of the network economy. It is an emerging type of economic environment arising from the digitization of fast-growing, multilayered, highly interactive, real-time connections among people, devices, and businesses.

Until now, the industrial economy is centered, but now the platform economy is leading the world economy. Table 1-1 shows the market value rankings in 2007; Apple, which created its own platform, is at the top position, followed by Google. Other platform companies, such as Amazon, Alibaba Group, Tencent, and Facebook, follow, in that order (Financial Times). Seven out of the top ten companies are a part of the platform economy.

Table 1-1 Rank change in market value (Financial Times)

Rank	2007	2010	2013	2017
1	PetroChina	Exxon Mobil	Apple Inc.	Apple Inc.
2	Exxon Mobil	PetroChina	Exxon Mobil	Alphabet Inc.
3	General Electric	Apple Inc.	Microsoft	Microsoft
4	China Mobile	BHP Billiton	Google	Amazon.com
5	ICBC	Microsoft	Berkshire Hathaway	Berkshire Hathaway
6	Microsoft	ICBC	General Electric	Alibaba Group
7	Gazprom	Petrobras	Johnson & Johnson	Tencent
8	Royal Dutch Shell	China Construction Bank	Wal-Mart	Facebook
9	AT&T	Royal Dutch Shell	Hoffmann-La Roche	ExxonMobil
10	Sinopec	Nestlé	Chevron Corporation	Johnson & Johnson

Research has focused on companies rather than consumers because there was no consideration of why network externality became important. However, to understand and suggest the future of the platform economy, a study centered on the consumer is important. There is too much information and users want to find reliable information. Based on the direct and indirect interaction with others, people are exposed to others' use information as the platform has been developing to gather the use information of other users. Thus, people consider the information about a product given by someone who is not an acquaintance as reliable information. Consumers take other users' use information from the online platform as information that affects their preferences. Because of this, increasing the number of users would not only play an important role in increasing the users' and sellers' utility, but also be essential for the early establishment of the technology.

In this light, a theoretical and empirical examination of the impact of network externality on consumer preferences in platform economics is very important.

1.2 Research purpose and outline

In this dissertation, the role of the network externality in the platform economy has been identified. This study suggests that the effect of others' use information on consumers' preference would be positive even if the platform provides low interaction with other users. Further, this study suggests that the platform should be classified according to the

degree of interaction with people, as well as the degree of functional integration, because the network externality is important from the consumers' perspective. The first study probes whether people's preferences depend on the number of users on a platform rather than the number of peers (hypothesis 1). The second study considers whether there is a change in the efficiency of sellers in a particular industry as the platform matures and secures the consumers (hypothesis 2). The third study enquires whether the number of users (penetration rate) plays an important role in solving technology uncertainty (hypothesis 3). Each study examines the hypotheses which are followed, respectively.

Hypothesis 1: the consumer's utility increases is influenced by the number of other consumers

Hypothesis 2: The increase in the efficiency of the seller is influenced by the number of consumers

Hypothesis 3: Even a technology that has no connectivity between people will be influenced by other users' use information.

This dissertation consists of 6 chapters with 3 essays (Figure 1-2). Chapter 1 introduces dissertation, and chapter 2 describes the theoretical background of this study based on previous studies and research framework. Chapter 3, 4, 5 discussed the results of three essays and policy implications. Finally, chapter 6 summarized this dissertation.

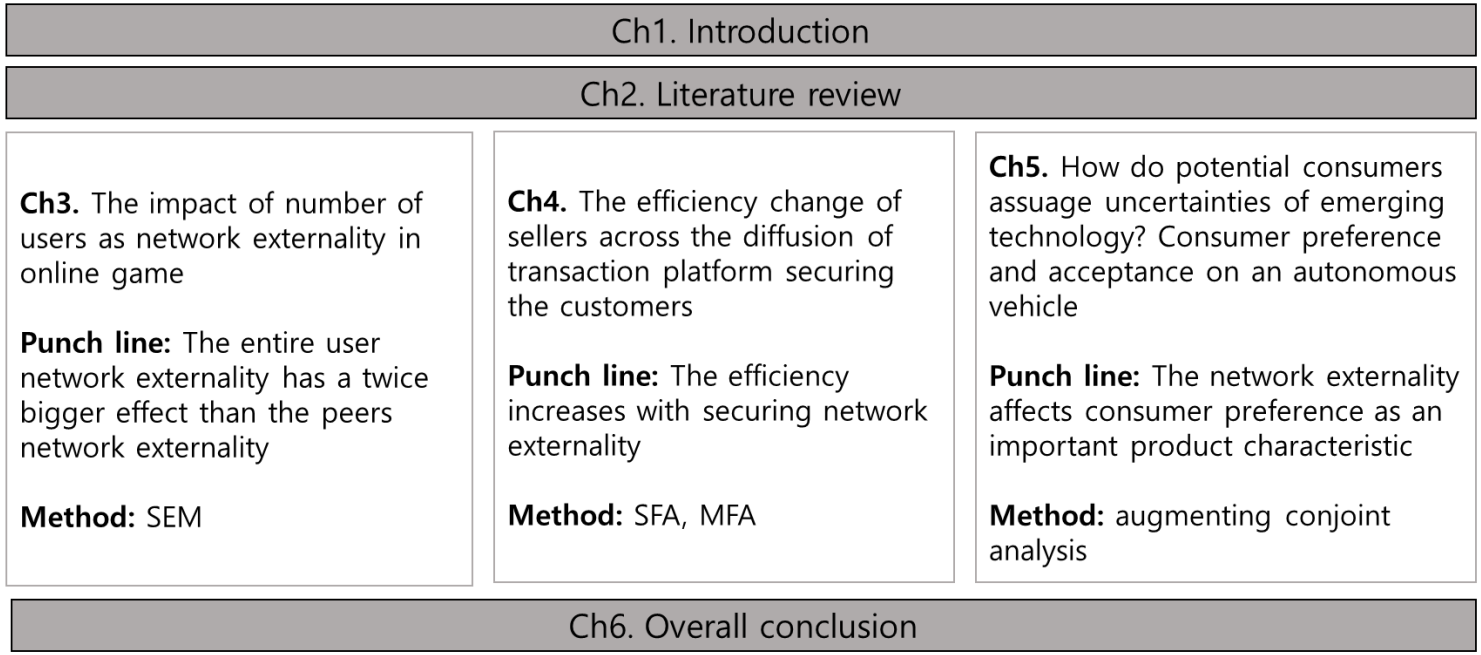


Figure 1-2 Thesis outline

Chapter 2. Network externality in the platform economy: A literature review and research framework

2.1 Introduction

The platform economy is an economy based on the concept of a two-sided market. This economy is also called the network economy and the digital economy. However, it is best to call it the platform economy because its characteristics are based on the connectivity provided through the platform. The platform economy can be defined as "an economy based on network externality that connects users who do not know each other to improve their utility”.

Network externality has played an important role in connectivity even before the platform emerged. In particular, the introduction of the concept of network externality in 1985 led to studies of the effect of network externality on the economy and society.

Since early 1999, researchers have been studying the characteristics of the platform economy. Since the 2000s, researchers have been studying the role of network externality in the main platform, such as social networking service (SNS). Since the late 2000s, research has actively been conducted on the impact of network externality on new products of the platform economy.

However, economists have been focusing on the platform operator and the firms' perspective, while there have been many attempts to understand the consumers' behavior through empirical studies. Thus, we first need to understand why network externality is important.

Based on the social learning theory, the use behavior of others can influence individual decision making. The effect of others' behavior on an individual's decision is more important because the development of the platform has made people more sensitive to others' use information. This means that other people's use information is recognized as important information about the product. Because of the instability of information, people are uncertain about the value of the information they have. Further, the individual wants to solve the uncertainty by considering the use of information by others. Thus, there is a possibility that network externality power in the platform economy is based on social learning theory, which states that people mimic others' behavior.

To study from the perspective of customers, the categorization of platform types should center on consumer needs. People use the platform to socialize and to get information at first. Nowadays, people want the platform to providing an environment similar to that available offline; this requires functional integration.

Therefore, this thesis suggests a dimension after considering the consumers' needs and investigates how the consumers' behaviors change according to network externality, as well as the development of platform.

Section 2.2 explains the background to explain why people have an urge to obtain the reliable information based on information asymmetry. The reason why network externality has become important is explained based on the social learning theory in section 2.3. Section 2.4 describes studies focused on firm-centered in platform economics and proposes the frame for categorizing platform types in the perspective of consumers. The empirical studies of network externality in platform economy as well as the limitation are categorized according to the proposed frame in this thesis in section 2.5 and section 2.6.

2.2 Importance of solving information asymmetry

The importance of information has begun to be emphasized in explaining economic phenomena since the 1970s. Scholars like F. Hayek have emphasized the importance of information in constructing economic theories. Traditionally, the core of economic theory is the competitive market economy theory, which can be summarized in three axioms: continuity of economic activity, convexity of economic conditions, and law of supply and demand. However, the traditional competitive market economy theory is limited to a specific theory in the sense that it is based on information assumption of complete information.

When the assumption of complete information is not established, various problems arising in each field of economic theory are presented (Stiglitz. 1985; Allen, 1990; Stiglitz,

2002). Stiglitz (2002) stated that there are two important factors in information asymmetry: Information about quality and intention. The information asymmetry in information about quality is important when a party do not have enough information about the characteristics of other parties. In the information on intention, asymmetry of information is important when a party worries about the intention of another party 's behavior or intention (Elitzur & Gavious, 2003).

Thus, the scholars have tried to solve information asymmetry. Especially, there are two main theories to solve the information asymmetry; screening and signaling. Screening is about inventing an appropriate device on the side where there is no information to induce the information of the other party as self-revealed (Stiglitz. 1975). The representative is insurance company's strategy by letting customers reveal their information as the insurance company providing several options to customers.

Signaling is first mentioned by Spence (Spence, 1974). When a person is disadvantaged because the other party does not know his / her own property, he / she is signaling actively about information of his / her property. For examples, there are several signaling such as a person seeking a job try to acquire a certification, a guarantee system for a company with a good quality product, and reputation with a recognized brand. In the case of Coca-Cola, the economic value is astronomical (Kreps & Wilson, 1982; Certo, 2003). The signaling mechanism is as follows (Connelly et al., 2011). There is a person, signaler, who sends a signal to show his information and the receiver receives it. And the receiver interprets the signal and sends feedback to the signaler.

Asymmetric information increases transaction costs. As the society is complicated, transaction costs increase so that the market economy can never achieve efficient resource allocation as well as the participants should pay more as much as transaction costs. Thus, the market economy has devised and implemented a device that not only has the property to expand the range of transactions that benefit each other, but also eliminates the factors that impede such transactions. With the development of the Internet, an online platform has emerged which allows users accessibility to the other users use information. Eventually, users' preference is affected by the information of other users (Figure 2-1).

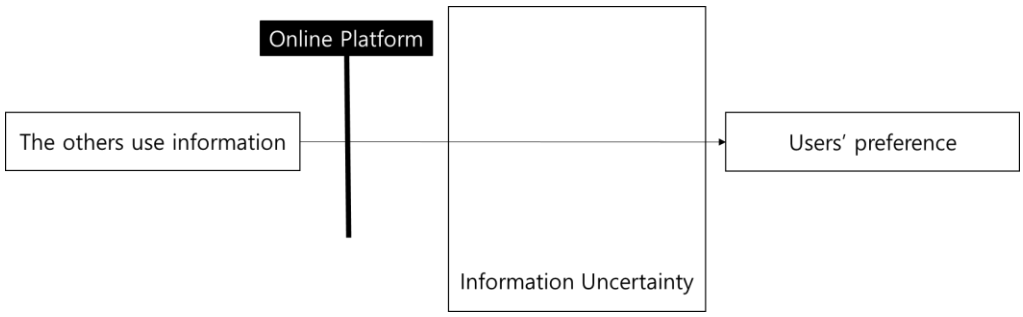


Figure 2-1 applying social learning theory in information uncertainty

2.3 Network externality

2.3.1 Social learning theory in the concern of network externality

Based on the social learning theory (SLT), individuals' behavior and thoughts are determined by observing others' use behavior (Bandura, 1971). "What other people think" has been always an important piece of information for most of us during the decision-making process. Long before the World Wide Web became widespread, people asked their friends to recommend a product or introduce a lawyer. However, the Internet and the Web have now made it possible to find out about the opinions and experiences of those in the vast pool of people that are neither their personal acquaintances nor well-known professional critics.

Indeed, according to two surveys of more than 2000 American adults each in 2008 (Horrigan, 2008), 81% of Internet users (or 60% of Americans) have done online research on a product at least once. And among readers of online reviews of restaurants, hotels, and various services (e.g., travel agencies or doctors), between 73% and 87% report that reviews had a significant influence on their purchase. Moreover, consumers report being willing to pay from 20% to 99% more for a 5-star-rated item than a 4-star-rated item (the variance stems from what type of item or service is considered).

Moreover, the interest of users showed as online opinions about products and services potentially influences vendors as users are paying more and more attention on the

products with increase in users (e.g., Rochet & Tirole (2003), Armstrong (2006), Armstrong & Wright (2007), Caillaud & Jullien (2003), and Parker & Van Alstyne (2005)). That is why the online platform has been developed to provide the organizing the users use information.

However, SLT has been focused on mainly based on vertical identification and horizontal identification when celebrity affects consumer behavior. In other words, there were many studies on how the decision of celebrities affects individual's choices. A typical example is that people's concerns, perceived risk, and sexual behavior have changed after Magic Johnson has been tested for HIV (Brown & Basil, 1995). In addition to this, the influence of celebrity through identification is significant in changing consumer behavior (Cohen, 2001; Hoffner & Buchanan, 2005; Cohen, 2006; Natarajan *et al*., 2018). The media campaign with celebrity is important to the behavior of consumers (Basil, 1996; Cohen, 2001; Fleck et al., 2012).

Based on interaction with strangers, consumers now think of other people's product use information as a feature of the product (Godes *et al*., 2005; Trusov *et al*., 2009; Chen & Xie, 2008; Park *et al*, 2007). Instead of accessing information only through mass media, the general public can share their opinions in the social network site such as facebook. In addition, information about the product can be obtained from a review of the online site selling the product or from the information sharing site. As celebrity's expertise, trustworthiness played an important role (Amos *et al*., 2008; Eisend & Langner, 2010; Jin & Phua, 2014), the review that the general public leaves after using the product builds

trustful information about the product (Karakaya & Ganim Barnes, 2010). This is also called word-of-mouth, which consumers have perception about the brand through social media communication (Schivinski & Dabrowski, 2016). As the number of consumers on the same side increases, the quality of these assessments improves (Melián-González, 2013). These evaluations can be an important element in addition to the price that people consider important (Ku, 2012). In other words, trustful information provided by the users in the same side is more important than identification.

Even though the other users use information is trustful, the information was not only diminishing over distance and time but also only effective within limited social contact boundaries (Bhatnagar & Ghose 2004; Ellison & Fudenberg 1995). It means that people who live far apart could not affect each other. Thanks to the internet and the development several platforms such as online social network sites drive the transmission of information as overcoming the traditional limitations (Laroche *et al*., 2005). With the growing availability and popularity of opinion-rich resources such as online review sites and personal blogs, people can obtain the product review information by other users.

SLT could be applied beyond the limits of time and distance, even to those who do not know each other personally. As people begin to accept other users use information as an information through the platform. In a system for purchasing goods online, other people's information affects their preference for goods. Beginning with viewing other people's usage information through the rating system and viewing the reviews directly, it determines the consumer's preference for a particular product (Chevalier & Mayzlin,

2006; dellarocas, 2003; Yang & Mai, 2010). It is said that there is a network externality that affects consumers' preferences based on reviews (Saito & Matsubayashi, 2018).

2.3.2 Network externality

Network externality means that one user of a good or service has on the value of that product to others. When a network externality is present, the value of a product or service increases according to the number of others using it (Katz & Shapiro, 1985). A typical example is an increase in network externality as the number of telephone users increases. Let's suppose there are two telephone companies; A and B. When the telephone company A has 100 people and the company B has 5 people, people will choose A because of the cost of connecting from B to A. However, most telephone companies do not use this strategy nowdays. Thus, an even easier example is the instant messaging service. Let's suppose there are two different instant messaging services apps; A and B. If 100 of my friends use A and another 5 of my friends use B, I will use A. But now it gets complicated. Because 5 people using B cannot communicate with those who use only A, I have to use B inevitably. It can be the B's strategy to survive. Even if there are more users in A, there is possibility of an increase in B users by satisfying a few. Moreover, those who use B inevitably could think B is better in terms of technical aspect and user interface. Eventually, if the more users prefer to use B, then those using A would be able to move to use B. However, B should can bear the cost while users move from A to B. Thus, the

number of users is important eventually.

Network externality has a significant effect on technology adoption. In 1992, banks studied ATM adoption (Saloner & Shepard, 1992). ATM machines allow customers to visit geographically close. As a result, the bank can increase the network size of the bank by allowing the ATM machine to cover a large area.

For the telecommunications industry, researchers also conducted network externality studies (Majumdar & Venkataraman, 1998). Since electronic switching technology is much more efficient, telecommunication firms have changed from electromechanical switching technology to electronic switching technology in the 1970s. The industry itself is based on the network itself so that the network externality was important.

Network externality begins to become more important as technology develops because of the influence of network externality as it connects both sides. The two-sided platform is beginning to play an important role in the market as online development has facilitated Internet access (Rochet & Tirole, 2003).

There are two types of network externality: indirect network externality and direct network externality. Indirect network externality exists when the utility of a product increases with the greater availability of compatible complementary products. In other words, increase in the number of the one side leads the other side's utility. Direct network externality exists when the utility of consumer increases as the number of consumers increases. The scholars have insisted that indirect network externality is the key factor in two-sided market (Rochet & Tirole, 2003; Evans, 2003)

With the advent of IT, the usefulness of technology products for end-users depends on complementary software and services. In order for a consumer to feel the value of a product, a computer needs a software, a camera needs a film, and a DVD player needs a program that can display a movie. A requirement for a hardware product that is mediated by the supply of complementary software is called as an indirect network externality. Indirect network externalities occur bi-directionally and eventually hardware and software manufacturers must work together (Gupta *et al*., 1999).

In the platform economy, network externality is pivotal as interrelation between technologies increases. The technology has network externality when the user considers the value of the technology higher as the number of users increase. Direct externality exists when a consumer's utility is directly affected by the consumption behavior of other consumers using the same goods or services (ie, not through price changes) through the market. The two- sided market is a market in which there is a special form of network externality. Externalities in the two-sided market are not only externality existing among users belonging to the same group but also externality arising from consumption behavior of users belonging to different groups. In other words, the utility of one side of the user is directly influenced by the number of users or consumption of the other side.

Network externality, which promotes more than two interactions among customers, makes many of the formulas created for traditional enterprises over the past century do not apply to platform companies. Traditional economics argues that selling products below cost does not yield revenue. The new platform economics, however, show that

companies can earn profit theoretically rather than selling products above cost (Evans & Schmalensee, 2016).

However, if the platform secures not enough users, the platform could not be survived. Platforms can only survive if both users increase. For example, YouTube tried to increase the number of videos posted and the number of videos watched. In the end, increasing the value through network externality means securing the number of users. Therefore, it is necessary to secure the customers to survive the platform.

2.4 Platform economy

2.4.1 Characteristics of platform economy

Before the on-line platform, people have gathered on a specific platform to do business that suits their needs. With the development of the Internet, Match making has become more important (Evance & Schmalensee, 2016). The basic attributes of the platform are the connections between needs and needs (Roth, 2015).

To succeed, platforms in industries such as software, portals and media, payment systems and the Internet, must “get both sides of the market on board.” Accordingly, platforms devote much attention to their business model, that is, to how they court each side while making money overall. Table 2-1 shows that platforms often treat one side as a profit center and the other as a loss leader.

Table 2-1 Illustrations of existing business models (rochet & tirole, 2003)

Product	Loss leader/break-even segment/subsidized segment	Profit-making segment/ subsidizing segment
	Software	
Video games	consumers (consoles)	software developers
Streaming media	consumers	servers
Browsers	users	Web servers
Operating systems (Windows; Palm, Pocket PC)	application developers (development tools, support, functionality, . . .)	clients
Text processing	reader/viewer	writer
	Portals and media	
Portals	"eyeballs"	advertisers
Newspapers	readers	advertisers
(Charge-free) TV networks	viewers	advertisers
	Payment systems	
Credit and differed debit cards (Visa, MasterCard, Amex, . . .)	cardholders	merchants
Online debit cards	merchants	cardholders
	Others	
Social gatherings	celebrities in social happenings	other participants
Shopping malls	consumers (free parking, cheap gas)	shops
Discount coupon books (Want Advertiser)	consumers	merchants
(Legacy) Internet	Web sites	dial-up consumers
Real estate	buyers	sellers

In the industry economy, the scale of economy is dominant, but in the platform economy, network externality plays an important role (Shapiro & Varian, 2013). Unlike the competition in an existing industry whose goods carry production costs, the success of a platform whose product (information) costs almost nothing to produce is decided based on network externality; the value of a platform increases as the number of participants on both sides increases (Rochet & Tirole, 2003).

Looking at the earnings of major companies, the S & P 500, over the past decade, the

overall net income of the S & P 500 companies has increased by 16%, while the net income of platform companies in the S&P 500 has increased 330% (Moazed, 2017 and Yardeni *et al*., 2017). 25 years later, according to Moazed (2017), 50% of the overall S&P 500 companies' net income will come from platform companies.

The network economy is the emerging economy within the information society. The name stems from a key attribute; products and services are created and value is added through social networks operating on large or global scales (Shapiro & Varian, 2013).

Platform economy is an emerging type of economic environment arising from the digitization of fast-growing, multilayered, highly interactive, and real-time connections among people, devices, and businesses. The term platform economy was used by Harvard University in 2014. There are companies like Amazon, Facebook, and Uber that are involved in a variety of our activities. We are in the midst of reorganizing the economy in the early days of the Industrial Revolution, where platform owners with greater power than factory owners had power (Kenney & Zysman, 2016). These digital platforms have a variety of functions and structures.

