Ph. D. Dissertation in Engineering

Study on the evolutionary patterns of product: agent-based simulation approach

행위자기반시뮬레이션을 활용한 제품의 진화 패턴 연구

August 2019

Graduate School of Seoul National University

Technology Management, Economics, and Policy Program

Jungsub Yoon

Study on the evolutionary patterns of product: agent-based simulation approach

지도교수 이정동

이 논문을 공학박사학위 논문으로 제출함

2019 년 8 월

서울대학교 대학원

협동과정 기술경영경제정책 전공

윤정섭

윤정섭의 공학박사학위 논문을 인준함

2019 년 8 월

위 원 장 황 준 석 (인)

부위원장 이 정 동 (인)

위 원 **Jörn Altmann** (인)

위 원 황 석 원 (인)

위 원 오 동 현 (인)

Dedicated to my beloved parents and family

For their endless love, support, and sacrifices

Abstract

Study on the evolutionary patterns of product: agent-based simulation approach

Jungsub Yoon
Technology Management, Economics, and Policy Program
The Graduate School
Seoul National University

As technological change has been accelerated and the forecasting and prediction of the industrial change becomes hard, new attempts have risen to investigate the future direction for the survival in the industry. One of the approach is the evolutionary approach, which considers the industry as the complex system and analyzes the system by analogies with the biological evolution.

Analogies with the biological evolution has been applied to the research on the product evolution. The product is regarded as evolving entity in the ecosystem composed of economic agents such as firms and consumers and their interactions that cause the technological innovation. Along with the stream of the research, this study proposes a

new approach to predict the industrial change by using the concept of the evolutionary patterns of products.

As the studies on the product evolution have limitations on the empirical case study only presenting the phenomena, this research uses the agent-based simulation model for the product evolution. The agent-based simulation model is helpful to interpret the interactions between the agents such as firms and consumers and their sequential impact on the evolution of products.

This research constructs the ecosystem of the product evolution and reviews the evolutionary patterns of the products and the simulation methodologies in Chapter 2. The empirical findings on the evolutionary patterns of the products are presented in Chapter 3, focusing on the three important evolutionary patterns for the industrial change—exaptation, genetic information transfer, and episodic change. Focusing on the emergence of the episodic change that drives the emergence of the new industry, the driving forces for the episodic change are defined as the episodic events and investigated by the example of the Korean mobile phone market in Chapter 4. Following the empirical studies, the role of the capability of the economic agents on the industrial change is identified by using the agent-based simulation model in Chapter 5.

The findings of the research help to expand the range of the research on the product evolution. As this research confirms the applicability of the biological evolution to the product evolution, the industrial change is expected to be predicted by the evolutionary patterns in the product market. Furthermore, focusing on the episodic change, the

industrial change, the emerging patterns of the episodic change are investigated, and the capability of the agents affecting the variation and selection of products is also significant to emerge the episodic change as the simulation results present. Further investigation on the evolutionary patterns and development of the simulation models help the decision-makers in firms and the government set up the industrial policy and market policy to enhance the competence.

Keywords: product evolution, evolutionary pattern, episodic change, agent-based model, pre-entry experience, imperfect information
Student Number: 2014-30282

Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Research motivation and purpose

As the pace of technological change has accelerated, it has become difficult to forecast future technology and its sequential impact on the dynamics of products, firms, and industries. The high volatility of technological change has forced firms to analyze events and trends that have occurred in industry as a basis for predicting the likelihood that a new technology will emerge and that products will adopt that new technology (Brownlie, 1992). The continuous recombination of technological characteristics makes the product market and the industrial environment more sophisticated, while also increasing technological uncertainty and demand uncertainty; the resulting dynamics can be regarded as a complex system (Negahban, Yilmaz, & Nall, 2014).

A powerful approach to investigating complex systems is to apply the evolutionary concepts of biology (Phillips & Su, 2009). Evolutionary approaches have long been applied to studies of technological change. A representative example is the logistic equation, which has its origin in the biological realm (Devezas, 2005). Concepts such as the dominant design (J. M. Utterback & Abernathy, 1975), diffusion (Bass, 1969), and technological trajectories and paradigms (Dosi, 1982) were also first introduced in biology, but they have been used to examine patterns of technological change and industrial evolution.