Scholars try to explain the new economy with several terms: network economy, digital economy, and platform economy. The scholars who call this economy as network economy defines based on the characteristics of network. Kelly (1998) clams that value in the network economy is created and shared by all members of a network rather than by individual companies and that economies of scale stem from the size of the network. An open system is preferable to a closed system because the former typically have more

nodes for building value flows from connectivity. Networks are also blurring the boundaries between a company and its environment (Boyett & Boyett, 2001). In the perspective of society, on the other hand, Benkler (2006) insists that communication and information are the most important cultural and economic outputs of advanced economies.

Tapscott (1997) explains the digital economy that is supposed to allow free accessibility of information and facilitate knowledge transfer across borders to different people. According to Mesenbourg (2001), there are three main components of the 'Digital Economy' concept can be identified: e-business infrastructure (hardware, software, telecoms, networks, human capital, etc.); e-business (how business is conducted, any process that an organization conducts over computer-mediated networks); e-commerce (transfer of goods, for example when a book is sold online).

However, the author believes that this new economy is an economy based on platform, so it is appropriate to call it platform economy because “platform” itself draw the easy information accessibility in the perspective of users.

The main difference between the platform economy and the industrial economy is due to network externality expansion. In the two-sided market mediated by platform, the traditional industrial theory does not apply so that it needs modification especially, due to the indirect network effect. For example, in the two-sided market, the Lerner condition is not established at the optimal price, and the optimal price may be lower than the marginal cost because inducing the one side customers with no fee would profit for the other side users.

Representatively, Rochet & Tirole (2003, 2006) stated that a two-sided market consists of two characteristics: network externality and different price policy. If a market is a two-sided market, Coase's theorem does not hold in that market. And pricing in the two-sided market does not meet the Lerner condition, and the profit maximizing price does not depend on the marginal cost. As a strategy to form a critical mass, both sides are encouraged to participate in the platform and set a different price for both sides.

By defining the aggregate demand as the product of the demand for each side, the user of each side regards the deal with all users on the other side. In practice, it is common for users on each side to do business with some of them, rather than on all other users. For example, in a dating club, a man wants to date one girl. Even in the case of a video game console, the user of the game buys only some of the games. Therefore, the demand function of Rochet & Tirole can be regarded as the maximization of cross-network externality. Platform operators' pricing in the two-sided market does not meet the Lerner condition, and the profit maximizing price does not depend on the marginal cost.

According to Evans (2003) and Evans & Schmalensee (2008), following three conditions are proposed as the requirements of the two-sided market. First, there must be two or more distinct groups that require interconnections. Second, the larger the customer group on the other side, the higher the utility. Third, it is impossible to directly deal with own efforts, so transactions must be made using platform because of high transaction costs

Demand for one side (eg, side A) is not sensitive to own price, it is inelastic while it

can become sensitive to self-price if cross-network externality exists between the two sides (Evans, 2003). Even if the price increase on the side A reduces the amount of demand on the side A (or the number of the customers) by a small amount, this greatly reduces the demand on the side B (or the number of customers) due to the cross network externality so that the demand (or the number of customers) of the side A is greatly reduced by the cross network externality. Therefore, the optimal price setting depends on the strength of the cross-network externalities. This implies that "network externalities" and "pricing characteristics" are closely linked in the two-sided market. As the cross-network externality of the side B on the side A increases, the price of the side B decreases and the price of the side A increases (Parker & Van Alstyne, 2002; Schmalensee, 2002). Therefore, sometimes the price charged on one side becomes negative, or subsidy may be paid.

Kenney & Zysman (2016) claims that platform is provoking reorganization of a wide variety of markets, work arrangements, and ultimately value creation and capture. And digital platforms facilitated by key technologies such as the cloud, including digital marketplaces such as Amazon and Internet firms such as Google and Facebook, are restructuring ever more parts of the economy platforms themselves then generate or organize the work of others by providing the digital locations for the connections that organize work and other activities.

Based on the other scholars' studies, platform economy can be defined as an economy in which the efficiency of people is enhanced by increasing the connectivity by matching

resources or people who have not been connected before the emergence of a specific platform. And the characteristics are followings: Network externality explains "value creation is two-way and recursive" in platform economy; the consumer's utility is influenced by the number of other consumers; the increase in the efficiency of the seller is influenced by the number of consumers; with the advent of the platform, the optimal price depends on the consumer's utility influenced by the number of consumers.

The phenomenon in the new economy is based on the platform and the characteristic of each markets based on the platform can be categorized. Moreover, the rapid information technology development leads the connectivity through the digital platform in unprecedented speed so that the importance of the platform is getting greater. Begin with the platform emergence, the society started to change but now we are facing the society system change.

In 1942, economist Joseph Schumpeter explained the consequences of innovation in the market economy (Schumpeter, 2013):

The process of industrial transformation constantly destroys the old system, constantly creates new systems, and constantly innovates the economic system from within. This process should be seen in the perennial gale of creative destruction.

The innovations destroy the old system. From the Internet, the things started to connected. Nowadays, people search the information using the Internet but not the

encyclopedia or books. Using the Internet gives us efficiency by reduction of costs and money. If the new technology makes the consumer rational and maximizes the utility, the new one will replace the old one (Davis, 1989; Rogers, 2010, Venkatesh *et al*., 2003).

The difference between a one-sided company and a platform company is clear. The one-sided company purchases various inputs from suppliers and makes them into finished products, and sells them to customers as goods or services. One-sided firms focus on selling on the premise that they can attract customers to earn money. On the other hand, a multi-faceted platform should attract customers by enabling more than one type of customer to interact with them under attractive conditions. The most important input to the multi-platform is usually the customer (Evans & Schmalensee, 2016).

Let’s suppose there is a one-sided company, A. The company will look for the right price for itself and confirm one fact. In order to make money, the price must be set above the marginal cost, which is the increment of the total cost required to produce one additional unit of product. A company cannot earn a clear penny that it has given away the product for free.

This is not the case for a multifaceted company. They can give a group of participants free-of-charge and even make money with paying for them. For example, Google has never charged people for search but Google's market capitalization reached $ 527 billion on November 20, 2015. Google sells ads to companies that want to grab the attention of the search engines and make almost all of their earnings.

The basic concept of this two-sided platform can be seen briefly as follows. By

joining the platform of two groups of customers, it is both sides. Platform participants all have the option to find partners through the platform. When making this choice, the consumer will find a place where the more sellers of the information or the service and vice versa.

2.4.2 Firm centered platform economy

The platform economy should consider not only the efficiency of the platform provider but also the utility of the seller and the consumer. In addition, two-sided market researchers say that direct network externality is not an important factor in the two-sided market. As the new economics scholars say, considering the importance of connectivity to others, direct network externality is an important factor in platform economics.

Research has been actively conducted to examine the effect of network externality on the platform. Both YouTube and Amazon share the same ability to share information as a platform, but their motivation to share is different. If so, it is necessary to distinguish the platform through specific criteria. The division of the platform type have been done in various ways to suit various research purposes.

Wright (2004) describes various examples of the two-sided market. The following examples are listed. Mediating platform is such as journal (author and reader) or airport (Suppliers and bidders), B2B market (enterprise suppliers and business users), automobile market. Flea market, shopping mall (buyer and seller), chatline (chatting participant),

married matchmaker (men and women), conferences (presenter and listener), commercial phone book, publishers (readers and authors), quality certifications providers (students and universities, investors and companies), and real estate agents (buyers and sellers). A credit card payment system platform and a platform associated with the advertisement such as magazine, newspaper. TV and Web portals (information / entertainment users and advertisers), search engines (searchers and websites). And the platform associated with entertainment platform.

Evans (2003) classified three types as follows. The first is a market maker that plays a role of connecting the two parties who wish to trade with each other such as buyers and sellers. The second is an audience maker that connects advertisers and audiences. It is a demand-coordinator that serves to create goods or services that create externalities.

As shown in Figure 2-2, there are four main categories of platform types depending on collaboration and front end ICT investment (Smedlund, 2012). In addition, according to (Boudreau & Lakhani, 2009), platforms can be broadly divided into three categories: integrator platform, product platform, and two-sided platform. Examples of an Integrator platform include apple, and examples of product platforms are Amazon and Google's cloud computing initiatives. An example of a two-sided platform is Facebook. Also, according to Moazed (2017), the platform is divided into eight depending on the care value exchanged as shown in Table 2-2.

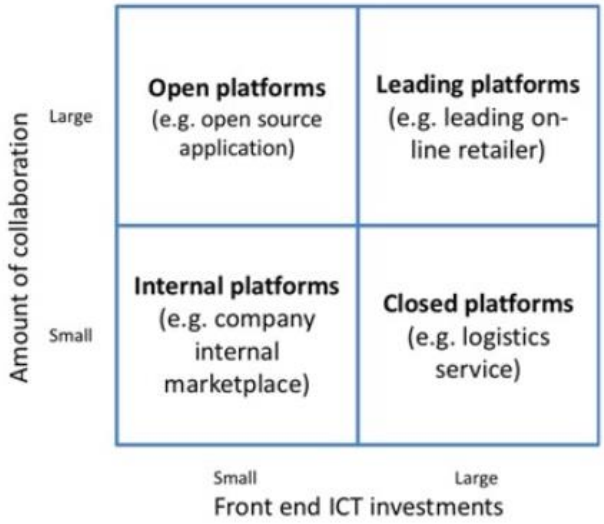


Figure 2-2 Platform types depending on collaboration and front end ICT investment (Smedlund, 2012)

Table 2-2 Platform types with the core value exchanged (Moazed, 2016)

Platform type	**Core value**
Services marketplace	A service
Product marketplace	A physical product
Payment platform	Payment
Investment platform	investment
Social networks	a network in which the core transaction is a double opt-in (friending) model of interaction
Communication platform	direct social communication (e.g., messaging)

Development platforms	· Closed development platform: software built across access to data (usually via an API) · Controlled development platform: software built in a controlled, integrated development environment · Open development platform: open-source and free software
Content platforms	· Social: a content platform in which the core transaction focuses on the discovery of and interaction with other people · Media: a content platform in which the core transaction focuses on discovery of and interaction with media

Considering the reasons for using the platform, the motives are different. Therefore, it is necessary to distinguish the platforms according to what the goal is to achieve through the platform.

In particular, there are classifications divided into business models. It is divided into nine models such as an intermediary model, an advertising model, and an information intermediary model (Rappa, 2003). Another classification is to concentrate distribution models (retail stores, marketplaces, aggregation types, information brokers, exchanges),

etc. (Applegate & Lynda, 2001; Laudon & Traver, 2007). Among them, Timmers model (1998) has been used the most in platform research (Figure 2-3).

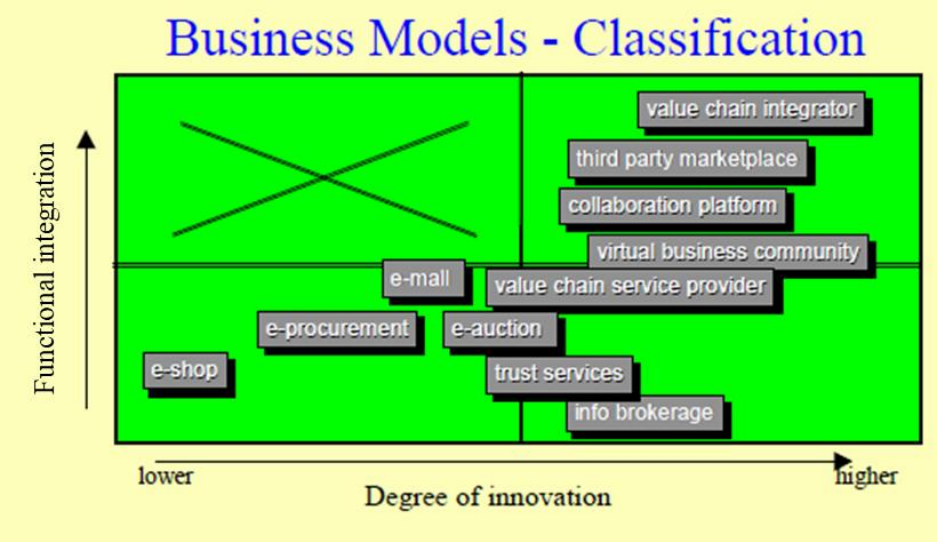


Figure 2-3 Business models (Timmers, 1998)

2.4.3 Proposed consumer centered platform economy

From the platform operator's point of view, the business model is divided into three categories: advertising, transaction, and software. However, it is difficult to apply an indirect network externality to customer from the customer side perspective.

First, based on having a user like Google, there is a business model where platform operators receive advertisements from firms. Advertisers want to be exposed to many consumers, but consumers do not like to be exposed to many ads. Unlike Google, if it's

not about advertising the user's tendencies, people feel uncomfortable when advertisements pop up in game windows or when advertisements pop up while reading the news (Cho, 1999; Bang & Choi, 2018).

On a platform that makes money by providing a transaction function, the indirect network externality that economists insist important in two-sided market is imperative. The more the number of the seller, the more consumers prefer the platform. However, the more reviews by the same side of the consumer, the more reliable the seller is for consumers.

In the case of software platform, the buyer does not care how many compatible complementary programs are provided in the operating system (OS). Unless the consumer is an expert, the consumer does not compare the OS versus the Linux with the Windows.

The classification of platforms for firms has been discussed as above. However, the platform economy departures from satisfying the users by providing better an environment for releasing information asymmetry. Thus, a classification in the perspective of users should reflect users need considering the platform classification depending on the stronger feature of platforms because the platform does not have a single feature.

In the evolution of platforms and products including the business models (Timmers, 1998), an innovation axis and a technology axis are considered as important axes. It is appropriate to measure the technology axis as to how much functional integration can be

provided by platform because consumers prefer the platforms with more functional integration (Jarvenpaa et al. 1999; Kim et al., 2018). In addition, the innovation axis was taken as an axis to measure how much interaction with other people can be provided because the platform has the function of eliminating the loneliness of people. As a result of examining what consumers want, it can be summarized as two important factors: Degree of interaction with people (DIP) and Degree of the functional integration (DFI) (Figure 2-4). Also, the network externality that is said to be important arises from consumers, so it is necessary to focus on what consumers want to get through the platform. Therefore, this thesis will measure whether network externality is important depending on platform characteristics.

High DIP and low DFI platforms like Facebook and Twitter is to continue the relationship between people. It is important to keep in touch with people who have a common interest, not a transaction. Medium DIP and DFI platforms are platforms that help each other find products that meet their desired criteria. More easily, it allows consumers to efficiently find the information they want. In a more advanced form, transactions are also made through the platform. This category is also divided into two categories. First, it is a platform for gathering information to find investors and scientific databases. Second, it is a marketplace or broker platform. This platform effectively connects the seller and the consumer wherever they are. There are a growing number of platforms that allow access to previously inaccessible resources. For example, there are things like Airbnb, which gives travelers their homes, and Uber, who drives someone else

with their own car. high DFI and low DIP refers the new technology to being connected to achieve any one to achieve a single purpose.

The technology development direction is to high degree of DIP and DFI. For example, the omni-channel strategy, which integrates online and offline, has received great attention recently. To be profitable, the sellers try to use several channels to approach and attract buyers (e.g., see Verhoef et al., 2007; Konuş et al., 2014; Ailawadi & Farris, 2017; Brynjolfsson et al., 2013). Unlike the previous studies insisting that eliminating offline stores is better for cost reduction, there is a rising objection that using the link between online and offline increases the buyer's satisfaction and therefore the profit (Argo et al., 2005; Hassanein & Head, 2007; Avery et al., 2012; Pauwels & Neslin, 2015; Chu et al., 2017; Bell et al., 2015; Wang & Goldfarb, 2017). As an online store linked to an offline store can be more attractive to buyers, buyers experience a social presence (Short et al., 1976; Rice & Case, 1983) that an online-only store cannot provide. However, it is not easy to maintain offline store so that it would be ideal if the online shop could offer social presence. Thus, there is an increase in their satisfaction when buyers experience an offline shop as they shop online (Argo et al., 2005; Hassanein & Head, 2005). It proves that buyers want to high degree of interaction with people such as communication with buyers and sellers through the platform as well as the high degree of functional integration. Thus, regardless the current characteristics of platforms, the platforms would be developed to provide high DIP and DFI as Kim et al. (2018) reveals.

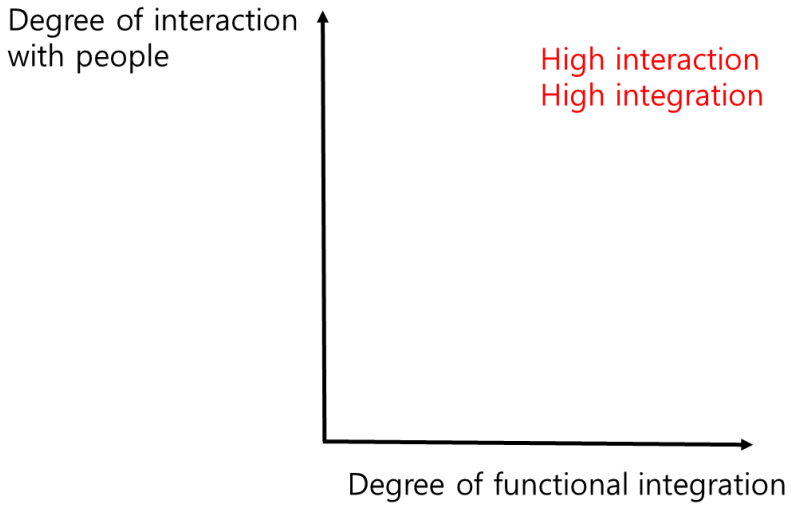


Figure 2-4 consumer centered platform dimensions

2.5 Empirical studies of network externality in platform economy

The literature is summarized on the basis of Figure 2-4. Section 2.5.1. explains the issue on the search platform which is a typical platform because it has low interaction with others and low functional integration. For companies that advertise on the search platform, it is better to increase the number of consumers, but consumers have negative feelings about ads. Section 2.4.2. explains the studies regarding a platform that provides high interaction with others but not high functional integration. Online games are representative because the users can be friends online. Section 2.4.3. explains the platform providing the technology allowing interaction which may not be as intimate as

an online game, but it does provide an interaction that allows the user to interact with the other side and observe the reviews from the same side. Also, it provides payment as a functional integration. The platform which allows transaction is representative. Finally, section 2.4.4. explains the platform with high functional integration. Thus, the autonomous vehicle is a typical platform where functional integration is large but interaction with others is not yet considered.

2.5.1 Low degree of interaction with people and low degree of functional integration

The simplest representation of the online platform is the search platform. People can obtain information through the search platform. (Wang *et al*., 2009; Wu et al., 2008). Because of the anxiety caused by having incomplete information, the desire to pursue new information can be solved through the search platform. Thus, the number of users using search platforms such as Google increased. From advertisers' point of view, it's good to expose themselves through platforms with a large number of users, so that they started advertising on search platform such as Google. And this has become Google's business model.

However, consumers do not want to expose to ads related to their searches, but want to obtain the closest results. Additionally, advertising adversely affects people's trust in the site (Fogg *et al*., 2001). That's why Google did not show ads as ads, but instead placed advertisers on top of search results. This is Google's way of doing business to attract

advertisers' ads using the dominant position in the search market. After investigating Google's business practices for seven years, the European Union concluded that it violated antitrust laws. Eventually, on June 27, 2017, the European Union charged Google with a penalty of about three trillion won (European Commission, 2017). As mentioned above, Google has chosen this type of business for reasons that consumers do not like to be exposed to advertising (Rohrer & Royd, 2004; Burke *et al*., 2005; Fogg *et al*. 2001). This explains that indirect network externality does not apply to consumers. In other words, the increase in the number of advertisers means that consumers do not like the platform more.

2.5.2 High degree of interaction with people and low degree of function integration

When the Internet first appeared, people worried that it would reduce people's ability to communicate. But now, apart from the Internet, we cannot think of communicating with other people.

After Katz & Shapiro (1985) introduces the concept of network externality, the academic researchers have investigated its impact on the motivation to use certain media or technologies in various different contexts (Bhargava & Choudhary, 2004; Wang *et al*., 2008; Lin & Bhattacherjee, 2008; Dickinger *et al*., 2008). Especially, in the social platform to communicate, the network externality is considered as an important factor because the accessibility to whom they want to communicate is important and the

connectivity to people who I want to be connected is paramount.

When researching why people use social platforms like Facebook, they have taken a lot of network externality into consideration (Lin *et al*., 2011; Chiu *et al*., 2013, Schilling, 2002; Dickinger *et al*., 2008). Cremer (2000) insists that the network value increases as the number of users increases, and thus does not distinguish between the number of peers and the number of total users. Zhao & Lu (2012) analyze the effect of network externality regarding the perceived interaction through network externality in micro-blogging. A study regarding social network sites (Chiu *et al*., 2013) also measures network externality by asking respondents about their perceived number of peers and total number of users. The intention to use peer-to-peer technology also has the effects of network size and social interaction (Song & Walden, 2007). Yang *et al*. (2010) also consider the total number of users as the network externality in order to study the intent of sharing videos via YouTube. In a study regarding instant messaging, Lin & Bhattacherjee (2008) measure the network externality using the perceived size of the peer network. Luo *et al*. (2005) measure the perceived critical mass using the number of friends playing a game. Further, a study on the success of new communication media (Kraut *et al*., 1998) investigates whether the use of a given communication medium by peers or colleagues affected respondents' intentions to use said communication medium.

However, even though network externality plays an important role in users' motivations to use several products and services, the implications are not clear because previous studies have failed to distinguish between the number of peers and the total

number of users. These can be categorized into three different types, as described in the table 2-3.

Table 2-3 Literature on the network externality measurement

Network externality	Study	Measurement/findings
Not distinguish the number of peers from the total number of users	Cremer (2000)	· The network value increases as the number of users increases, and thus does not distinguish between the number of peers and the number of total users.
	Zhao & Lu (2012)	· The perceived network size to measure the network externality · Survey asks for respondents' perceptions of the number of users and the number of peers when they measure network externality.
	Kim *et al.* (2013)	· This study uses the results in Zhao and Lu (2012) to measure the perceived network size.
	Chiu *et al*. (2013)	· Network externality by asking respondents about their perceived number of peers and total number of users
	Wei & Lu (2014)	· This study divides the network externality into the number of peers and the total number of users, but their study only determines the effects of the sum of these two measurements on the motivation to play social mobile games relative to increased enjoyment

Network externality	Study	Measurement/findings
the total number of users as the only measure of network externality	Song & Walden (2007)	· They study the effects of network size and social interaction on the intent to use peer-to-peer technology. · In particular, they measure the network size as the perceived membership size and the network externality as the perceived potential benefit due to the network size.
	Yang *et al*. (2010)	· This study considers the total number of users as the network externality in order to study the intent of sharing videos via YouTube
only the number of peers.	Lin & Bhattacherjee (2008)	· They study the network externality using the perceived size of the peer network
	MäNtymäKi & Salo (2013)	· They measure the network size using the number of friends
	Gao & Bai (2014)	· This study measures the referent network size using the number of friends
	Luo *et al*. (2005)	· They measure the perceived critical mass using the number of friends playing a game
	Kraut *et al*. (1998)	· The success of new communication media depends on whether the use of a given communication medium by peers or colleagues affected respondents' intentions to use said communication medium.

The network externalities generated by the number of peers and total users are considered as the same in a myriad of studies. However, the effects are clearly different because users consider the other users' use information as an important factor with the development of the reviewing systems.

Thus, there is need to find out whether people care about the total number of users rather than the number of peers (Figure 2-5).

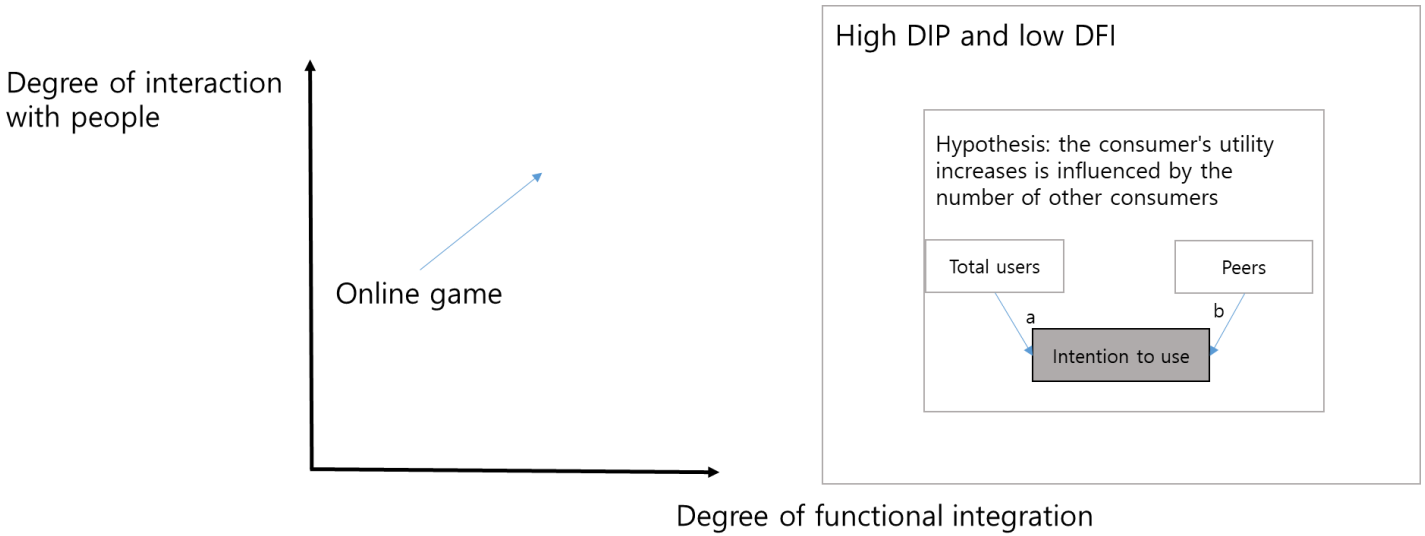


Figure 2-5 hypothesis 1 in high degree of interaction with people and low degree of functional integration platforms

2.5.3 Medium degree of interaction with people and degree of functional integration[1]

The medium DIP and DFI platform studies so called gatekeeper or mediator. A myriad of studies place weight on network externality to convince sellers and buyers to join a platform, (e.g., Rochet & Tirole (2003), Armstrong (2006), Armstrong & Wright (2007), Caillaud & Jullien (2003), and Parker & Van Alstyne (2005)).

There are two types of the platforms; search platforms such as Google, where information is exchanged, and transactions, such as Amazon, occur. Many offline sellers are trying to enter the ecommerce market through ‘online stores,' which sellers construct easily at a low cost to advertise and sell products through the web. According to eMarketer (retail & ecommerce, 2016), online sales are expected to reach $23 trillion by 2020. However, as the size of the ecommerce market continues to grow, the opportunities for sellers to expose their online stores to consumers are steadily declining. Thus, seller strategies use platforms that entice potential buyers by exposing their online stores to several platforms that have already secured potential buyers (e.g., see Nelsin *et al*., 2006; Verhoef, *et al*., 2007; Konuş *et al*., 2014; Ailawadi & Farris, 2017; Brynjolfsson *et al*., 2013).

The simplest form of platform is ‘information brokerage’. According to Timmers (1998), information brokerage is an information service provider that adds value to the

[1] A draft version of this chapter was accepted in *Sustainability*

enormous amount of data on the Internet. Price comparison sites such as Trivago are the archetype of information brokerage, as this platform allows buyers to search individual online stores. Sellers that are not well known can be exposed to more buyers without any intervention on the part of the platform (Baye & Morgan, 2001; Edelman *et al*., 2016). However, profit depends on the buyer's brand preference or loyalty (Kocas, 2002; Saeed *et al*., 2005), so there is a possibility that the increase in a business' net profit will not be sufficient compared to the fee for joining the platform for unknown sellers.

Another representative of platform is the 'online mall'. The online mall is an aggregation of online stores that enhances the transaction function by offering a common frame such as the store structure or payment (Timmers, 1998). For a small business with a low reputation and trust, inducing buyers is easier using an online mall such as Amazon because the online mall already has the established buyer's trust (Pavlou & Gefen, 2004). Also, buyers seek familiarity and convenience with their previous interactions and experiences (Van Bruggen *et al*., 2010; Gefen, 2000), and they want to purchase through a mediator because they trust it due to its reputation (Jarvenpaa *et al*. 1999). Thus, sellers can reap the benefits of inducing buyers easily by following the online mall's frame.

However, there is a drawback in that sellers using an online mall pay larger fees than when using information brokerage. There are studies that brokerage platform lowers seller's efficiency (for example, see Edelman & Wright (2015) and Wang & Wright (2016)). To be profitable and survive in the competition with other platforms, the platform service provider requires a fee and the lowest prices from sellers.

The sellers efficiency can be improved as the platform matured securing the number of users so that the sellers efficiency should be analyzed depending on platform maturation (Figure 2-6).

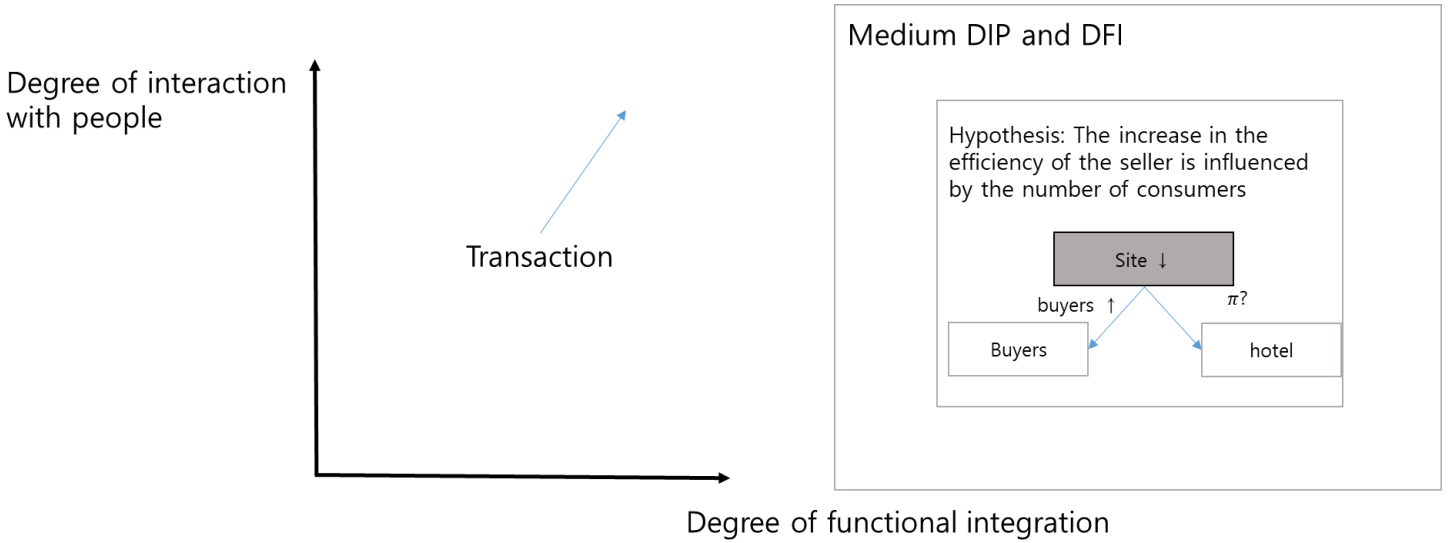


Figure 2-6 hypothesis 2 in medium degree of interaction with people and degree of functional integration platforms

2.5.4 Low degree of interaction with people and high degree of functional integration

The high degree of functional integration is a platform for a new system which derives the disruptive innovation. Through this platform, it will be a society where people are connected through the communication of humans' machines beyond the communication between humans in the future. In order to make one function possible, the technology for the platform is been developing by collecting scattered elements and making order to operate efficiently. One simple example of the platform is the healthcare management through a wearable device. The device can collect owner’s health data and transmit to your doctor to advise based on the collected data. Also an autonomous vehicle is an example. Not only does the driver have to interact with the car, but the car and the car must also be connected. And the car must also interact with the road traffic. Also, the connection between the vehicle and the control center is needed to automated vehicle.

Consumer acceptance is important for this innovative technology to take root. Thus, research that reveals the acceptance of this technology is important. While many characteristics of the product are important in acceptance of the consumer, network externality plays an important role in adopting new technologies in platform economy so far (Chih-Chien *et al*., 2005; Lin & Bhattacherjee, 2008; Dickinger *et al*., 2008; Zhou & Lu, 2011) even when it was not platform economy, network externality played an important role. In an industry where network externality is important, a technology

dominates as it becomes a standard. At this time, competition technology is pushed out. Network externality plays an important role in success, depending on how much complementary goods are available and installed base (Schilling, 2002). The success of entrants in a platform-based market is also important for platform quality, but network externality is also important. Due to network externality in the video game industry, the Xbox entry made the playstation 2 unsustainable (Zhu & Iansiti,2012)

The importance of technology is indispensable, but it is becoming increasingly important to make efforts to have network externality. The launch strategy has had a significant impact on product performance due to the emergence of high tech products (Lee & O'Connor, 2003). Especially with the rapid growth of information technology, network externality is changing competitive game. Now it is crucial to be introduced to people as soon as possible to preempt the network externality, not to market it in perfect condition.

Thus, it should be examined whether the other users' use information has an influence on uers' preference as the characteristic of product (Figure 2-7).

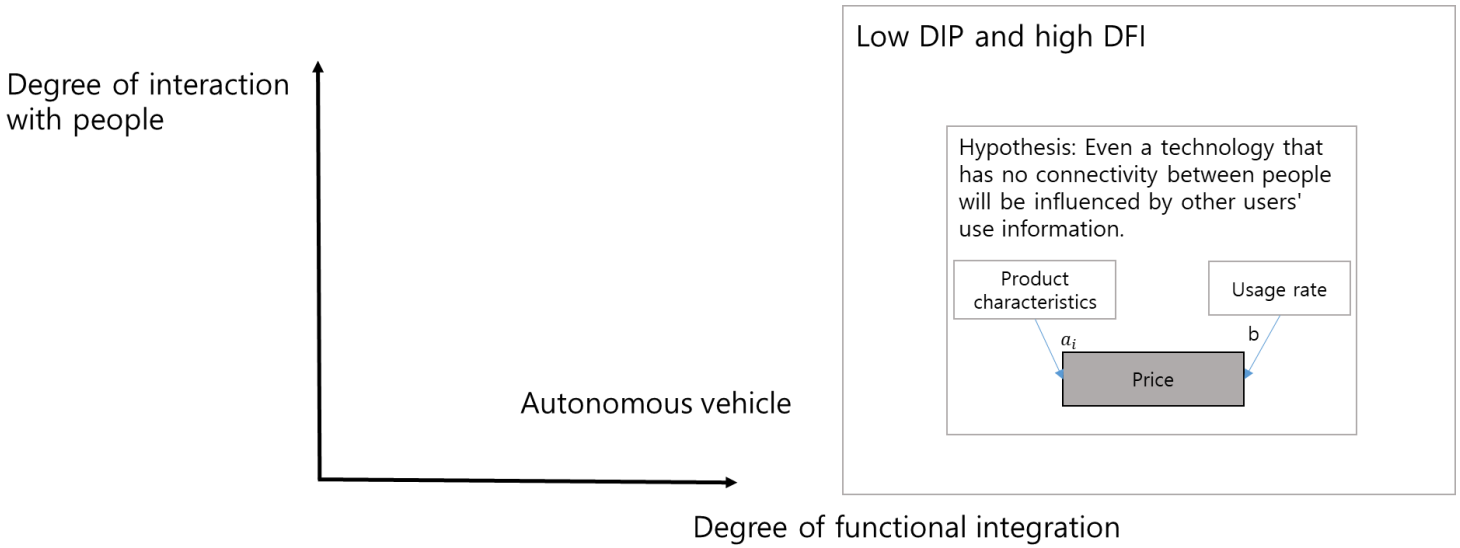


Figure 2-7 hypothesis 3 in low degree of interaction with people and high degree of functional integration platforms

2.6 Conclusions and future research agenda

The debate about a new economy based on the characteristics of the two-sided market has been continuing, but the definition of the economy has not been clear. Therefore, a new economy is defined platform economy based on the opinions of scholars on the two-sided market and the new economy. Platform economy refers to an economy in which the efficiency of people is enhanced by increasing the connectivity by matching resources or people who have not been connected before the emergence of a specific platform

The role of network externality, which is important only in the network-related industries in the industry economy, is becoming important in all industries due to the growing role of the platform industry in our society. Thus, a myriad of studies on the effect of network externality have been done so far. Scholars argue that direct network externality is not important in the two-sided market. However, it is important to note that direct network externality is also important because connectivity to other people or objects is paramount in the platform economy. In addition, it should be revealed whether the indirect network externality caused by the number of consumers improves the seller's efficiency. And it is necessary to disclose that the number of consumers also affects the optimal price of newly emerging technology.

The literatures are reviewed regarding the effect of network externality in each platforms. First, in the high DIP and low DFI platform, the study of the network externality method to measure the effect of the network externality was used differently

in each research. Thus, the study is needed to clarify the difference in the different measurement. And in the medium DIP and DFI platform, consumers are able to meet sellers, while sellers are exposed to more consumers. However, there is no consensus on whether the platform increases the sellers' surplus. The efficiency of the seller will depend on the maturity of the platform, so it is necessary to study it. And the studies on to find out the effect of others use information in low DIP and high DFI platform have not been focused on the effect of network externality. In platform economy, the consumers acceptance would depend on network externality so that it should be revealed with the empirical study to verify the definition of platform economy.

Chapter 3. The impact of number of users as network externality in online game[2]

3.1 Introduction

In October 2016, Google possessed 90.37% of the Internet search engine market share, showing a distinguishable monopoly (Statista, 2017). Based on its strong market share, Google's advertisement profits reached $79.38 billion in 2016 (Statista, 2017). It is known that Google retains its dominant position not only by the superiority of its search engine and algorithm (Brin & Page, 2012; Barroso *et al.*, 2003), but also by network externality (Argenton, 2012), an increase in users that leads to an increase in the value of products or services (Katz, 1985). As the information and communication technology (ICT) industry develops, the role of network externality is becoming more crucial for securing users.

Studies of network externality have been conducted in several areas with diverse results. Previous studies can be categorized into three groups according to the factors considered in measuring network externality: the first group considers the number of peers and the total number of users at the same time without distinction (Cremer, 2000; Zhao & Lu, 2012; Kim *et al*., 2013; Chiu *et al*., 2013; Wei & Lu, 2014), and the second

[2] A draft version of this chapter was accepted in *Information Technology and People*

(Song & Walden, 2007; Yang *et al*., 2014) and third (Lin & Bhattacherjee, 2008; MäNtymäKi & Salo, 2013; Gao & Bai, 2014; Luo *et al*., 2005; Kraut *et al*., 1998) groups consider the number of peers and the number of users, respectively.

However, it has been proved theoretically that network externality would differ depending on the number of peers and the number of total users (Sundararajan, 2007; Jackson & Yariv, 2007). From the perspective of the importance of the number of peers, there is a suggestion to target the people most connected to others (Candogan *et al*., 2012). Moreover, in a study of the motivation behind intention to use social network service (SNS), Lin & Lu (2011) divides network externality into number of peers and number of total users and find that the two metrics have different effects.

Thus, previous studies have used these different forms of network externality without exact distinction, and even Lin & Lu (2011) and Wei & Lu (2014) fails to consider the factors that create the difference they find. To emphasize the importance of this distinction, it is necessary to investigate the factors that create the difference in these two network externalities. Therefore, this paper investigates the different effects of these two forms of network externality and the factors that induce the differences between them. In addition to considering the different effects of the number of peers and the total number of users, the perception of life quality is used as a moderator because the intensity of network externality would be different depending on an individual's perception of his/her life quality according to the "user gratification theory" (UGT) suggested by Katz & Blumler (1973). One innate human instinct is the desire to spend time with others

(Simmel & Hughes, 1949), so loneliness (Hughes *et al*., 2004; Pittman, 2015; Pittman & Reich, 2016; Skues *et al*., 2012; Shaw & Gant, 2002; Kim *et al*., 2009) would change the effects of network externality. In addition, happiness (Lyubomirsky & Lepper, 1999; Uysal *et al*., 2013; Kim & Lee, 2011) and satisfaction with life (Diener *et al*., 1985; Basilisco & Cha, 2015; Malik *et al*., 2015) are considered because they are also important factors in quality of life (Pittman *et al*., 2016). Escapism would be another explanation for why people react differently to the two forms of network externality because it is a crucial factor in media use (Korgaonkar & Wolin, 1999; Ko, 2000; Xu *et al*., 2012; Jeng & Teng, 2008). In addition, the study also attempts to determine the relationship between people's online tendencies and moderators.

To study the two forms of network externality and the moderating effects, data from the online game market, which is expected to reach $79 billion according to online game market forecast reports (DFC Intelligence, 2013), is analyzed. Network externality plays a key role in user attitudes (Hsu & Lu, 2007) and profits (Shankar & Bayus, 2003), along with the rapid growth of the online game market made possible by the development of computer, Internet, and smartphone technology that allows communication in games. Online communities, such as guilds and clans, form in games through online communication, which means that people play with new acquaintances meet online as well as with peers they know offline. Thus, the online game industry is a proper venue for the study of network externality.

"Self determination theory" (SDT), which is used to analyze motivation within games

(Ryan *et al*., 2006) is applied here to investigate the effects of autonomy, competence, and relatedness on enjoyment (Rogers, 2017; Ho *et al*., 2017). Also, the effects of enjoyment (Davis *et al*., 1992; Ha *et al*., 2007; Shin & Shin, 2011), flow (Csikszentmihalyi & LeFevre, 1989; Ha *et al*., 2007; Shin & Shin, 2011), and the two forms of network externality on attitudes will be examined.

The second section of this study explains general concepts and discusses previous studies on this subject. This is followed by a research model section, which presents arguments supporting the hypothesized relationships. In the methodology section, information is provided about data collection and analysis processes. In the results section, the overall results are presented. In the final section, the theoretical and practical contributions of this study are discussed.

3.2 Background and theoretical foundation

3.2.1 Network externality measurement

Katz & Shapiro (1985) introduced network externality, and other researchers have investigated its impact on the motivation to use certain media or technologies in various different contexts, including electronic banking (Kauffman *et al*., 2000), intermediary services (Bhargava & Choudhary, 2004), messaging (Wang *et al*., 2005; Wang *et al*., 2008; Lin & Bhattacherjee, 2008), and media (Dickinger *et al*., 2008). Even though network externality plays an important role in users' motivations to use several products

and services, the implications of this are not clear because previous studies have failed to distinguish between the number of peers and the total number of users. These can be categorized into three different types, as described below.

First, there are many studies that measure network externality but do not distinguish the number of peers from the total number of users. Cremer (2000) insists that the network value increases as the number of users increases, and thus does not distinguish between the number of peers and the number of total users. In a study regarding the perceived interaction through network externality in micro-blogging, Zhao & Lu (2012) use the perceived network size to measure the network externality. Their survey asks for respondents' perceptions of the number of users and the number of peers when they measure network externality. In addition to this, Kim *et al.* (2013) use the results in Zhao & Lu (2012) to measure the perceived network size. A study regarding social network sites (Chiu *et al*., 2013) also measures network externality by asking respondents about their perceived number of peers and total number of users. Wei & Lu (2014) divide the network externality into the number of peers and the total number of users, but their study only determines the effects of the sum of these two measurements on the motivation to play social mobile games relative to increased enjoyment.

The second set of studies considers the total number of users as the only measure of network externality. For example, Song & Walden (2007) study the effects of network size and social interaction on the intent to use peer-to-peer technology. In particular, they measure the network size as the perceived membership size and the network externality

as the perceived potential benefit due to the network size. Yang *et al*. (2010) also consider the total number of users as the network externality in order to study the intent of sharing videos via YouTube.

The third group of studies measures the network externality by considering only the number of peers. In a study regarding instant messaging, Lin & Bhattacherjee (2008) measure the network externality using the perceived size of the peer network. In addition, MäNtymäKi & Salo (2013) measure the network size and Gao & Bai (2014) measure the referent network size using the number of friends. Luo *et al*. (2005) measure the perceived critical mass using the number of friends playing a game. Further, a study on the success of new communication media (Kraut *et al*., 1998) investigates whether the use of a given communication medium by peers or colleagues affected respondents' intentions to use said communication medium.

If the fundamental differences between the two network externalities can be determined, the effects of network externality can be made clearer. Thus, this study investigates whether the perception of quality of life results in a difference between these two forms of network externality.

3.2.2 User gratification theory and self determination theory

User gratification theory (UGT) is a well-established framework for studying different kinds of media (Katz *et al.,* 1974; Sundar & Limperos, 2013). The basic assumption of

UGT is that people choose different media to satisfy their own specific needs. Pittman & Reich (2016) use loneliness, happiness and satisfaction with life (SWL) as the UGT factors. With the development of media, there is a clear desire for socialization through social media (Chen, 2011; Lee & Ma, 2012). Thus, loneliness is considered as a well-known motivation to use media (Pittman, 2015; Pittman & Reich, 2016; Skues *et al.*, 2012; Shaw & Gant, 2002; Kim *et al.*, 2009). Loneliness lowers the frequency of media use (Pittman, 2015; Pittman & Reich, 2016; Shaw & Gant, 2002), and people use SNS to compensate for a lack of offline relationships (Skues *et al*., 2012). However, loneliness can result in problematic Internet use (Kim *et al*., 2009). Further, media products as a whole try to increase SWL to increase the number of users (Basilisco & Cha, 2015) by satisfying users' needs (Malik *et al*., 2015). Although SNS addiction negatively affects happiness (Uysal *et al*., 2013), the support from online friends can actually enhance happiness (Kim & Lee., 2011). Additionally, escapism is an important factor for users that motivates them to play games (Xu *et al.*, 2012; Jeng & Teng, 2008). Thus, the motivation will differ depending on factors related to their perception of quality of life.

In this paper, SDT is used to analyze various motivation factors, and playing online games is used as the beginning framework since SDT also focuses on satisfaction, similar to UGT. In its early development, the focus of SDT dealt with intrinsic motivation, i.e., the motivation resulting from inherent satisfactions derived from action (Deci & Ryan, 1985; Deci & Ryan, 2000; Ryan & Deci, 2000). Especially, Ryan *et al*. (2006) propose the "player experience of need satisfaction" (PENS) to investigate the motivations of

playing online games. PENS is used to study topics related to games such as changes in health-related behavior using game-based story (Baranowski *et al*., 2008), the problems associated with game playing (Wu *et al.*, 2008; Gentile, 2009), and the intent to purchase in-game content (Hamari *et al*., 2017). Recently, this has been applied to analyze the motivations of game feedback (Rogers, 2017) and the motivations to use exergame (Ho *et al*., 2017). Extent PENS is useful for studying the motivation to play games. Thus, the concept of flow is added into the basic model, as it is considered to be an important factor for online gaming motivation (Chang, 2013; Chang & Zhu, 2012; Mahnke *et al*., 2014; Novak *et al*., 2000; Wu & Chang, 2005; Ozkara *et al*., 2016), and network externality is added into the basic PENS model as well. Additionally, factors related to the perception of quality of life are considered as moderate motivation factors. To enhance the effects of network externality as well as investigate its moderating effects, the model is simplified as much as possible.

3.3 Research model & hypotheses

Using SDT to study the motivation to play games, Ryan *et al*. (2006) proposed that the "player experience of need satisfaction" (PENS) can estimate the effects of autonomy, competence, and relatedness on enjoyment and future game play by assuming that desire is satisfied through playing games. A desire for autonomy is satisfied by an activity that produces interest or a feeling of individual value (Ryan & Deci, 2000). Competence is

about the skill or ability to meet a challenge, so a game with controls that are intuitive or easy to master would produce high competence (Ryan & Deci, 2000). Relatedness is a psychological need in SDT that enhances motivation by creating a feeling of connection with others (Ryan & Deci, 2000). The present study states one hypothesis for the effect of all three of those factors on enjoyment (Przybylski *et al*., 2010).

Hypothesis 1. Competence, autonomy, and relatedness have a positive effect on enjoyment.

Davis *et al*. (1992) defines enjoyment as the extent to which computer system usage is perceived to be personally enjoyable in its own right, aside from the instrumental value of the technology. Ha *et al*. (2007) claims that mobile games must provide users with enjoyment, and that enjoyment positively influences flow experience and attitude. Shin & Shin (2011) argues that when content or a service is hedonic, enjoyment is more relevant than ease of use. Moreover, several studies have found enjoyment to affect attitudes and intention to use (Teo & Noyes, 2011; Luo *et al*., 2005).

Hypothesis 2. Enjoyment has a positive effect on attitude.

Csikszentmihalyi & LeFevre (1989) introduces the original concept of flow, defining it as "the holistic experience that people feel when they act with total involvement." Prior research indicates that flow can be an appropriate factor for understanding user behavior in online environments (Chang 2013; Chang & Zhu, 2012; Mahnke *et al*., 2014; Novak *et al*., 2000; Wu & Chang, 2005; Ozkara *et al*., 2016). Other studies have established that

flow is a common experience among videogame players during play (Admiraal *et al*., 2011; Cowley *et al*., 2008, Keller & Bless, 2008). Moreover, Ha *et al*. (2007) finds that, in mobile games, an experience of flow positively affects attitude, and Hsu & Lu (2004) concludes that flow positively affects the intention to use online games. Shin & Shin (2011) also finds that flow positively influences the intention to use social network games.

Hypothesis 3: Flow has a positive effect on attitude.

Katz & Shapiro (1985) defines network externality as "the value or effect that users obtain from a product or service will bring about more values to consumers with the increase of users, complementary product, or service." With the rise of the Internet, the barrier between buyers and sellers disappears; now they can interact directly on platforms known as two-sided markets (two-sided markets have network externality (Rochet & Tirole, 2003)). Thus, network externality should be considered to accurately analyze its effects. There are two kinds of network externality: direct network externality (the number of users) and indirect network externality (compatible services or products). This study focuses on direct network externality.

Many studies have considered network externality in several areas, such as SNS (Gruzd *et al*., 2012; Hamari & Koivisto 2013; Lin & Bhattacherjee, 2008; Luo *et al*. 2005; MäNtymäKi & Salo, 2013; Zhao & Lu 2012). However, in much of the literature, the number of peers and the total number of users are considered as one form of network externality (Chiu *et al*., 2013; Wei & Lu, 2014; Zhao & Lu, 2012), the total number of

users is considered alone as network externality (Song & Walden, 2007), or the number of peers is considered alone as network externality (Kraut *et al*., 1998; Lin & Bhattacherjee, 2008; MäNtymäKi & Salo, 2013). However, it has been theoretically shown that the effects of the number of peers and the total number of users are different (Jackson & Yariv, 2007; Sundararajan, 2007). Moreover, the effect of the number of peers is larger than that of the total number of users on the intention to use SNS, as shown in Lin & Lu (2011). Thus, the effects of the number of peers and the total number of users on attitudes would differ.

Hypothesis 4-1. The number of peers has a positive effect on attitude.

Hypothesis 4-2. The total number of users has a positive effect on attitude.

What factors will drive the difference in the effects of the number of peers and the total number of users? No one has yet considered the causes of that difference. To investigate those factors, moderators are used in this study. The moderating effects are based on UGT, the theory that people choose different media to achieve specific needs or goals (Katz *et al*., 1974; Sundar & Limperos, 2013). In particular, Sundar & Limperos (2013) uses UGT to illustrate that the desire to satisfy innate needs is the trigger for people to seek new media. This paper extends that desire to loneliness, happiness, SWL, and escapism. Most studies on UGT have focused on general media consumption for need gratification (Johnson & Kaye, 2015; Dhir *et al*., 2015); studies on game playing games are limited. Pittman *et al.* (2016) extends UGT to consider loneliness, SWL, and

happiness as desire. In the present study, escapism (Korgaonkar & Wolin, 1999; Merhi, 2016), an important factor in game playing, is considered as a moderator, along with loneliness, SWL, and happiness. According to UGT, perceived life quality should have differential moderating effects.

Hypothesis 5-1. The effect of the total number of users on attitude in the lonely group is more positive than that in the less lonely group.

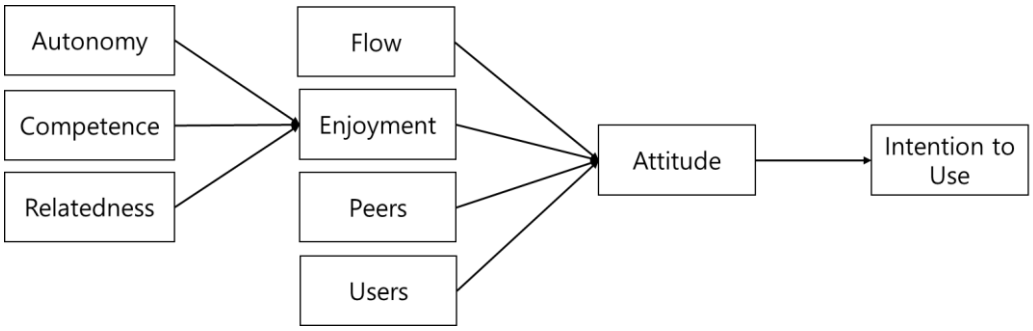
Hypothesis 5-2. The effect of the number of peers on attitude in the satisfied group is more positive than that in the less satisfied group.

Hypothesis 5-3. The effect of the number of peers on attitude in the happier group is more positive than that in the less happy group.

Hypothesis 5-4. The effect of the total number of users on attitude among those who want to escape from reality is more positive than it is among those who do not want to escape.

In the technology acceptance model (Davis, 1989), attitude affects intention to use. Other studies (Teo & Noyes, 2011; Suki & Suki, 2011; Chang, 2013; Kim *et al*., 2015) have also shown that attitude affects intention to use.

Hypothesis 6. Attitude has a positive effect on intention to use.



Note: the number of peers = peers, the total number of users = users

Figure 3-1. Research model

The model is intentionally simplified to measure the different effects of the number of peers and the number of users. There might be other relevant variables not included in the model. Nonetheless, the model is developed as shown in Figure 3-1, with the specific purpose of testing the above-stated hypotheses. Further research might help extend the current model and find different relationships.

3.4 Survey and estimation results

3.4.1 Survey and data

The survey covered 508 game players in South Korea through online by “dataSpring” in 2016. The respondent characteristics are summarized in Table 3-1. Of the total respondents, 55.7% are male, and 44.3% are female. In terms of age distribution, 10% of respondents are teenagers, and 30% are in their twenties, thirties, and more than forties,

respectively. Most respondents check either undergraduate student/university graduate or above graduate school (around 83%), but 17% of the group have no more formal education than a high school diploma. Most respondents have played games for more than 7 years (52.6%), followed by 3 to 5 years (17.3%), 1 to 3 years (11.4%), and less than 1 year (4%). In terms of daily online game playing, most respondents play 1 to 2 hours per day (67.5%), followed by 14.8% who play 3 hours, 6.7% who play 4 hours, 5.7% who play more than 6 hours, and 4.9% who play 5 hours. Most respondents (80.1%) pay to play games.

Table 3-1 Respondent characteristics

Measure	Frequency	Percentage
Age (years)		
10–19	51	10.0
20–29	157	30.9
30–39	150	29.5
40+	150	29.5
Gender		
Male	283	55.7
Female	225	44.3
Education (highest level achieved)		
Less than high school graduation	85	16.7
Undergraduate student or university graduate	391	77.0
Graduate school	32	6.3
Years playing online games		
Less than 1 year	21	4.1
1–3 years	58	11.4
3–5 years	88	17.3
5–7 years	74	14.6
More than 7 years	267	52.6
Hours playing online games/day		
Less than 1 hour	2	0.4
1 hour	180	35.4
2 hours	163	32.1
3 hours	75	14.8
4 hours	34	6.7
5 hours	25	4.9
More than 6 hours	29	5.7
Pay to play		
Yes	407	80.1
No	101	19.9
Total	508	

The questionnaires in this paper have already been validated in previous research about online games (Table A-1). The questionnaire about the number of peers and the total number of users is from the study of Lin & Lu (2011). The questionnaire on competence, autonomy, and relatedness is from the PENS. The questionnaire for enjoyment is from Hsu & Lu (2007), the one for flow from Ha *et al*. (2007), the one for attitude from Hsu & Lu (2004), and the one for intention to use from Lin & Lu (2011) and Shin & Shin (2011).

To measure the moderating effects, this study categorized the sample into two groups for each category of life quality: loneliness, SWL, happiness, and escapism. The levels of the four characteristics are estimated based on the previous research (Diener *et al*., 1985; Ko, 2000; Korgaonkar & Wolin, 1999; Lyubomirsky & Lepper, 1999; Pittman *et al.*, 2016). The questionnaire for happiness is based on Lyubomirsky & Lepper (1999), for SWL is based on Diener *et al*. (1985), for loneliness is based on Hughes *et al*. (2004), and for escapism is based on Korgaonkar & Wolin (1999) and Ko (2000). The moderating effects are evaluated by comparing each pair of groups using the mean of responses to the questions.

Various statistical tests are conducted on the survey data, referring to Hair *et al*. (2010). First, a construct validity test is conducted, followed by checks for convergent validity and discriminant validity. Construct validity indicates whether the measured variables accurately represent the theoretical latent constructs. Construct validity is high when the items loaded onto each factor are relevant and is measured by assessing convergent

validity and discriminant validity. The Cronbach's alphas need to be higher than 0.7, and the average variance extracted (AVE) needs to be above 0.5. Discriminant validity can be assessed by comparing the correlation between construct pairs and the AVE of each construct. The squared correlation between each pair of latent variables needs to be less than the AVE. Also, the comparative fit index (CFI) and Tucker-Lewis index (TLI) need to be above 0.9. The root mean square error of approximation (RMSEA) needs to be lower than 0.08. After confirming all of those conditions, the hypotheses are assessed using structural equation modeling (SEM).

3.4.2 Estimation results

Table 3-2 shows the descriptive statistics of the analysis. Positive intention to use is reported, and all other variables had means higher than 3. From the positive responses to the items related to enjoyment, it is inferred that the respondents found game play enjoyable. The items related to flow also display positive results. Based on the positive answers about the number of peers and the total number of users, network externality is also important.

Table 3-2 Descriptive statistics

Variable	Mean	Std. Dev.
Autonomy	3.53	0.72
Competence	3.34	0.82
Relatedness	3.36	0.88
Peers	3.45	0.77
Users	3.52	0.76
Flow	3.42	0.91
Enjoyment	3.92	0.74
Attitude	3.86	0.70
Intention to Use	3.72	0.70

The acceptability of the measurement model is assessed using the reliability of the individual items, the internal consistency between items, the convergent and discriminant validity, and the fit indices. All constructs achieve scores above the recommended value of 0.7 for Cronbach's α. Convergent validity is assessed using AVE and factor analysis. In this study, all AVEs are above the required value of 0.5 (Chin, 1998), as shown in Table 3-3.

Table 3-3 Internal consistency correlations and reliability tests

Variable	Cronbach's α	AVE	Autonomy	Competition	Relatedness	Peers	Users	Flow	Enjoyment	Attitude	Intention to Use
Autonomy	0.89	0.62	0.79								
Competence	0.89	0.67	0.61	0.82							
Relatedness	0.90	0.65	0.42	0.53	0.81						
Peers	0.89	0.72	0.54	0.53	0.45	0.85					
Users	0.89	073	0.59	0.51	0.43	0.73	0.86				
Flow	0.89	0.75	0.59	0.61	0.44	0.52	0.52	0.86			
Enjoyment	0.90	0.67	0.46	0.47	0.45	0.38	0.38	0.43	0.82		
Attitude	0.89	0.62	0.65	0.53	0.42	0.54	0.56	0.54	0.56	0.79	
Intention to Use	0.897	0.81	0.61	0.52	0.41	0.50	0.51	0.50	0.52	0.70	0.9

Note: Diagonal elements are the square roots of AVE. Off-diagonal elements are correlations among constructs. For discriminant validity, diagonal elements should be larger than off-diagonal elements.

After evaluating reliability and validity, the overall fit of the research model is tested. Table 3-4 shows the results: $\chi^2/d.f.$ = 3.721, CFI = 0.918, TLI = 0.907, and RMSEA = 0.070. The overall fit indices indicate that data from the survey are well represented by the model.

Table 3-4 Fit indices of the research model.

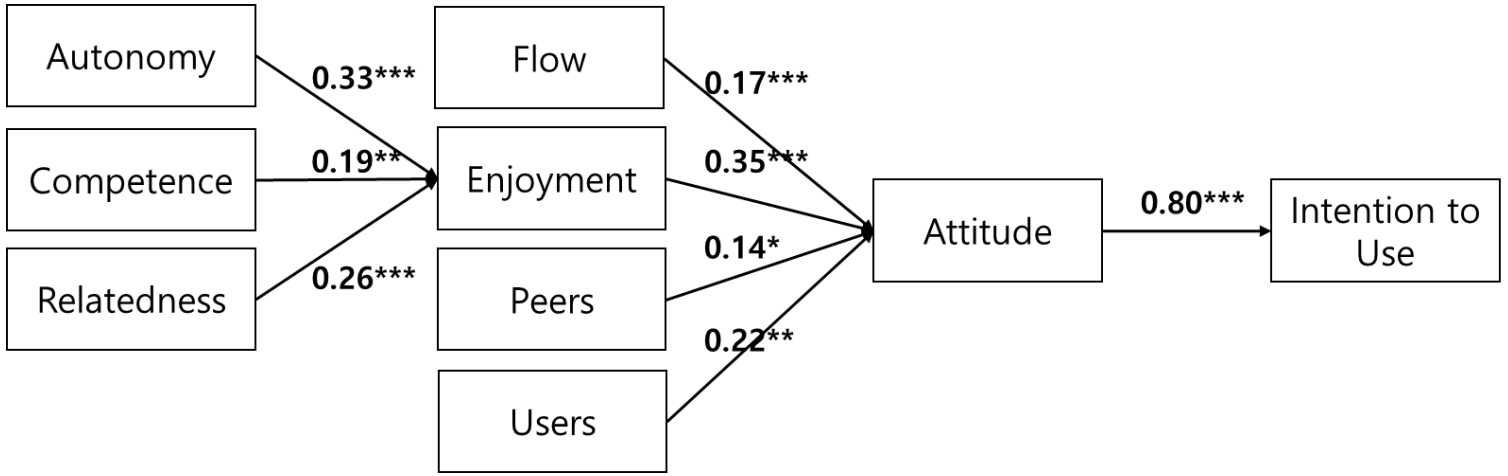
Fit index	Recommended value	Results
$\chi^2/d.f.$	< 5.00 (Bentler & Bonnet, 1980)	3.721
Comparative fit index	> 0.90 (Bagozzi & Yi, 1988)	0.918
Tucker-Lewis index	> 0.90 (Bagozzi & Yi, 1988)	0.907
Root mean square error of approximation	< 0.08 (Brown & Cudeck, 1993)	0.070

The results of hypothesis testing through SEM for hypotheses 1–4 are described in Figure 3-2. Competence ($P < 0.05$), autonomy ($P < 0.01$), and relatedness ($P < 0.01$) each has a positive effect on enjoyment, which supports hypothesis 1.

The effect of flow on attitude is positive and significant ($P < 0.01$), which supports hypothesis 2. The effect of enjoyment on attitude is positive and significant ($P < 0.01$), which supports hypothesis 3.

The effect of the number of peers on attitude is positive, supporting hypothesis 4–1. The effect of the total number of users on attitude is also positive, supporting hypothesis 4–2. The effect of the total number of users on attitude is around 1.6 fold greater than the

effect of the number of peers on attitude. The effect of attitude on intention to use is positive, supporting hypothesis 6.



Note: * Significant at 0.1 level; ** Significant at 0.05 level; *** Significant at 0.01 level.

peers = number of peers, users = total number of users

Figure 3-2. Estimation results

The results for the moderating effects are described in Table 3-5. When loneliness is used as the moderator, the effect of autonomy on enjoyment ($P < 0.05$), the effect of relatedness on enjoyment ($P < 0.01$), and the effect of enjoyment on attitude ($P < 0.01$) are all significant in both the lonely and less lonely groups. Also, attitude improves as the total number of users increased, regardless of feelings of loneliness.

However, when people are lonelier, the effect of flow on attitude is larger ($P < 0.05$) than it is among less lonely people. Moreover, flow has a significant effect on attitude ($P < 0.01$) in the lonely group, but it has no significant effect in the less lonely group. In addition, the less lonely group care 1.7 fold more about the number of peers than the number of users.

The number of peers does not have a significant effect on attitude in the lonely group, but it does have a significant effect on attitude in the less lonely group ($P < 0.05$). Moreover, the effect of the number of peers on attitude is larger when people are less lonely, which supports hypothesis 5–1 ($P < 0.1$).

In the case of SWL, the effect of relatedness has a significant effect on enjoyment in both the satisfied and unsatisfied groups ($P < 0.01$). In addition, enjoyment has a significant positive effect on attitude in both groups.

On the other hand, autonomy ($P < 0.01$) and competence ($P < 0.1$) are significant only among those in the unsatisfied group. Moreover, the effect of enjoyment on attitude is around 1.5 fold greater among those in the unsatisfied group than among those in the satisfied group ($P < 0.01$). The total number of users has a significant effect in the low

SWL group ($P < 0.05$) but no significant effect in the high SWL group. The number of peers has no significant effect on attitude regardless of SWL, so hypothesis 5–2 is rejected.

Whether people are happy or not, the effect of relatedness on enjoyment ($P < 0.01$) and the effect of enjoyment on attitude ($P < 0.01$) are significant. However, the effect of enjoyment on attitude is around 1.5 fold more in the unhappy group than in the happy group ($P < 0.05$). Also, the effect of autonomy on enjoyment is only significant among less happy people. When happiness is high, the number of peers has a significant effect on attitude ($P < 0.05$), but the total number of users has no significant effect. When the level of happiness is low, the total number of users has a significant effect on attitude ($P < 0.05$), but the number of peers has no significant effect, which supports hypothesis 5–3.

With high escapism, the effect of autonomy on enjoyment ($P < 0.05$) and the effect of relatedness on enjoyment ($P < 0.01$) are both significant. Specifically, the effect of relatedness on enjoyment is two times larger among those who want to escape from reality than it is among those who do not ($P < 0.1$). The effect of enjoyment on attitude ($P < 0.01$), the effect of flow on attitude ($P < 0.01$), and the effect of the number of users ($P < 0.01$) are all significant among those who want to escape from reality. Moreover, among those who want to escape from reality, the number of peers has no significant effect on attitude, but flow ($P < 0.01$) and the total number of users ($P < 0.01$) do have significant effects on attitude. Flow ($P < 0.1$) and the number of users ($P < 0.1$) are significant only in the group with a desire to escape reality, which supports hypothesis 5–

4. Moreover, the number of peers has no significant effect in the group with high escapism, but it is significant in the group with low escapism ($P < 0.1$).

Table 3-5 Clustering analysis

	Loneliness			**SWL**			**Happiness**			**Escapism**		
	No	Yes	Pairwise Parameter Comparison	No	Yes	Pairwise Parameter Comparison	No	Yes	Pairwise Parameter Comparison	No	Yes	Pairwise Parameter Comparison
Enjoyment ←Autonomy	0.264**	0.414**	0.842	0.408***	0.175	-1.212	0.442***	0.195	1.426	0.393***	0.355**	-0.210
Enjoyment ←Competence	0.177*	0.147	-0.185	0.170*	0.209	0.232	0.193	0.161	0198	0.207**	0.074	-0.807
Enjoyment ←Relatedness	0.328***	0.201**	-1.152	0.230***	0.305***	0.682	0.236***	0.289***	-0.483	0.162**	0.359***	1.765*

Note: * Significant at 0.1; ** Significant at 0.05 level; *** Significant at 0.01 level.

	Loneliness			SWL			Happiness			Escapism		
	No	Yes	Pairwise Parameter Comparison	No	Yes	Pairwise Parameter Comparison	No	Yes	Pairwise Parameter Comparison	No	Yes	Pairwise Parameter Comparison
Attitude ←Enjoyment	0.381***	0.361***	-0.273	0.516***	0.261***	-3.587***	0.461***	0.290***	2.346**	0.402***	0.351***	-0.731
Attitude ←Flow	0.067	0.239***	2.327**	0.114**	0.171**	0.735	0.162**	0.117**	0.636	0.063	0.205***	1.956*
Attitude ←Peers	0.264**	0.001	-1.834*	0.127	0.183	0.308	0.061	0.235**	-1.185	0.302**	0.022	-1.873*
Attitude ←Users	0.154*	0.291**	0.950	0.187**	0.250	0.366	0.280**	0.142	0.951	0.062	0.345***	1.888*
IU ←Attitude	0.788***	0.809***	0.190	0.815***	0.766***	-0.459	0.841***	0.754***	0.779	0.806***	0.801***	-0.040

Note: * Significant at 0.1; ** Significant at 0.05 level; *** Significant at 0.01 level.

3.5 Discussion

This study finds that competence, autonomy, and relatedness, concepts from SDT, have a significant and positive effect on enjoyment, which supports the previous literature. In addition, flow has a positive effect on attitude, similar to the results of previous works (Ha & Choi, 2007; Hsu & Lu, 2004), and enjoyment has a positive effect on attitude, similar to previous results (Ha & Choi, 2007; Shin & Shin, 2011). However, the primary aim in this study is to prove a difference between two network externality measures: the number of peers and the total number of users. Previous research shows that network externality has a positive effect to use social service but the implication of the network externalities can be confusing and blurry because there is no strict boundary between these two network externalities. As a first primary result, there are different effects of the number of peers and the total number of users, as shown in Lin & Lu (2011) and Wei & Lu (2014). The effect of the total number of users is larger in the present study, unlike the number of peers had a bigger effect in Lin & Lu (2011) and Wei & Lu (2014) doesn't try to study difference.

Another important task here is to find the factors that caused the different effects of the two forms of network externality. First, the effect of forming online relationships (relatedness) is lower in the lonely group (people who feel uncomfortable in offline social activity) than in those who are not lonely offline. Also, the lonely group cares more about autonomy and flow than about relatedness. Only the total number of users has a

significant effect in the lonely group but not the number of peers. Unlike previous research (Pittman, 2015; Pittman & Reich, 2016; Skues *et al*, 2012; Shaw & Gant, 2002; Kim *et al*., 2009), online socializing is not the most important factor lonely people. In other words, those who feel uncomfortable with friends or have few friends offline devalue the importance of online relationships, whereas online relationships are also important to people who have many friends offline and care about their offline relationships. In short, from the perspective of sociability, the offline tendency is reflected online.

On the other hand, the results regarding enjoyment present a different implication. If people feel less enjoyment and less SWL, their level of happiness would also be low (Rojas, 2005). The results show that people with lower SWL and lower happiness offline pursue enjoyment online. Certainly, the effect of enjoyment on attitude is always significantly positive, regardless of the level of SWL or happiness. However, enjoyment has a significantly larger effect on attitude in the less satisfied and less happy groups than it does among those who are satisfied and happy. That is, online life complements offline life by meeting the demand for increased enjoyment, which is in the same context with other works (Basilisco & Cham, 2015; Malik *et al*., 2015), SWL or happiness is an important factor for SNS providers to induce users.

Thus, the different effects of the number of peers and the total number of users are explained: people's offline tendencies are reflected online in terms of loneliness, but online life complements offline life regarding enjoyment.

This study contributes to the literature in two primary ways. This is the first study to show that the two forms of network externality should be considered as clearly distinct. Second, this study provides an opportunity to consider the differences between two forms of network externality as they are derived from each individual's perceived quality of life.

This study contributes to:

1. supporting that the SDT factors are important in the study of online games;
2. consider differences in the number of peers and the total number of users for scholars;
3. suggest that the perceived life quality (loneliness, SWL, happiness, and escapism) has an impact on why people react differently to the two forms of network externality.

This study has some limitations, primarily that the sample is unlikely to fully represent the population of online game players. Most notably, the sample probably underrepresents those who play for the longest periods, which could cause bias. Also, caution is recommended concerning the generalizability and external validity of the results because other ICT industries have network externality. With further empirical research in the other areas, the results could become generalizable. Second, the survey methodology is less accurate than observational data or alternative reporting methods such as experience sampling. Future research should further explore the associations identified in this study through experiments and longitudinal studies using a range of data collection techniques

with qualitative methods. Finally, the model is simple, so future research could work to better understand the differences in the two forms of network externality by considering other variables.

Chapter 4. The efficiency change of sellers across the diffusion of transaction platform securing the customers[3]

4.1 Introduction

In the development of a new computer- and Internet-based economy (Shapiro & Varian, 2013, p. 173 - 175), anything can be information with digitalization. Thus, the new economy has started to involve abounding information by including a wide array of offline goods such as food and hotels. There is almost zero cost to reproduce digitalized information after its creation (Shapiro & Varian, 2013, p. 3), so the speed of information diffusion through the Internet has been increasing at an astronomical rate. However, now people must spend time and money to find the proper information within the copious information flood.

The platform mediating information between sellers and buyers came to the forefront of society because customers need to find proper information. This platform has been called several things, such as intermediation (Edelman & Wright, 2015), a search platform (Edelman & Wright, 2016), and an information gatekeeper (Baye & Mogan,

[3] A draft version of this chapter was accepted in *Telematics and informatics.* Available online at http://authors.elsevier.com/sd/article/S073658531730165X

2001) and it has been studied as a part of platform study primarily from the viewpoint of network externality. It provides information about existing goods depending on buyer preferences rather than producing goods. Buyers reap benefits from using the platform because it reduces their search costs (Baye & Morgan, 2001) and allows them to make rational purchases (White & Weyl, 2016). Sellers use platform services for exposure to more buyers (Edelman *et al*., 2016). For example, Priceline provides information and the price of hotels to people preparing to travel and creates an online link between sellers and travelers.

As the information provided through the Internet becomes more diverse and enormous, platforms that provide information based on buyer preferences and suggest rational prices for goods have been growing gradually. As one example, the sales of the hotel booking platform Priceline increased more than 6 times, from 1.41 billion dollars in 2007 to 9.22 billion dollars in 2015 (Statista, 2016). Moreover, platforms such as Amazon and eBay have grown continuously. For the past 10 years, the overall net income of the S&P 500 companies has increased 16%, while the net income of platform companies in the S&P 500 has increased 330% (Moazed, 2017; Yardeni *et al*., 2017). Furthermore, according to Moazed (2017), 50% of the overall S&P 500 companies' net income will come from platform companies 25 years later. In addition, the effect of platforms already settled in a market tend to grow increasingly over time because the market mediated by the platform is two-sided; an increase in the number of sellers on the platform engenders an increase in information, stimulating a new increase in buyers, which makes the platform more

attractive to sellers.

On the other hand, there is a possibility that platforms reduce the benefits to sellers and buyers (for example, see Edelman & Wright, 2015; Wang & Wright, 2016). To be profitable, it is indispensable for the platform service provider to require a fee and the lowest prices from sellers to compete with other platforms. This burden is transferred from sellers to buyers, which can make the average final price for buyers higher than it will be without the platform. Thus, the platform might have a detrimental effect on both sellers and buyers surplus (Edelman & Wright, 2015). However, Hunold *et al*. (2016) shows the opposite result by analyzing data; sellers use platforms more without a narrow best price clause (BPC) than with a BPC. Also, taking into account the drawbacks of the platform (increase in input cost for sellers because of the fee and BPC), sellers can still benefit from the positive effect of the platform with market size accreting due to more buyers accessing to information of sellers (Edelman *et al*., 2016) by platform service reduces the search costs of buyers (Baye & Morgan, 2001).

Therefore, this study investigates whether the advent of platforms leads to positive changes in a specific industry by comparing the efficiencies of sellers in that industry. The time-considered diffusion of a platform is divided into 3 periods following the diffusion theory suggested by Gort & Klepper (1982); (1) before the platform interferes in a specific industry (pre-platform period), (2) while the platform is forming the market in a specific industry (transitioning period), and (3) a period of stabilization of the platform (stabilizing period). Also, the efficiencies of each period are measured using stochastic

frontier analysis (SFA) and compared using meta-frontier analysis (MFA). To study the effects of platforms on an industry, the hotel industry is chosen because the platform, including companies such as Priceline and Hotels.com, is stable now. To measure efficiency, data on net sales, number of employees, total assets, and cost of goods sold (COGS) was analyzed from 1986 to 2015.

The second section of this study describes previous studies on platforms and the 3 periods of diffusion. Section 3 discusses the methodologies, SFA and MFA, for measuring and comparing efficiency, respectively. The results section presents the overall efficiency results. The last section discusses the conclusion and implications of this study

4.2 Network externality on platforms

Unlike the competition in an existing industry whose goods carry production costs, the success of a platform whose product (information) costs almost nothing to produce is decided based on network externality; the value of a platform increases as the number of participants on both sides increases (Rochet & Tirole, 2003). A myriad of studies place weight on network externality to convince sellers and buyers to join a platform, (e.g., Armstrong, 2006; Armstrong & Wright, 2007; Caillaud & Jullien, 2003; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003).

Platforms divide markets into two sides (sellers and buyers), and the size of one side determines whether the other side will join the market (Armstrong, 2006). However, not

only do sellers and buyers want to join to more than one platform, but also sellers share zero profits because of severe competition (Caillaud & Jullien, 2003). Thus, it is paramount that platform service providers focus on increments in the number of buyers, which is the base for sellers' profits, instead of using direct competition to induce sellers to join (Armstrong & Wright, 2007). Strategies among platform service providers to attract buyers differ from those of existing industries. Parker & Van Alstyne (2005) claims that offering a service for free to either sellers or buyers can increase profits for all based on externality, in contrast to old-fashioned strategies such as bonding and lock-in. However, it is essential for platform service providers to require a BPC to sellers to attract buyers (Wang & Wright, 2016), which adversely affects consumer welfare because sellers transfer the burden of their fee and BPC to buyers (Edelman & Wright, 2015). Nevertheless, sellers' surplus can increase if the market grows with the expansion of buyers (Edelman *et al*., 2015) using the platform to reduce their search costs (Baye & Morgan, 2001). Although a platform can become attractive by reducing the search costs of buyers, it can be better for sellers not to join it because of the severe competition with other sellers (Loginova & Mantovani, 2015). Thus, companies must decide strategically whether to join a platform (Galeotti & Moraga-Gonzalez, 2009).

Sellers adapt to the changes created by the advent of platforms with their own strategies. There is no consensus among scholars on the effect of platforms on sellers' utility, so that this study analyzes whether the advent of a platform positively affects sellers.

4.3 Hotel industry and its platforms

The hotel industry has a long history, and online booking platforms are in the last stage of diffusion according to Gort & Klepper (1982)'s diffusion theory of new products. Also, a plethora of research has considered the effects of the Internet on tourism from the customer side (for example, see Lang (2000)) and industry side (for example, see Buhalis & Law, 2008; Koo *et al.,* 2011; Lu *et al*., 2015; O'Connor & Frew, 2002). Of the firms active in developing and making a sector's products and in generating and utilizing a sector's technologies as the perspective of sectoral innovation systems (SIS) (Breschi & Malerba, 1997; Gort & Klepper, 1982), innovation types can be categorized into 5 in tourism; product or service, process, managerial, marketing, and institutional (Hjalager, 2010)). It is hard to separate each innovation so that the combination of innovations such as the service innovation and managerial innovation improve the hotel performance in long-term (Crnogaj *et al*., 2014). Moreover, the more hotels innovate, the higher net sales is (Mattsson & Orfila-Sintes, 2014; Ivankovič *et al*., 2010). In addition, the diffusion of innovation leads the evolution of the market (Peres *et al*., 2010). Thus, this study investigates the effects of platform diffusion on the efficiency of the hotel industry.

Gort & Klepper (1982) suggests a theory on the diffusion of new products based on a study of 46 new products. For the present study, the diffusion of platforms is divided into 3 periods based on Gort & Klepper (1982) to determine its effects on the efficiency of the hotel industry, as shown in Figure 4-1; (1) before platforms interfere in the hotel industry

(pre-platform period), (2) while platforms were forming a market in the hotel industry (transitioning period), and (3) the period of final equilibrium (stabilizing period).

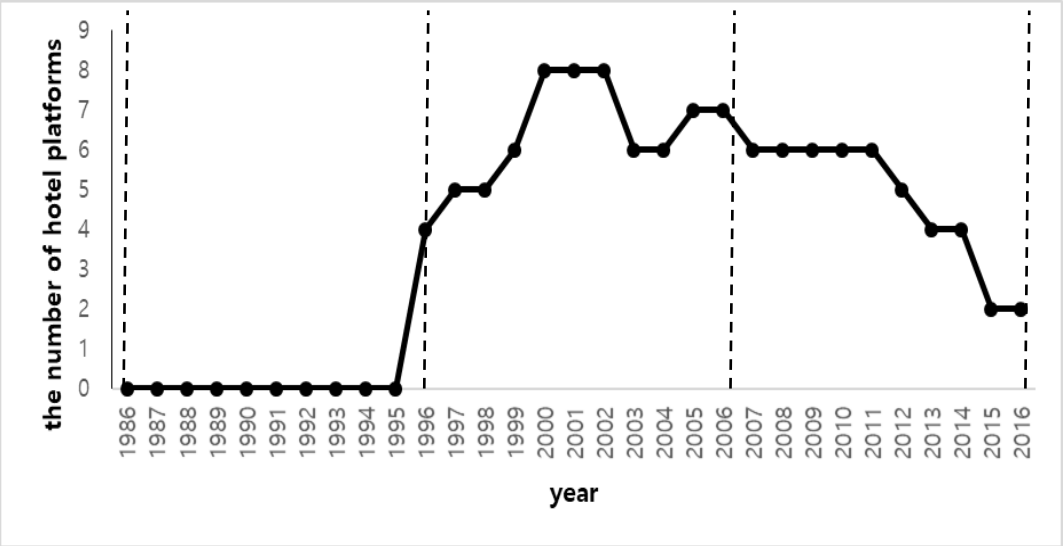


Figure 4-1 The diffusion of hotel platforms

The first of the 3 periods is from 1986 to 1995, and this period represents the hotel industry before the advent of platforms. The second period is from 1996, when the first platform emerged, until 2005. From 1996, the net entry of platforms in the hotel industry increased with the rapid emergence of Expedia, booking.com, and hotels.com, but the net entry decreased, which is the second stage in diffusion theory (Gort & Klepper, 1982). Until 2005, new companies were established while Expedia took over hotels.com and Hotwire in 2003, and Priceline established a solid position by taking over booking.com in 2005, leaving the hotel platform roughly balanced. The last period is from 2006 to 2015;

the number of companies decreased toward the last stage of diffusion and is the smallest at the last stage. From 2006, the number of hotel platform companies showed a tendency to shrink, which is stage 4 in the diffusion theory (Gort & Klepper, 1982). During that period, platform companies underwent structural change with M&As. According to Forbes (Trefls Team, 2014), Expedia, Priceline, Orbitz worldwide, and Travelocity occupy 95% of the online travel agency market in the US. Recently, the hotel platform has been dominated by 2 groups; Priceline (Priceline, booking.com, Agoda, Kayak) and Expedia (Expedia, hotels.com, Hotwire, Tripadvisor, Trivago, Travelocity, Orbitz worldwide). That is, platform was in the last stage of diffusion in 2015. Table 4-1 presents information about the foundation and mergence of hotel platform companies in the United States.

Table 4-1 The foundation and mergence of hotel platform companies

Group	Company	Foundation (year)	Mergence (year)
Priceline	Priceline.com	1997	
	Booking.com	1996	2005
	Agoda	2005	2007
	Kayak	2004	2012
Expedia	Expedia.com	1996	
	Hotels.com	1996 (starting the Internet service)	2003
	Hotwire.com	2000	2003
	Tripadvisor	2000	2004
	Trivago	2005	2013
	Travelocity	1996	2015
	Orbitz worldwide	1999	2015

4.4 Methodology

To measure the efficiency value of the hotel industry across the diffusion of platforms, the SFA method is applied to obtain the efficiencies in the 3 periods. Then, the efficiencies of the 3 periods of firms engaged in production activities under different production functions are compared using the MFA method.

4.4.1 Stochastic frontier analysis

SFA presents the relationship between input and output as a production function and estimates technical efficiency using the frontier production function, which gives the maximum output from a given input. Technical efficiency (TE) describes the technology level of a given firm by comparing the firm's actual production with the frontier production function. As a given firm's technology level becomes further from the frontier production function, its efficiency becomes lower.

To reflect changes in efficiency over time, the SFA model is used, as given in Equation (1), based on Battesse & Coelli (1992).

$$\boldsymbol{Y_{it} = f(x_{it}, \beta)e^{V_{it}-U_{it}}, \mathrm{i} = 1, 2, \dots, \mathrm{N}, \mathrm{t} = 1, 2, \dots, \mathrm{T}} \quad \text{(Eq. 1)}$$

where Y_{it} is the output of firm i in period t, x_{it} is an input vector for firm i in period t, f is

the production function, β is the parameter of the production function, V_{it} is independent from U_{it} and is a random error following a distribution of $N(0, \sigma_v^2)$, and U_{it} is a non-negative random variable that represents the TE of firm *i* in period *t*. If V_{it} is a typical random error in a regression, U_{it} represents the firm's inefficiency. To be sure it is always inefficient, U_{it} is not negative, and it is assumed that U_{it} follows a half-normal distribution.

From Equation (1), TE_{it}, the technical efficiency of firm *i* in period *t*, is given as follows:

$$\boldsymbol{TE_{it} = e^{-U_{it}} = \frac{Y_{it}}{f(X_{it}, \beta)e^{V_{it}}}, i = 1, 2, \dots, N, t = 1, 2, \dots, T} \quad \text{(Eq. 2)}$$

Generally, either the Cobb-Douglas function or the translog function is used. The Cobb-Douglas function has a tendency for oversimplification in considering the output variable as a log-linear combination of the input variables. Thus, the translog function is used here, particularly random effects time-varying. By assuming the translog production function, Equation (1) can be expressed as Equation (3):

$$\boldsymbol{lnY_{it} = \beta_0 + \sum_{m=1}^{3} \beta_m lnx_{mit} + \sum_{m=1}^{3} \sum_{k \geq m}^{3} \beta_{mk} lnx_{mit} lnx_{kit} + V_{it} - U_{it}} \quad \text{(Eq. 3)}$$

where x_{1it} is the amount of capital (K) of the *i*th firm in period *t*, x_{2it} is the amount of cost

(M) of the *i*th firm in period *t*, and x_{3it} represents the number of employees of the *i*th firm in period *t*. The total assets are used for K, the COGS is used for M, and the number of employees is used for L. Lastly, net sales are used for output Y.

4.4.2 Meta-frontier analysis

It is difficult to compare technical efficiencies across groups with different technology using classical SFA. Thus, the meta-frontier production function encompassing the production functions of different groups is used to compare efficiency levels across groups (Battese and Rao, 2002). MFA was first used in the agriculture industry, but recently it has been widely used in the information and communication technology (ICT) industry (e.g., see Hong *et al*., 2011; Lee *et al*., 2015; Lee *et al.*, 2016; Na *et al*., 2017; Yang *et al*., 2013). Specifically, Kim *et al*. (2016) compare the efficiency of each period with MFA after dividing a specific industry into 3 periods. The meta-frontier production function is defined as follows, based on Battese *et al*. (2004):

$$\boldsymbol{Y_{it}^{*} = f(x_{it}, \beta^{*}) = e^{x_{it}\beta^{*}}, \mathrm{i} = 1, 2, \dots, \mathrm{N}, \mathrm{N} = \sum_{i=1}^{R} N_j, \mathrm{t} = 1, 2, \dots, \mathrm{T},} \quad \text{(Eq. 4)}$$

$$\boldsymbol{\mathrm{s.t.}\, x_{it}\beta^{*} \geq x_{it}\beta_{(j)} \;\; for \;\; all \;\; j = 1, 2, \dots, T}$$

where j denotes the group, and the different periods are represented as follows: period 1

(j=1), period 2 (j=2), and period 3 (j=3). β^* is the unknown vector variable of the meta-frontier function. As shown by Equation (4), the meta-frontier production function graph is located above each group's production frontier function graph during all periods. That is, the meta-frontier production function envelops the frontier function of each group based on identical technology. To simplify, assuming function f in Equation (1) as $e^{X_{it}\beta_{(j)}}$, Equation (1) can be transformed as follows:

$$\boldsymbol{Y_{it} = e^{-U_{it(j)}} \times \frac{e^{x_{it}\beta_{(j)}}}{e^{x_{it}\beta^*}} \times e^{x_{it}\beta^* + V_{it(j)}}} \quad \text{(Eq. 5)}$$

If Equation (5) is divided by $e^{x_{it}\beta^* + V_{it(j)}}$, it becomes Equation (6):

$$\boldsymbol{\frac{Y_{it}}{e^{x_{it}\beta^* + V_{it(j)}}} = e^{-U_{it(j)}} \times \frac{e^{x_{it}\beta_{(j)}}}{e^{x_{it}\beta^*}}} \quad \text{(Eq. 6)}$$

The first part of the right side of Equation (6), $e^{-U_{it(j)}}$ is the TE[4] of group j. The second part is the ratio of group j's frontier production function to the meta-frontier production function, and it is called either the technical gap ratio (TGR) or the meta-technology ratio. TE* represents the TE of the meta-frontier production function, and it is the combination of TE and TGR as follows:

[4] TE is also generally used as the efficiency.

$$TE^{*}_{it} = \frac{Y_{it}}{e^{x_{it}\beta^{*}+V_{it(j)}}} = TE_{it} \times TGR_{it} \qquad \text{(Eq. 7)}$$

There are two ways to measure the parameters of the meta-frontier production function: linear programming (LP) and quadratic programming (QP). LP minimizes the sum of the absolute value of deviation, and QP minimizes the sum of squared deviations. LP and QP are defined as follows in Battese et al. (2004):

$$\textbf{LP}: \ \min_{\beta^{*}} L^{*} = \sum_{t=1}^{T}\sum_{i=1}^{N} |x_{it}\beta^{*} - x_{it}\hat{\beta}_{(j)}| \, , x_{it}\beta^{*} \geq x_{it}\hat{\beta}_{(j)} \qquad \text{(Eq. 8)}$$

$$\textbf{QP}: \ \min_{\beta^{*}} L^{*} = \sum_{t=1}^{T}\sum_{i=1}^{N} \left(x_{it}\beta^{*} - x_{it}\hat{\beta}_{(j)}\right)^{2} , x_{it}\beta^{*} \geq x_{it}\hat{\beta}_{(j)} \qquad \text{(Eq. 9)}$$

4.5 Data and results

4.5.1 Data

In this study, data on the US hotel industry are collected from the Compustat database at Wharton. Information about 119 firms categorized using Standard Industry Classification codes 7000 and 7011 is collected, and the GDP deflator (Index 2015) provided by the World Bank is applied to the collected data. The sum of the total number of firms from each period is 172, but some are overlapped across periods so that the actual number of firms investigated is 119.

As input, the number of employees, total assets, and COGS are used, and net sales is used as the output variable. Table 4-2 contains the sample statistics for the collected firms. Group 1 is from 1986 to 1995 as the pre-platform period; group 2 is from 1996 to 2005 as the transitioning period, and group 3 is from 2006 to 2015 as the stabilizing period.

Table 4-2 Sample statistics (Number of firms: 119)

	Group 1 (pre-platform period)	Group 2 (transitioning period)	Group 3 (stabilizing period)
Period	1986 -1995	1996 - 2005	2006 - 2015
Number of Firms	75	67	30
Net Sales (million dollars)	16.875[#] (2.090)	18.430[#] (2.239)	19.728[#] (2.002)
Number of Employees (thousands)	6.195[#] (2.284)	7.161[#] (2.644)	7.725[#] (3.019)
Total Assets (million dollars)	17.496[#] (2.064)	19.145[#] (2.168)	20.305[#] (1.847)
COGS (million dollars)	16.530[#] (2.062)	17.978[#] (2.342)	19.205[#] (2.281)

Note: [#]: mean. Numbers in parentheses are standard deviations.

4.5.2 Estimation results

To analyze the difference in efficiency across the diffusion stages of the platform, SFA is used to estimate production functions for all 3 groups; the efficiency of each group is then calculated as the distance from the production function. Also, efficiency is compared across groups using the meta-frontier production function, which is calculated to embrace the estimated production functions. Table 4-3 shows each group's production functions using SFA and the meta-frontier production function, calculated using MATLAB.

Table 4-3 Estimation results of groups and meta-frontier production functions

	Group 1 (pre-platform period)		Group 2 (transitioning period)		Group 3 (stabilizing period)		Meta-frontier	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	LP	QP
Constant	-1.011	2.742	5.836***	1.670	23.673***	1.270	23.673	23.673
$\ln x_1$	0.217	0.328	0.181	0.254	-0.486	0.588	-0.910	-0.237
$\ln x_2$	0.859**	0.358	0.023	0.252	-1.257**	0.607	-0.893	-1.932
$\ln x_3$	0.354	0.328	0.595***	0.159	0.943***	0.275	1.089	1.639
$(\ln x_1)^2$	0.053***	0.011	0.052***	0.016	0.072**	0.036	0.112	0.078
$(\ln x_2)^2$	0.042*	0.025	0.066***	0.014	0.154***	0.028	0.153	0.160
$(\ln x_3)^2$	0.002	0.013	0.000	0.008	-0.009	0.008	-0.001	-0.005
$\ln x_1 * \ln x_2$	-0.095***	0.031	-0.093***	0.029	-0.145**	0.057	-0.180	-0.132
$\ln x_2 * \ln x_3$	0.029	0.030	0.015	0.014	-0.108***	0.016	-0.063	-0.069
$\ln x_3 * \ln x_1$	-0.048**	0.019	-0.041***	0.014	0.064***	0.021	0.006	-0.019

Note: * Significant at 0.1; ** Significant at 0.05 level; *** Significant at 0.01 level.

Based on the estimates in Table 4-3, the technical efficiencies of each group based on the platform diffusion level are calculated in Table 4-4. The pre-platform period has the highest TE (0.706), followed by the transitioning period (0.619) and stabilizing period (0.518). However, it is impossible to compare the technical efficiencies of different groups because SFA assumes different production functions. The TGR or TE*, based on

meta-frontier production function, can better compare different groups. In the LP result, the stabilizing period shows the highest TGR value (0.921), followed by the transitioning period (0.654). The pre-platform period has the lowest TGR value (0.478) even though it has the highest in TE value. The TE* values are the same as the TGRs: the stabilizing period (0.477) and transitioning period (0.405) showed higher TE* values than the pre-platform period (0.337).

Table 4-4 SFA estimates of technical efficiencies and meta-technology ratios

Group	Mean		St. dev.		Minimum		Maximum	
TE								
Group 1	0.706		0.172		0.050		0.980	
Group 2	0.619		0.121		0.337		0.936	
Group 3	0.518		0.170		0.238		0.959	
TGR	LP	QP	LP	QP	LP	QP	LP	QP
Group 1	0.478	0.511	0.154	0.113	0.056	0.066	0.962	1.000
Group 2	0.654	0.638	0.157	0.128	0.090	0.031	1.000	1.000
Group 3	0.921	0.779	0.100	0.140	0.502	0.403	1.000	1.000
TE*	LP	QP	LP	QP	LP	QP	LP	QP
Group 1	0.337	0.361	0.109	0.080	0.040	0.047	0.680	0.706
Group 2	0.405	0.383	0.097	0.079	0.056	0.019	0.619	0.619
Group 3	0.477	0.404	0.052	0.073	0.260	0.209	0518	0.518

In other words, the efficiency in a group, TE, is relatively high in the pre-platform period because most firms in the hotel industry are close to the group frontier production function, whereas the TGR shows that the pre-platform period production function is further from the meta-frontier production function than those of the other periods. Lee & Hwang (2011) show a similar result by analyzing the content industry. Music streaming services are difficult to differentiate from competitors and so have high TE but low TGR. According to Lee & Hwang (2011), there are almost no innovation factors in music streaming services (except web page design); most music streaming services provide similar services, which leads to high average TEs but low TGRs because they do not move their group frontier production function toward the meta-frontier production function. Likewise, the hotel industry has a long history with well-known factors, such as kindness of employees, cleanliness, interior, and foods, but not many innovation factors. Therefore, the TE values are high, but the TGR values are low, as explained by Lee & Hwang (2011). That is also why TE*, which is the estimate from the meta-frontier production function, is low.

However, the advent of platform has let hotels innovate in several ways, and some companies have achieved unprecedented efficiency as they succeeded in elevating their production function, which was very difficult in the pre-platform period. Even though the rest of the firms cannot match the efficiency of the successful firms after platform appeared (so the average efficiency is lower than in the pre-platform period), TE*, which indicates the efficiency based on the meta-frontier production function, and TGR both

increase in the transitioning and stabilizing periods. That is, the TE* of groups selling their services through a platform is higher than that of groups that do not use a platform.

4.6 Conclusion

As the ICT industry has developed at an unprecedented speed, platforms have shown continuous growth and will continue responding to buyers' needs for a reasonable purchase and sellers' need to be exposed to more buyers. However, some studies explicitly state that platforms increase sellers' input costs and reduce seller surplus by causing competition among sellers. There has been no consensus among scholars on the effect of platforms on sellers. Thus, to investigate the effect of platform on an existing industry, platform diffusion is divided into 3 periods following the new products' diffusion theory of Gort & Klepper (1982); (1) pre-platform period, (2) transitioning period, (3) stabilizing period. In calculating each period's efficiency using SFA, the pre-platform period shows the highest average efficiency (TE), followed by transitioning period and stabilizing period. However, the SFA method cannot compare the different groups using different production functions. Therefore, TGR and TE* are measured using MFA, and the estimates based on MFA show the opposite result from TE values using SFA. The stabilizing period has the highest TGR and TE*, followed by the transitioning period, and the pre-platform period's TGR and TE* are the lowest, even though this period has the highest TE. The increment in TE* and TGR as the maturation of platform

shows us the efficiency improvement. However, it is clear that the efficiency improvement is led by some successful firms from the result of SFA, the decrement in TE as platform matures.

That is, improvements in the productivity of successful sellers lead the overall industry's production function toward the meta-frontier production function as the platform matures. This result is in the same context as Edelman *et al*. (2016)'s study that explains that sellers' profits increase because platforms offer buyers information about sellers and goods. Edelman *et al*. (2016) shows that the online discount vouchers through platform is more profitable to sellers. Likewise, the sellers who adapt to the platform improve their efficiency. In other words, the positive effect of reducing buyers' search costs through a platform (Baye & Morgan, 2001) yields an increase in buyers which leads the seller's output increases that outweighs the disadvantage to sellers of a reduction in surplus (Edelman & Wright., 2015) which means that seller's input increases. Thus, even if the competition on platform can be severe, it would be better to join platform for sellers rather than not to unlike others suggest that sellers should follow their strategy to decide whether to join platform (Loginova & Mantovani, 2015; Galeotti & Moraga-Gonzalez, 2009).

As hotel platforms have entered the last maturation stage recently, there is an empirical study claims that platforms can be more attractive to sellers without a narrow BPC (Hunold *et al*., 2016) opposite to a theoretical study that claims that platforms cannot survive without a BPC (Wang & Wright, 2015). That is, as a platform stably

secures network externality, it has market power so that letting sellers to be free from a BPC can be more attractive to sellers as the previous studies regarding platform point out that network externality is vital in the new economy (Armstrong, 2006; Caillaud & Jullien, 2003; Parker & Van Alstyne, 2005). In addition, the maturation of platforms can improve productivity, making platforms more attractive to sellers.

However, the firms might not be interested in the innovation because the combination of innovations is needed for higher firm performance (Crnogaj *et al*., 2014; Mattsson & Orfila-Sintes, 2014; Ivankovič *et al*., 2010) and many of innovations should be considered such as product/service and process innovations, management, institutional and information-handling innovations to be sustainable (Hjalager, 1997) even that the innovation is not positively affecting hotel performance in short-term (Crnogaj *et al*., 2014). Additionally, the innovation speed is unprecedented, focusing on customer's habit and the convenience of booking in the hotel industry (ALICE, 2016). It can be hard for the hotel managers to catch up so that they might be resistant to innovation, which is a platform here. As a result, where innovation is not embraced, the firm's efficiency will fall behind those firms that pursue and lead the innovation.

In conclusion, when platform interferes in an existing industry, the seller's productivity increases with stabilization of network externality as platform matures. In particular, an increase in input costs with the advent of platforms is marginal, but the productivity improvement based on securing network externality is substantial. Thus, it might be a better option for sellers to opt for using platform as platform matures.

However, a firm's strategy is crucial when an innovation appears, as seen in the differing efficiencies in each group as platforms mature.

One of the limitations of this study is that it analyzed firms listed in Compustat, which includes only companies of a certain size. Numerous small firms operate in addition to the large firms, and analyzing those firms will also be meaningful. Despite that limitation, analyzing efficiencies across platform maturation contributes to the overall understanding of the effects of platforms on an existing industry even as platforms will continue to be a significant part of industries.

Chapter 5. How do potential consumers assuage uncertainties of emerging technology? Consumer preference and acceptance on an autonomous vehicle[5]

5.1 Introduction

Autonomous vehicles are drawing attention because the technology solves inconveniences of traditional automobiles. In modern society, automobiles have many positive effects on human life, including convenience of movement and improved productivity. However, the negative impacts of automobile cannot be overlooked, as a main cause of death is automobile accident. It is argued that the negative aspects of automobile use will be resolved quickly through the introduction of new technologies, with autonomous vehicle technology being most prominent. Autonomous vehicles are self-driving, with the potential to remove the human driver and human error.

Autonomous vehicles are expected to contribute to solving social problems such as traffic accidents caused by lack of concentration, drinking, etc. during driving.

[5] A draft version of this chapter was under review in *Technological Forecasting and Social Change*

Quantitatively, it is estimated to reduce about $4,000 caused by car accidents per autonomous vehicle per year (Fagnant & Kockelman, 2015; Manyika *et al*., 2013). Also, based on the fuel efficiency of the autonomous vehicle and parking benefit, it is estimated to reduce cost by about $250 per new autonomous vehicle (Litman, 2012). In addition, people realize that autonomous vehicles will have benefits such as reduction of car accidents and driving time (Accenture, 2011; Bansal *et al*., 2016; Fraedrich & Lenz, 2014; Howard & Dai, 2014; Schoettle & Sivak, 2014).

However, there are factors that hinder consumer acceptance of autonomous vehicles. Not only is it a new technology, but it is a technology that goes against the habits of people, producing fear. Consumers are afraid of system failure, system breech, and safety (Bansal *et al*., 2016; Caldwell, 2014; Casley *et al*., 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014; Schoettle & Sivak, 2014). Thus, people are afraid to give up manual control of cars (Accenture, 2011; Howard & Dai, 2014). People will not accept autonomous vehicles if they cannot get rid of fears despite the benefits of autonomous driving. Given that context, what regulations could resolve these fears and positively impact consumer acceptance?

According to social learning theory (SLT), people base their own consumption decisions on others' behaviors (Bandura, 1971). The degree of impact of other people's behavior on individual preference has increased due to the Internet. There is now little restriction on time and distance, allowing people to obtain information not only from acquaintances (Bhatnagar & Ghose 2004; Ellison & Fudenberg 1995; Laroche *et al*.

2005). Thus, other user information should be considered as an important factor affecting the preference of consumers (Avery *et al*., 1999; Chen & Xie, 2008; Saito & Matsubayashi, 2018). As use by others becomes a reliable source of information about the product, the use of others' opinions has an important influence on consumers' preferences when accepting new technology (Saito & Matsubayashi, 2018). Therefore, it is necessary to analyze how other users' use information affects consumers' preferences in the autonomous vehicle market.

This study reviews the literature on network externality based on social learning theory and autonomous vehicles in section 5.2, describes the methodology and data in section 5.3, presents the estimated results and simulation in section 5.4, and discusses important implications and limitations of the study in section 5.5.

5.2 Literature review

5.2.1 Network externality based on social learning theory

Conventional interpersonal communication is only effective within limited social contact boundaries, and the influence diminishes quickly over time and distance (Bhatnagar & Ghose 2004; Ellison & Fudenberg 1995). However, advances of information technology and the emergence of online social network sites have transcended traditional limitations and profoundly changed the way information is transmitted (Laroche *et al*. 2005). Now people can exchange messages with people all

over the world. In addition, people obtain information online or can connect with people they do not know in person.

With the development of the Internet, consumers began to perceive the use information of others as additional information about products. Based on social learning theory, individual behaviors and thoughts are determined by interaction with others and simultaneously observing other people's use behavior (Bandura, 1971). In a system that sells goods online, other people's information affects preferences for goods. The rating system determines the consumer's preference for a particular product based on information gained from other people's usage information and viewing reviews (Chevalier & Mayzlin, 2006; Dellarocas, 2003; Yang & Mai, 2010). As others' use information becomes important, sites such as Amazon try to increase consumers' purchase intentions by allowing consumers who use the product to leave an evaluation of the product (Chen & Xie, 2008; Pang & Lee, 2008; Shi *et al*., 2018).

Use information of a stranger has played an important role in consumer decision. It is said that there is a network externality that affects consumers' preferences based on reviews (Saito & Matsubayashi, 2018). The consumer utility of using products increases as the number of users increases, which is called a (positive) network externality. As such, consumers have begun to address the uncertainty of information about the product or service with information from others (Avery *et al*., 1999; Chevalier & Mayzlin, 2006; Dellarocas, 2003; Duan *et al*., 2008). Among network externality, direct network externality caused by the number of consumers is more important than the number of

peers (Kim *et al*., 2018). Based on interaction with strangers, people now think of other people's information as a feature of the product (Chen & Xie, 2008; Godes *et al*., 2005; Park *et al*, 2007; Trusov *et al*., 2009).

Therefore, the number of other users has become important as a factor influencing consumer preferences as it becomes possible to access the opinions of other unknown people.

5.2.2 Consumers' attitudes toward an autonomous vehicle

Research on the acceptance of autonomous vehicles and the prediction of future autonomous vehicle development is increasing (Childress *et al*., 2015; Fagnant & Kockelman, 2015; National Highway Traffic Safety Administration, 2013; Schoettle & Sivak, 2014). High production costs prevent mass scale production and prevent mass consumers from purchasing (Casley *et al*., 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014). Bansal & Kockelman (2017) simulated eight scenarios based on the reduction of technology production costs, increasing willingness to pay, and changes in government regulations.

The autonomous vehicle is already part of our life. In the early 2000s, active safety / convenience technologies were first installed only in the highest-end vehicles of each vehicle manufacturer. However, various active safety technologies have been installed even in small car class vehicles as an indicator of vehicle safety evaluation technology in

each country (Euro NCAP (New Car Assessment Program), the North American IIHS (Insurance Institute for Highway Safety), and the KNCAP (Korean New Car Assessment Program)). National Highway Traffic Safety Administration (NHTSA) also requires that all vehicles produced after 2020 be connected (Automotive Digest, 2014). Moreover, Morgan Stanley predicts that autonomous vehicle technology and infrastructure will be complete and restrictions on popularizing autonomous vehicles will be resolved by 2026 (Morgan Stanley, 2013).

However, to operate autonomous vehicles in accordance with the actual control laws and regulations, related laws and systems including standards and technical requirements for approval of autonomous vehicles must be improved (Fagnant & Kockelman, 2015; Milakis *et al*., 2017). Even though it is expected that autonomous vehicles will reduce costs of automobiles (Accenture, 2011; Fraedrich & Lenz, 2014; Kyriakidis *et al*., 2015; Schoettle & Sivak, 2014), people are afraid of autonomous vehicles. People still hesitate to accept autonomous vehicles because they are afraid of system failure, system breech, and safety regulation (Bansal *et al*., 2016; Caldwell, 2014; Casley *et al*., 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014; Schoettle & Sivak, 2014). Although acceptance of technology may increase based on other users' use information, the regulations needed to resolve perceived risks must be determined. In other words, analysis based on the number of users and regulations is paramount.

To date, discrete choice analysis to reveal consumer preferences for autonomous vehicles has progressed but has not included other users' usage information as

information the consumer accepts. One study analyzed preferences by demarcating individual demographic characteristics (Howard & Dai, 2014), and another study investigated the preferred level of autonomy (Megens, 2015). Thus, this study investigates what kind of regulations should be offered to maximize the influence of the degree of usage rate on individual preference.

5.3 Methodology and data

Since the autonomous vehicle market is at an early stage, market data has not been accumulated sufficiently, and it is difficult to analyze consumers' revealed preferences for autonomous vehicles. Therefore, this study conducts a discrete choice experiment and gathers consumers' stated preference data. In the choice experiment, the respondents are asked to choose the most preferred among the designed hypothetical alternatives (Louviere *et al*., 2000). After obtaining the stated preference data from the choice experiment, we analyze consumers' preferences for autonomous vehicles by applying an econometric model (Train, 2009).

5.3.1 Survey design

To design the discrete choice experiment, we identify attributes that can describe an autonomous vehicle. The attributes are also regarded as the factors affecting consumers'

preferences of autonomous vehicles. We derive six significant attributes of autonomous vehicles after reviewing abundant previous literature. Detailed explanations of the attributes are as follows.

First, we consider the price of an autonomous package as one attribute and assume that price ranges between 10 million KRW and 40 million KRW based on the market prices of Tesla and Google's autonomous vehicles. We refer to the estimated future prices of advanced autonomous vehicles in specifying the attribute levels of the price (Bansal & Kockelman, 2017; Boston Consulting Group, 2015).

Second, autonomous vehicles are characterized by the autonomy level in the discrete choice experiment. Even though the level of automation is categorized into six different levels in general (National Highway Traffic Safety Administration, 2016), it is not easy for respondents to understand and distinguish the six levels due to the technological complexity of their description. Therefore, we reclassify the level of automation as driver assistant, conditional automation, and full automation by grouping adjacent levels to make the levels more distinguishable. Here, we define 'driver assistant' as the level that an automated driving system offers simple assistance tasks such as automatic braking and lane recognition (NHTSA level 1 and 2), 'conditional automation' as the level to which an automated driving system can replace a driver in a specific driving environment such as highways and specified routes (NHTSA level 3 and 4), and 'full automation' as the level that an automated driving system performs all driving tasks under all environmental conditions while allowing driver intervention (NHTSA level 5).

Third, the level of information protected is another significant attribute because people care about their privacy (Fagnant & Kockelman, 2015; Milakis *et al*., 2017). Since an automated driving system collects various kinds of information (e.g., driver information, real-time location, and driving history), information protection technologies such as encryption are needed in the system. Therefore, we consider the level of information protected as an attribute and assume that it can be categorized into three levels: low (protecting only driver information), medium (protecting driver and real-time location information), and high (protecting all information including driver, real-time location, and driving history).

Fourth, whether specialized laws are applied for an autonomous vehicle or not might significantly affect consumer acceptance. Previous literature finds that consumers recognize the differences in operating mechanism between autonomous vehicles and traditional driver-controlled cars. Thus, consumers tend to be afraid of potential accidents caused by inattention of drivers, sensing errors, etc. (Bansal *et al*., 2016; Caldwell, 2014; Casley *et al*., 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014; Schoettle & Sivak, 2014). One way to relieve consumers' perceived risks related to the consequence of potential accidents is by applying specialized laws for autonomous vehicles.

Fifth, we also consider the infrastructure coverage utilized in operating automated driving system. The level of infrastructure coverage is assumed to be categorized into three levels: highway only, highway and wide-area road (city road), and all roads nationwide.

Finally, we assume that consumers' preferences of autonomous vehicles are affected by network externality. In other words, consumers would interact indirectly with each other when they purchase an autonomous vehicle by obtaining information and enhancing trust based on others' acceptance of autonomous vehicles. In this study, network externality is measured by penetration rate. Table 5-1 summarizes the attributes used in the discrete choice experiment and their descriptions.

Table 5-1 Designed attributes and levels in discrete choice experiments for autonomous vehicles.

Attributes	**Description**	**Attribute levels**
Price	Extra cost as adding the automated vehicle option	10 million KRW 20 million KRW 30 million KRW 40 million KRW
Autonomous level	The level of automated driving without driver's intervention	Driver assistance Conditional automation Full automation
Level of information protected	The level of encryption for driver and system information using automation	Low (only driver information) Medium (driver and real-time location information) High (all information including driver, real-time location and driving history)

Attributes	**Description**	**Attribute levels**
Specialized law	Whether the autonomous driving law exists	Applied or Not applied
Infrastructure coverage	How much road infrastructure is available for autonomous driving	Highway only Highway and wide-area road (city road) All roads nationwide
Network externality (Penetration rate)	The market penetration rate of autonomous vehicles	10% 30% 50%

The number of possible alternatives derived from combinations of attribute levels is 648. However, choosing the most preferred among all possible alternatives is time-consuming and costly for respondents, so this study utilizes a fractional factorial design. As a result, 32 orthogonal alternatives are drawn from a fractional factorial design method and divided into 8 choice sets consisting of 4 alternatives each. Then respondents are asked to choose their most preferred among the 4 alternatives in the choice set (Table A-2). An example of the choice experiments is shown in Figure 5-1.

In addition, we ask respondents questions about perceived risks of technological problems that need to be regulated such as information security, incident response manual, and technical standards (system stability standard and technology certification) (National Highway Traffic Safety Administration, 2016). The questions are answered rated with a five-point Likert scale in order to investigate the impact of perceived risks on the acceptance of autonomous vehicles. People fear autonomous vehicles because of the possibility of system failure. Thus, standards and technical requirements for approval of autonomous vehicles must be improved (Fagnant & Kockelman, 2015; Milakis *et al*., 2017). The most fearful elements to be regulated should be understood.

■ **Questionnaire 1**

	Type A	**Type B**	**Type C**	**Type D**
Price	30 million KRW	40 million KRW	40 million KRW	40 million KRW
Autonomous level	Driver assistance	Driver assistance	Conditional automation	Full automation
Level of information protected	Low	Low	Medium	Low
Specialized law	Not applied	Applied	Not applied	Not applied
Infrastructure coverage	Highway and wide-area road	Highway only	Highway only	Highway only
Network externality (Penetration rate)	30%	50%	10%	30%
Choose the most preferred one				

Figure 5-1 An example of the choice experiment

5.3.2 Model specification

Data obtained from the choice experiment can be analyzed by a discrete choice model to estimate consumers' preference parameter for each attribute of a product or service. Therefore, we employ the mixed logit model to investigate consumers' preferences for autonomous vehicles. The mixed logit model is based on the random utility model framework (Thurstone, 1927; McFadden, 1974) and can express heterogeneity in consumers' preferences by assuming that preference parameters follow specific distributions. The distribution of the parameters can be assumed as various distributions such as normal, log-normal, truncated normal, or censored normal distribution, but the normal distribution is used most often.

Equation (1) shows the utility of consumer n for alternative i in choice situation t (McFadden & Train, 2000). Here, the preference parameter β_n is assumed to follow the normal distribution with mean b and variance W. The utility U_{nit} consists of the deterministic term V_{nit} and stochastic term ε_{nit}, which is assumed to follow the type I extreme value distribution.

$$\begin{aligned} U_{nit} &= V_{nit} + \varepsilon_{nit} = \beta_n' x_{nit} + \varepsilon_{nit} \\ \beta_n &\sim N(b, W) \end{aligned} \qquad (1)$$

Under the assumption that consumers make choices that maximize their utility, the choice probability of consumer n choosing alternative i in choice situation t can be expressed as equation (2).

$$\begin{aligned} P_{nit} &= P(U_{nit} > U_{njt},\ \forall j \neq i) \\ &= P(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt},\ \forall j \neq i) \\ &= P(\varepsilon_{njt} < \varepsilon_{nit} + V_{nit} - V_{njt},\ \forall j \neq i) \end{aligned} \qquad (2)$$

Considering that the stochastic term ε_{nit} follows type I extreme value distribution, equation (2) can be rewritten as equation (3). Here, $f(\beta_n \mid b, W)$ is the density function of β_n. Moreover, the likelihood function of the sample can be derived as equation (4) where y_{nit} indicates whether consumer n chooses alternative i or not in choice situation t.

$$P_{nit} = \int \left(\frac{e^{\beta_n' x_{nit}}}{\sum_j e^{\beta_n' x_{njt}}} \right) f(\beta_n \mid b, W) d\beta_n \qquad (3)$$

$$L = \int \prod_{n=1}^{N} \prod_{t} \prod_{i} \left(\frac{e^{\beta_n' x_{nit}}}{\sum_j e^{\beta_n' x_{njt}}} \right)^{y_{nit}} f(\beta_n \mid b, W) d\beta_n \qquad (4)$$

Based on the preference parameters, the relative importance (RI_k) of attribute k can be calculated. Here, RI_k is the weight of the part-worth for attribute k in the total sum, as in equation (5) (Woo *et al*., 2017; Moon *et al.*, 2017). The part-worth for attribute k can be derived when the individual preference parameter of attribute k, β_k, is multiplied by the interval of the attribute's level.

$$RI_k = \frac{part-worth_k}{\sum_k part-worth_k} \times 100 \qquad (5)$$

5.3.3 Data description

Data are obtained from an online survey of 500 residents aged 20-59 in seven major cities[6], and the survey is conducted by MACROMILL EMBRAIN. The sample is collected using a purposive quota sampling method based on demographic characteristics of region, gender, and age to reflect the real proportion of population in South Korea, as shown in Table 5-2[7]. Because we are researching car purchases, we limit the study to comprise people with a driver's license. In the sample, there are 122 people with no driving experience and 398 people with driving experience. The average duration of

[6] The seven major cities cover almost half of the South Korean population

[7] The real population in South Korea was offered by the Korean Ministry of the Interior and Safety (http://www.mois.go.kr/frt/sub/a05/totStat/screen.do). There were 14,290,793 citizens aged from 20 to 59 years in the seven major South Korean cities as of August 2017.

driving experience is 13.3 years.

Table 5-2 Demographic characteristics of survey respondents.

Criteria		**Real population (2017)**		**Respondents**	
		Number of population	**Proportion**	**Number of sample**	**Proportion**
Total		14,290,793	100.0%	500	100.0%
Region	Seoul	6,270,453	43.9%	219	43.8%
	Incheon	1,866,622	13.1%	66	13.2%
	Busan	2,081,631	14.6%	72	14.4%
	Daegu	1,508,404	10.6%	52	10.4%
	Gwangju	891,317	6.2%	31	6.2%
	Daejeon	932,358	6.5%	34	6.8%
	Ulsan	740,008	5.2%	26	5.2%
Gender	Male	7,189,288	50.3%	251	50.2%
	Female	7,101,505	49.7%	249	49.8%
Age	20-29	3,222,199	22.5%	110	22.0%
	30-39	3,450,065	24.1%	122	24.4%
	40-49	3,853,466	27.0%	136	27.2%
	50-59	3,765,063	26.3%	132	26.4%

5.4 Results

5.4.1 Estimated results

As mentioned above, we employ a mixed logit model to investigate consumers' preferences for autonomous vehicles. We construct three models: Model 1 is a basic model in which the utility function consists of the attributes of autonomous vehicles. Model 2 additionally considers perceived risks of potential problems that need to be regulated, such as information security, incident response manual, and technical standard. It is assumed that the perceived risk would affect the marginal utility of network externality in model 2. Model 3 divides technical standard risk into two factors – system stability risk and technology certification risk. The estimation results of each model are presented in Table 5-3.

Table 5-3 Estimation results of consumers' preferences for autonomous vehicles

		Model 1		Model 2		Model 3		Relative importance
Variables		**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	
Price		-0.205***	-0.024***	-0.205***	0.241***	-0.205***	0.240***	39.3%
		(0.047)	(0.043)	(0.046)	(0.436)	(0.047)	(0.044)	
Level of automation	Conditional automation	0.129**	-0.107	0.128**	-0.107	0.127 **	-0.122	10.2%
		(0.059)	(0.294)	(0.058)	(0.281)	(0.059)	(0.256)	
	Full automation	-0.033	0.167	-0.032	0.147	-0.033	0.156	
		(0.064)	(0.209)	(0.063)	(0.245)	(0.063)	(0.218)	
Level of information protected		0.004***	-0.005***	0.004***	0.005***	0.004***	0.005***	16.0%
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	
Specialized law		0.0203	0.347***	0.020	0.347***	0.020	-0.352***	1.2%
		(0.053)	(0.086)	(0.053)	(0.087)	(0.053)	(0.086)	
Infrastructure coverage		0.002*	0.000	0.002*	0.000	0.001*	0.000	9.1%
		(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	
Network externality		0.010***	-0.009**	0.018***	-0.002	0.015***	-0.001	24.2%
		(0.002)	(0.003)	(0.003)	(0.013)	(0.004)	(0.009)	

	Model 1		Model 2		Model 3		Relative
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**importance**
Network externality			0.003	-0.000	0.003	-0.001	-
× Information security risk			(0.002)	(0.015)	(0.002)	(0.013)	
Network externality			-0.002	0.001	-0.001	0.000	-
× Incident response manual risk			(0.003)	(0.009)	(0.003)	(0.008)	
Network externality			-0.010**	0.010**			-
× Technical standard risk			(0.004)	(0.004)			
Network externality					0.003	0.001	-
× System stability risk					(0.004)	(0.009)	
Network externality					-0.011***	-0.010***	-
× Technology certification risk					(0.003)	(0.003)	

Note: MWTP = marginal willingness to pay. Standard errors in parentheses. * Significant at 0.1; ** Significant at 0.05 level; *** Significant at 0.01 level.

Based on the estimation results of model 1, it is confirmed that the price of an autonomous package most significantly influences consumer utility, followed by network externality. Specifically, consumers tend to like lower price and higher penetration rate for autonomous vehicles. In addition, it is found that consumers prefer conditional automation to full automation. There is no statistically significant difference in preference for driver assistance or full automation. Thus, this study confirms the result of previous studies showing that drivers regard the condition in which their vehicle cannot be controlled by themselves as a risk (Accenture, 2011; Howard & Dai, 2014). Furthermore, it seems that consumer preference increases with higher level of information protection and infrastructure coverage. However, whether specialized laws for autonomous vehicles are adopted or not does not significantly affect consumer preference.

The results of model 2 reveal that information security risk and incident response manual risk do not make a significant difference on the marginal utility of network externality. On the other hand, perceived risk from not regulating technical standards negatively influences the impact of network externality on consumer preference. This means that consumers tend not to choose autonomous vehicles even if the penetration rate increases when they are concerned about technical standard risk. Among technical standard risks, perceived risk from not setting up a technology certification system has significant negative effects on the marginal utility of network externality, while perceived risk from not regulating the operational stability of autonomous systems has no effect, as shown in the estimation result of model 3.

5.4.2 Market simulation

We conduct scenario analysis to examine changes of market acceptance for emerging technology in the automobile industry (autonomous vehicles) when consumers' perceived risks related to regulation were resolved.

For the simulation, we assume that the level of technology certification risk can be categorized into three levels: 'high' indicates the current level, 'medium' indicates the situation where the proportion decreased by 30% point, and 'low' indicates the situation where the proportion decreased by 60% point. And the scenarios involve penetration rate change from 5% to 30% and perceived risk of technology certification reduced from high (current level) to low while the other attributes remain constant. The proportion of respondents who consider the technology certification issue as the greatest among the perceived risks was 76.6% at the current situation. Thus, it can be a perceived risk of technology certification baseline while we assume that the price of an autonomous package is 10 million KRW, the level of automation is driver assistance, the level of information protected is low, specialized laws for autonomous vehicles are not adopted, and the coverage of infrastructure is highway only for all scenarios to control other factors effects for high lightened the effect of penetration rate (network externality) and technology certification risk.

Then we compare acceptance rates of autonomous vehicles under the scenarios. The results of scenario analysis are shown in Table 5-4 and Figure 5-2.

Table 5-4 Acceptance rate of autonomous vehicles by scenarios

	High technology certification risk	**Medium technology certification risk**	**Low technology certification risk**
5% PR	35.00%	38.40%	43.80%
10% PR	43.60%	52.00%	60.80%
15% PR	52.40%	64.20%	73.60%
20% PR	58.40%	72.80%	83.40%
25% PR	64.00%	79.60%	93.40%
30% PR	69.40%	86.60%	98.00%

Note: PR indicates penetration rate.

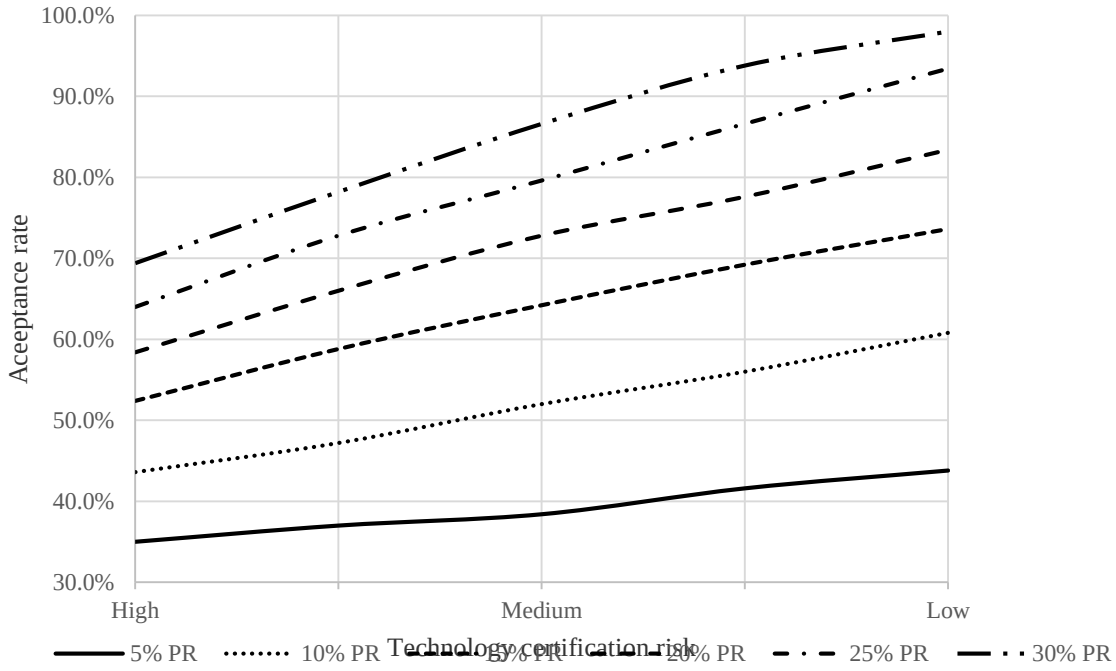


Figure 5-2 Acceptance rate of autonomous vehicles by scenarios

The scenario analysis found that a consumer is more likely to accept an autonomous vehicle when penetration rate (network externality) is high. In addition, the impact of network externality on consumer acceptance was strengthened by resolution of perceived risk related to technology certification. In other words, there would be a synergy effect derived from network externality and reducing consumers' perceived technology certification risk in the diffusion of autonomous vehicles. These results imply that the government needs to discuss and implement appropriate regulations for technical standards, especially related to technology certification, in order to relieve consumer concern and accelerate the diffusion of emerging technology in the automobile industry.

5.5 Discussion

As continuous and remarkable technological innovation has accumulated, autonomous vehicles have been introduced to the automobile market and attracted great attention. Autonomous vehicles are expected to provide convenience to drivers and solve problems including traffic accidents and congestion. However, some consumers hesitate to purchase an autonomous vehicle despite its benefits because of concerns regarding potential risks. A number of studies have attempted to investigate consumer preferences for autonomous vehicles and factors affecting preferences (e.g. Howard & Dai, 2014; Megens *et al*., 2014).

However, the previous literature seems to be limited by not focusing on how to

address consumers' concerns. Some studies have analyzed consumer preference for autonomous vehicles and others focus on regulation issues, but few have focused on potential consumers' fears. To address new technology uncertainty, reviews from other users and the number of users play important roles (Avery *et al*., 1999; Chevalier & Mayzlin, 2006; Dellarocas, 2003; Duan *et al*., 2008; Saito & Matsubayashi, 2018). People prefer products or services that have been used by a large number of users (Chen & Xie, 2008; Godes *et al*., 2005; Pang & Lee, 2008; Park *et al*, 2007; Shi *et al*., 2018; Trusov *et al*., 2009). Therefore, this study regards network externality as important information and the impact of perceived risk affecting consumers' preferences for autonomous vehicles.

The results and implications of this study can be summarized as follows. First, it is confirmed that penetration rate, which indicates the rate of market acceptance, significantly affects consumer preference for autonomous vehicles. When penetration rate is high, consumer acceptance of autonomous vehicles increases accordingly. This result implies that consumers would interact indirectly as well as directly with each other when they purchase innovative products in the automobile market. In other words, acceptance by other consumers of an autonomous vehicle provides information (e.g., safety, stability, and usefulness) to potential consumers and increases trust in the innovative technology. Next, this study finds that regulations, especially related to technology certification, should be made for diffusion of autonomous vehicles. Since an autonomous vehicle is operated in different ways from traditional driver-controlled cars, consumers have perceived risks related to the technological problems of an autonomous vehicle (*Bansal et*

al., 2016; Caldwell, 2014; Casley *et al*., 2013; Fraedrich & Lenz, 2014; Howard & Dai, 2014; Schoettle & Sivak, 2014). This appears to be why perceived risks significantly affect consumer acceptance of autonomous vehicles. Therefore, the government needs to discuss and enact appropriate regulations for technical standards of autonomous vehicles to accelerate market acceptance. Finally, the results of this study suggest that autonomous vehicle manufacturers should focus on improving and boosting conditional automation technologies to secure the users rather than developing full automation technology for now.

In conclusion, this study emphasizes that network externality is a significant factor affecting consumer acceptance of emerging technology in autonomous vehicles, since consumers tend to gather information and enhance their trust toward autonomous vehicles by observing other consumers' adoption patterns. Furthermore, this study draws the remarkable implication that the government should introduce proper regulations to relieve consumers' perceived risks of technological uncertainties for market expansion of autonomous vehicles.

Although this study tries to comprehensively analyze the factors that determine the acceptability of an autonomous vehicle, there are two important limitations. First, this study could not reveal the origin of the heterogeneity of consumers' preferences. By applying more improved discrete choice models such as latent class model and hierarchical Bayesian logit model, the factors that cause heterogeneity of consumers' preferences can be investigated in further research. Second, this study does not consider

country context. If further study investigates country context that might affect adoption of autonomous vehicles, it would be able to derive more generalized policy implications across different countries as well as global market strategies.

Chapter 6. Overall conclusion

6.1 Summary and policy Implications

This dissertation suggests a platform that should be viewed as a consumer-centered rather than a firm-centered in platform economics. In the perspective of consumer needs, the characteristics of the platform economy should be centered on the degree of interaction with people and degree of functional integration.

As extension of Roth (2015) study, the platform acting as matchmaker in the platform economy is to satisfy the users needs to reduce information asymmetry. Especially, the network externality that is pivotal in consumer choice based on SLT to solve information asymmetry. As part of efforts to solve information asymmetry in information economics, it has been suggested that the acquisition of new information could be achieved based on signaling and screening. This thesis suggests to expand SLT to emphasize the reason users behavior affected by other users' use information.

This dissertation investigates the role of network externality in platform economy. First, definition of platform economy is done based on the characteristics of the two-sided market and scholarly studies on this new economy. Platform economy refers to an economy in which the efficiency of people is enhanced by increasing the connectivity by matching resources or people who have not been connected before the emergence of a

specific platform. The consumer's utility increase is influenced by the number of other consumers and the increase in the efficiency of the seller is influenced by the number of consumers. Moreover, with the advent of the platform, the optimal price depends on the consumer's utility influenced by the number of consumers.

In particular, first study shows that there is an influence of the direct network externality of consumers on consumer utility. Also, it reveals that using network externality measurement indiscriminately is wrong by investigating that there is a difference between the measurements. Also, the second study examines the increase in the efficiency of the seller is influenced by the number of consumers. This study shows that the seller 's technical efficiency increases with the diffusion of the platform. Lastly, the third study investigates that the users preference depends on the consumer's utility influenced by the number of consumers. This study reveals that network externality is considered as the product characteristic.

In Chapter 3, we examined the effect of network externality in the high DIP platform. The network externality is divided into the number of peers and total users. The game industry is chosen as a representative industry because it can emphasize the different effect of two network externalities. Online game players can chat with someone they do not know offline which means online games allow you to create connections between people you do not know at all. When we look at the impact of network externality, along with the key factors that motivate playing the game, the number of total users is more important than the influence of peers. Thus, hypothesis 1 is not rejected. In order to

analyze the factors that indicate this difference, we examine the effects of life satisfaction, happiness, loneliness, and escapism. Those who do not socialize off-line well, less happy, and less satisfied do care the number of other users. But when they are happier, less lonely, they care the number of peers.

Hypothesis 1: the consumer's utility increases is influenced by the number of other consumers

In Chapter 4, we search for answers to whether there is increase in the sellers' efficiency in the medium DIP and DFI platform. Some insist that seller can be more profitable due to more exposure to buyers while the others insist that it is possible that the fee and advertisement costs can reduce sellers' profit. When the platform starts to compete with each other, it can be bad for the seller to compete with each other, but if it stabilizes, it can be good for the seller. Therefore, based on the idea that the efficiency of the seller will depend on the diffusion of the platform, we examine whether there is a change in the seller's efficiency through the platform diffusion. The target industry is the hotel industry because the industry to be analyzed must be a stable industry before the platform emerges and the sellers should belong to one industry. And the platform industry in the hotel industry has recently entered a period of stabilization, which is appropriate to see the effects of platform maturity. In conclusion, the hotel industry has increased efficiency as the platform is diffused securing the consumers. Thus, hypothesis 2 is accepted.

Hypothesis 2: The increase in the efficiency of the seller is influenced by the number

of consumers

In Chapter 5, we examined whether the network externality can affect the consumers' preference in the high DFI platform. we target autonomous vehicles, a technology that is attracting attention as a next-generation platform. It is revealed that that network externality can solve people's uncertainty about the dangers of autonomous vehicles. In addition, the network externality among the characteristics of the autonomous vehicles is found to have the highest relative importance. Thus, hypothesis 3 is accepted. Moreover, people are less interested in fully autonomous driving, but as network externality increases, users preference increase. When it is a conditional automated vehicle, it needs a strategy to enter the market and preempt the network externality rather than trying to enter the market by developing the technology to fully automation. And the government needs to make institutional certification so that the ethics of autonomous vehicles can be developed in a better way to society.

Hypothesis 3: Even a technology that has no connectivity between people will be influenced by other users' use information.

After all, all three hypotheses to verify the definition of platform economy are accepted. When using technology with the emphasis on connectivity, the network externality of the total number is more affected than the network externality effect of the peers. In addition, uncertainty about the platform can be solved through network externality. Moreover, consumers acceptance increases due to network externality. If

some of these platforms dominate with securing the number of users, the seller's efficiency will also be better. Therefore, it is important for platform operators to collect users to survive in platform economy and analyze consumers needs for increase in the acceptance level. In the perspective the government policy, the technology certification standard should be developed to solve perceived risk. Moreover, although monopoly is important for market stability, government policy should be developed to prevent the dominance of oligopoly from inhibiting developing better technology by start-up companies.

6.2 Contribution and limitations

This study suggests that the way platform economy works while solving the problems of previous studies. Firstly, the platform economy from the consumer perspective is defined based on the consumers' needs. It is important to categorize the platform types considering consumers needs for the platform operator and the sellers using the platform. The direction of technology development is to satisfy consumers. However, the previous studies have been focused on the firm's profit mode, even though the consumers' satisfaction is important in platform economy. Thus, the studies regarding on the consumer satisfaction could not be organized in the platform categorization. With categorization, the important factors in each characterized platform can be revealed and have more implications. To suggest the platform categorization with consumer

perspectives, it is important to investigate what consumers needs is. Consumers satisfy with more developed technology for the interaction with people and function integration. Thus, it is proper to propose as the platform dimensions with the degree of interaction with people and the degree of functional integration.

Secondly, this thesis explains the reason why people considers other users use information as an important factor by expanding the information economics based on the social learning theory. The other users use information can be another root for resolving the information uncertainty in information economics. Instead of social learning only through celebrity, social learning is based on the behavior of users on the same side to build trust of the product information. As the number of users of the mediation platform increases, the quality of the review of the platform increases, which leads to increase trust.

Each representative platform categorizing as the degree of interaction with people and the degree of functional integration is analyzed to verify the hypotheses. This dissertation shows that direct network externality, which is not considered to be important among scholars studying the two-sided market, is important in a platform economy and that indirect network externality to sellers is also important by analyzing the utility of the vendor. In addition, it also reveals that this direct network externality also affects the consumer acceptance for the new technology. Thus, this dissertation reveals that the network externality of consumers plays an important role in the recursive value creation of platform economy.

Thirdly, by analyzing the different effect between the network externality of the total

number of users and peers, we have established a basis for the distinction between the two. It was also revealed that these effects are different depending on the perception of people's quality of life.

Fourthly, studying whether the seller's surplus was improved due to the platform with the maturity of the platform by analyzing technical efficiency reveals the importance of studying the platform's effect considering the maturity of the platform. Not only that, but the fact that after the platform emerged that technology efficiency is improving, the exposure of the seller to more users plays a bigger role in increasing their efficiency.

Fifthly, this study found that network externality is important in acceptance analysis by considering network externality that was not considered in the conjoint model in the analysis of intent to use new technology. Especially, in case of autonomous vehicle, network externality has a great influence on formation of reference price because it has the highest relationship with network externality and uncertainty. When companies take into account the impact of technology and network externality, technology development is also needed, but efforts are needed to preempt network externality. The government should set up a systematic environment in which technologies of superiority can be developed rather than the technology of large companies that can market the technology.

As information is more abundant, consumers should select information but many consumers try not to think of increasingly complex ideas. Consumers are more likely to be influenced by network externality rather than by product characteristics, which means that when a large number of wrong products are selected, everyone can choose one

without diversity. Thus, more government regulation is needed for diversity and safety.

However, this dissertation has limitations. In this study, the purpose was to investigate how the effect of network externality on users' preference in the platform economy, so there is a limit to seeing only one representative case to verify the hypotheses. Since there are many industries belonging to each platform, it is necessary to investigate each of these industries. Also, the characteristics of industries can be different by sub-industry. Therefore, it would be meaningful to try and compare the same methodology in each platform type. It is also meaningful to analyze each hypothesis by a different methodology. In addition, since each study has been analyzed through a sample, it is necessary to study with another sample.

Moreover, the further studies needed as follows. Research to investigate how people are affected by other people's opinions by analyzing whether people in the search platform respond positively or negatively to media or other users' comments. To build strategies to provide information to people to reduce the negative impact of social learning theory network externality, research on the different types of platforms used for information gathering, depending on the characteristics of people is needed. Lastly, research is needed to show that the wrong product dominates the market as the diversity disappears when a large number of wrong products are selected. It can be done by investigating that misinformation or products dominate the market when many accepts the wrong information.

Despite these limitations, this dissertation contributes by suggesting the classification

of platforms based on the clear definition of platform economy in the perspective of consumers as the extension of matching of Roth (2015) and matchmakers suggested by Evans & Schmalensee (2016).

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Appendix 1: Survey Questionnaire

Table A-1 Survey questionnaire for online games motivation

Q. Please answer with scores from 1 (Strongly disagree) to 5 (Strongly agree) for each question.

The number of peers
- I think many friends around me play an online game.
- I think most of my friends are playing an online game.
- I anticipate many friends will play an online game in the future.
The number of total users
- I think a good number of people play an online game.
- I think most people are playing an online game.
- I think there will still be many people joining.
Flow
- Do you think you have ever experienced flow in playing an online game?
- Most of the time I play an online game I feel that I am in flow.
- I tend to play an online game in flow.

Enjoyment
- Playing an online game provides me enjoyment.
- I have fun playing an online game.
- I enjoy playing an online game.
Competence
- I feel competent at an online game.
- My ability to play an online game is well matched with the game's challenges.
- I feel very capable and effective when playing an online game.
Autonomy
- An online game I play provide me with interesting options and choices.
- An online game I play let me do interesting things.
- I experience a lot of freedom in an online game I play.
Relatedness
- I find the relationships I form in online games fulfilling.
- I find the relationships I form in online games important.
- I feel close to others who play a same online game.

Attitude
- I have an affinity for playing an online game.
- I like playing an online game.
- Playing an online game makes me feel good.
Intention to use
- I intend to keep playing an online game in the future.
- I expect that I will continue to play an online game.
- I want to play an online game soon.
Loneliness
- In general, I feel like I lack companionship
- In general, I feel like I am often left out of social situations
- In general, I feel isolated from others
Satisfaction
- So far I have gotten the important things I want in life.
- The conditions of my life are excellent.

- I am satisfied with life.
Happiness
- In general, I consider myself happy
- Compared with most of my peers, I consider myself happy.
- I totally think my life is happy.
Escapism
Please rate your agreement with the following statements ‘I play games on an online game’.
- So I can escape from reality.
- So I can get away from what I am doing.
- So I can forget about work/study.

Table A-2 Survey questionnaire for autonomous vehicle preference

Q. Please choose the preferred type of the autonomous vehicle from among the four hypothetical options provided below.
Note: Assume that all the other attributes, besides the six proposed here, remain the same.

■ **Questionnaire 1**

	Type A	**Type B**	**Type C**	**Type D**
Price	30 million KRW	40 million KRW	40 million KRW	40 million KRW
Autonomous level	Driver assistance	Driver assistance	Conditional automation	Full automation
Level of information protected	Low	Low	Medium	Low
Specialized law	Not applied	Applied	Not applied	Not applied
Infrastructure coverage	Highway and wide-area road	Highway only	Highway only	Highway only
Usage rate	30%	50%	10%	30%
Choose the most preferred one				

■ **Questionnaire 2**

	Type A	**Type B**	**Type C**	**Type D**
Price	40 million KRW	30 million KRW	40 million KRW	30 million KRW
Autonomous level	Driver assistance	Full automation	Driver assistance	Driver assistance
Level of information	Medium	Low	Low	Low

protected				
Specialized law	Not applied	Not applied	Not applied	Applied
Infrastructure coverage	Highway and wide-area road	Highway only	All roads nationwide	Highway only
Usage rate	50%	10%	10%	10%
Choose the most preferred one				

■ **Questionnaire 3**

	Type A	**Type B**	**Type C**	**Type D**
Price	20 million KRW	40 million KRW	40 million KRW	30 million KRW
Autonomous level	Driver assistance	Driver assistance	Conditional automation	Driver assistance
Level of information protected	Low	High	Low	Low
Specialized law	Not applied	Applied	Applied	Applied
Infrastructure coverage	Highway and wide-area road	Highway only	Highway and wide-area road	Highway only
Usage rate	10%	10%	10%	30%
Choose the most preferred one				

■ **Questionnaire 4**

	Type A	**Type B**	**Type C**	**Type D**
Price	10 million KRW	20 million KRW	10 million KRW	30 million KRW
Autonomous level	Conditional	Driver	Driver	Conditional

	automation	assistance	assistance	automation
Level of information protected	Low	Low	Low	Medium
Specialized law	Not applied	Applied	Applied	Applied
Infrastructure coverage	Highway only	Highway only	Highway only	Highway and wide-area road
Usage rate	10%	30%	10%	10%
Choose the most preferred one				

■ **Questionnaire 5**

	Type A	**Type B**	**Type C**	**Type D**
Price	20 million KRW	20 million KRW	30 million KRW	20 million KRW
Autonomous level	Full automation	Conditional automation	Driver assistance	Conditional automation
Level of information protected	Medium	Low	High	Los
Specialized law	Not applied	Not applied	Not applied	Applied
Infrastructure coverage	Highway only	Highway only	All roads nationwide	All roads nationwide
Usage rate	10%	30%	10%	10%
Choose the most preferred one				

■ **Questionnaire 6**

	Type A	**Type B**	**Type C**	**Type D**
Price	20 million KRW	30 million KRW	20 million KRW	10 million KRW
Autonomous level	Driver assistance	Conditional automation	Driver assistance	Driver assistance
Level of information protected	High	High	Medium	Low
Specialized law	Applied	Not applied	Not applied	Not applied
Infrastructure coverage	Highway only	Highway only	All roads nationwide	Highway and wide-area road
Usage rate	10%	50%	30%	10%
Choose the most preferred one				

■ **Questionnaire 7**

	Type A	**Type B**	**Type C**	**Type D**
Price	10 million KRW	40 million KRW	10 million KRW	10 million KRW
Autonomous level	Driver assistance	Conditional automation	Conditional automation	Full automation
Level of information protected	Low	High	Low	High
Specialized law	Not applied	Applied	Applied	Not applied
Infrastructure coverage	All roads nationwide	All roads nationwide	Highway and wide-area road	Highway only
Usage rate	50%	30%	30%	30%
Choose the most				

preferred one				

■ **Questionnaire 8**

	Type A	**Type B**	**Type C**	**Type D**
Price	10 million KRW	10 million KRW	30 million KRW	20 million KRW
Autonomous level	Full automation	Driver assistance	Full automation	Full automation
Level of information protected	Medium	Medium	Low	High
Specialized law	Applied	Applied	Applied	Applied
Infrastructure coverage	All roads nationwide	Highway only	All roads nationwide	Highway and wide-area road
Usage rate	10%	50%	50%	50%
Choose the most preferred one				

Abstract (Korean)

산업 혁명 이후로 산업 경제가 주류를 이루었던 우리 사회에서 2000년대부터 인터넷이 발전하면서 이제는 플랫폼 경제가 주류를 이루기 시작했다. 산업 경제에서는 네트워크를 기반으로 하는 산업에서만 네트워크 외부성이 중요했지만 플랫폼 경제에서는 다른 사람과의 연결성이 중요하다. 그래서 플랫폼에서의 네트워크 외부성 연구가 활발히 진행되었다. 하지만 그럼에도 불구하고 플랫폼 종류를 나누는 기준이 모두 다 다를 뿐 아니라, 네트워크 외부성에 대한 정의도 연구마다 제 각각이다. 그렇기에, 이 연구를 통해 네트워크 외부성의 정의와 함께, 플랫폼 경제에서 하는 역할을 조사하는 것을 목표로 한다.

양면시장의 등장으로 인한 새로운 경제를 네트워크 경제, 디지털 경제 등으로 불러왔다. 하지만 플랫폼을 중심으로 발전하는 경제이기에 플랫폼 경제라고 부르는 것이 적합하다. 이 플랫폼 경제는 “특정한 플랫폼의 등장 전에는 연결될 수 없었던 연결성이 플랫폼의 등장으로 인해 가능해짐으로써 소비자의 효용을 증가시키는 경제” 라고 정의할 수 있다. 플랫폼 경제에서 가치 창출이 순환적이라는 것을 설명함에 있어 소비자의 네트워크 외부성이라는 용어가 사용된다. 소비자는 더 신뢰할 수 있는 정보를 얻고자 하는 열망을 해결하기 위해 다른 이용자의 이용 정보를 중요하게 받아들이기 때문이다.

먼저, 이 연구는 네트워크 효과의 중요성에 대한 고찰을 통해서 소비자의 니즈를 중심으로 한 플랫폼 경제학 연구가 필요하다고 주장한다. 소비자는 인터넷의 발전을 통해 소비자의 정보비대칭성 해소 욕구를 만족시키고 싶어한다.

플랫폼을 통해서 거리나 시간적인 제한 없이, 개인적으로 알지 못하는 다른 사람의 이용정보까지 알 수 있게 됨으로 인해서 다른 사람의 이용 정보를 제품에 대한 하나의 새로운 정보로 인식하고 있는 양상을 보인다. 사회적 학습 이론을 바탕으로 하여 소비자는 다른 사람의 경험을 새로운 정보로 받아들이기 시작하는 것이다. 이것은 정보 경제학에서 정보의 비대칭성을 해결하기 위한 노력의 일환으로, 시그널링 이론과 스크리닝 이론을 중심으로 한 연구들의 연장선상에 있는 것이다. 그러므로 이 연구는 소비자가 플랫폼 이용에 있어서 중요하게 생각하는 요소를 기반으로 한 플랫폼 분류 틀을 제시하였다. 소비자는 검색을 넘어서서 다른 사람과의 연결성, 기능성 통합성을 원하고 있기에, 이 두 가지의 축을 기준으로 하는 플랫폼 분류틀을 제시하였다. 그리고 대표적인 3가지의 플랫폼에서 실증 분석을 하였다. 지인과 전체 사용자 네트워크 효과가 소비자에게 각기 다른 영향을 준다는 것을 조사한 후, 소비자가 직접 모르는 사용자의 수가 증가함으로써, 판매자의 효율성도 증가하는지 조사하였다. 마지막으로, 네트워크 효과가 제품의 한 특성으로서, 소비자의 선호에 미치는 영향을 분석하였다.

먼저, 연결성이 높은 플랫폼에서는 구조방정식을 이용하여, 다른 소비자의 수가 나의 효용에 영향을 미치는지를 분석하였다. 이 플랫폼에서의 연구들은 지인의 수를 바탕으로 한 네트워크 외부성과 전체 이용자수를 기반으로 한 네트워크 외부성을 무분별하게 동일한 네트워크 외부성 효과로 보면서 연구가 되어오고 있었다. 그렇기에, 사회성 중심 플랫폼에서 이 두 가지의 효과에 차이가 있다는 것을 밝히려고 하였고, 삶의 질에 대한 인지에 따라서 이 차이가

다르게 인식된다는 것을 조사함으로써, 이 두 가지의 네트워크 외부성의 효과는 구분해서 보아야 한다는 주장의 근거를 마련하였다. 이 연구에서는 가설의 검증을 위해, 인터넷의 발전으로 오프라인에서는 알지 못했던 사람과 친분을 쌓을 수 있게 되는 게임 산업을 대상으로 하였다. 연구 결과로, 지인의 네트워크 외부성 효과보다 전체 이용자수의 네트워크 외부성 효과가 2배정도 더 크다는 것을 알 수 있었다. 즉, 플랫폼 경제에서는 개인적으로 알지 못하는 사람들의 수가 이용자의 이용 의도에 더 중요한 영향을 주는 것으로 결론 내릴 수 있다.

이어서 소비자의 수가 판매자의 효용에 주는 영향을 보기 위한 두번째 실증 분석에서는, 기능적 통합과 연결성 둘 다 어느 정도 갖춰진 플랫폼에서 소비자수의 증가가 판매자의 효용을 증가시키는지에 대한 연구를 하였다. 판매자가 더 많은 소비자에게 노출되게 됨으로써 이익이 증가한다는 주장과 함께, 플랫폼에서 판매자들끼리 해야 하는 경쟁과 수수료 때문에 판매자의 이익이 감소한다는 주장이 있다. 판매자의 경쟁은 플랫폼이 등장한 직후의 플랫폼 간 경쟁을 할 때와 안정된 시기(의 경쟁은 다른 양상을 띨 것이다. 그리고 이제까지의 연구에서 고려하지 못했던 기술효율성까지 고려하기 위해서, 플랫폼의 확산 정도에 따라서 메타프론티어 분석을 사용해서 플랫폼이 플랫폼 경제에서 소비자를 확보함으로써, 판매자에게 미치는 영향에 대해서 조사했다. 이 연구에서는 플랫폼 산업 등장 전에 안정적이었다고 볼 수 있고 최근에 안정기까지 접어들었으며, 플랫폼 산업에서의 판매자가 특정하게 하나의(산업으로 자리매김한 호텔 산업을 대상으로 하여 가설을 검증하였다. 플랫폼이 소비자를 확보

하게 됨으로써, 판매자의 효용이 증가한다는 결과를 얻을 수 있었다.

전체 이용자의 네트워크 효과는 소비자의 수가 증가하여 소비자의 효용을 증가시킬 뿐만 아니라, 판매자의 효용도 증가시키는 것을 알 수 있다. 그렇다면, 소비자의 선호에는 얼마나 영향을 줄까? 기능적 통합이 높은 플랫폼에서 소비자의 선호에 소비자의 수가 영향을 준다는 가설을 검증하였다. 플랫폼 경제에서 네트워크 외부성이 중요함에도 불구하고 컨조인트 분석으로 수용 의도 분석을 할 때, 네트워크 외부성은 제품이 가진 하나의 특성으로 고려되지 않았었다. 그렇기에, 네트워크 외부성이 소비자의 선호에 미치는 영향에 대해서 조사하였다. 이 연구에서 자율주행 자동차의 특징들 중에서 네트워크 외부성의 상대적 중요도가 가장 높았다. 즉, 네트워크 외부성을 확보하는 것이 기업 입장에서 매우 중요하다는 것을 알 수 있다. 하지만 기술 인증 규제가 마련되지 않으면 네트워크 외부성 효과는 희석된다는 것도 알 수 있다. 그렇기 때문에, 정부는 사람들이 가지는 기술 인증 규제에 대한 위험성 해소를 시켜줄 규제를 마련해야 한다. 또한, 소비자들은 완전 자율주행자동차와 주행보조만 해주는 자율주행에 대해서 차이를 체감하지 못하면서도 향후 1, 2년 내로 자율주행자동차를 구입하려는 사람이 13%에 이르고 있음을 고려할 때, 기업은 조건적으로 자율주행을 할 수 있는 자율주행 옵션을 시장에 빨리 내놓고 사용자를 확보할 수 있는 전략을 펼쳐야 할 것이다. 또한, 정부는 대기업이 시장을 선점하는 것이 아니라, 윤리의식을 함께 가진 기술이 발전할 수 있는 제도적 방안을 마련해야 할 것이다.

결국 소비자의 이용률로 인한 네트워크 외부성은 직접 네트워크 외부성과

간접 네트워크 외부성이 모두 중요할 뿐만 아니라, 새로운 기술에 대한 선호 형성에 중요한 역할을 한다. 인터넷으로 인해서 강조된 연결성으로 인해서 소비자들은 제품이나 서비스를 선택할 때 지인의 네트워크 외부성 영향보다는 전체 이용자 수에 대한 네트워크 외부성 영향을 많이 받는다. 또한 플랫폼에 대한 불확실성은 네트워크 외부효과를 통해서 해결될 수 있다. 네트워크 외부효과의 영향을 희석시키는 요소로서, 기술 인증 표준 부재로 인해 소비자가 인지하는 위험성있다. 이것은 정부가 기술 인증 표준을 마련해줌으로써 사람들이 규제의 부재로 인해서 인지하는 위험성을 해결할 수 있다. 불확실성을 해소시키는 것에서 나아가, 네트워크 외부성은 사람들이 인지하는 제품에 대한 가장 중요한 정보라고 할 수 있다. 게다가 플랫폼이 과점하면서, 소비자의 수를 확보하는 것으로 인해 플랫폼에서 판매자의 효율성도 더 좋아지게 된다. 그렇기에 과점을 하기 위해 사용자들을 모으는 것이 플랫폼 사업자에게 중요하다. 비록 이 과점은 시장의 안정이라는 관점에서 중요한 것이지만, 다른 한편으로 정부는 대기업들의 과점으로 인해 더 나은 기술이 발전하는 것을 막지 않도록 도울 수 있는 일련의 정책을 마련해야 한다.

주요어 : 플랫폼, 사회학습이론, 네트워크 외부성, 기술 효율성, 구조방정식, 메타프론티어, 컨조인트 분석

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