The methods for predicting changes that will occur in a complex system have been improved (Phillips & Linstone, 2016). Previous researchers have developed both quantitative and qualitative models. Qualitative methods derive future items or scenarios via surveys, including the Delphi method (Y. Y. Cho, Jeong, & Kim, 1991; Rowe & Wright, 1999), the analytical hierarchy process (AHP) (Calabrese, Costa, Levialdi, & Menichini, 2019), and the technology acceptance model (TAM) (Chun, Lee, & Kim, 2012). In contrast, quantitative methods such as network analysis, clustering analysis, and regression analysis help to investigate the likelihood of the emergence of future directions of technologies and product development using patent data and product specification data (R. S. Campbell, 1983; Chang, 2012; Daim, Rueda, Martin, & Gerdsri, 2006).

Previous research has adopted the theories of the technological trajectory, technological paradigms, and dominant design and attempted to identify the emergence of technological trajectories and the dominant design quantitatively (Castaldi, Fontana, & Nuvolari, 2009; Coccia & Wang, 2015; Frenken, Saviotti, & Trommetter, 1999; Grodal & Suarez, 2015; Saviotti & Trickett, 1992). This strand of research has focused on the emergence of the dominant design due to paradigm formation, changes in the paradigm, and sequential changes in the technological trajectory (Abernathy & Utterback, 1978). For example, Castaldi et al. (2009) examined the technological trajectories of tanks by using principal component analysis (PCA) and the t-test. Other studies also have investigated the evolution of products developed by the recombination of existing technologies, identifying evolutionary patterns and the factors affecting product evolution.

Meanwhile, numerous studies have applied evolutionary concepts originally articulated in biology. They adopted the concept of biological evolution to explain evolution in the product market and industry by generalizing evolutionary patterns from Darwinian gradualism to the universal Darwinism of Dawkins (Coccia, 2018; Cordes, 2006; Hodgson, 2002, 2005; Levinthal, 1998; Merker, Morley, & Zuidema, 2015; Nelson, 2007; A. Wagner & Rosen, 2014). The use of these concepts helps to identify the evolutionary patterns of products in industries and society; however, these discussions have long been qualitative. Most previous studies have analyzed various product categories, rather than investigating the dynamics involved in a single product, and have relied on anecdotal evidence (Andriani & Carignani, 2014; Coccia, 2018; A. Wagner & Rosen, 2014). They did not operationalize the patterns that occur during the evolutionary process of products. Instead of proving the applicability of a single evolutionary pattern through examples of various products, they presented various evolutionary principles through a broad range of examples, yielding limitations in identifying consistent evolutionary patterns in industry.

Understanding the evolutionary patterns of products is important for investigating the changes that occur in industry. As the boundaries between industries become vague and industries consist of numerous products, changes in an industry can be predicted by investigating the evolutionary patterns of products. Two types of approaches are useful to identify the factors affecting evolutionary patterns: ex-post empirical analysis and ex-ante simulation approach. The former approach identifies the evolutionary patterns that have occurred in industry using real data, whereas the latter helps to understand the changes that result from strategic decisions and environmental changes by simulating multiple scenarios. Empirical studies contribute to analyses of phenomena using observable evidence, whereas simulation studies are useful for investigating the impact of unobserved factors.

1.2 Research purpose and outline of the study

The purpose of this study is to propose a method of quantitatively defining the evolutionary patterns of products and deriving evolutionary patterns in order to predict changes in products and their surrounding environment. As product evolution occurs in a complex system, this study uses both empirical analyses and an agent-based simulation. First, the evolutionary patterns of products are defined and explained based on data from the Korean mobile phone industry. Then, to illustrate evolutionary patterns in industry, the factors affecting the occurrence of specific evolutionary patterns are investigated using an agent-based simulation model (ABSM). Finally, this study proposes a new approach to support the establishment of firms' strategies, as well as industrial and market policy.

This research consists of six chapters. **Figure 1** presents an outline of the research. Chapter 2 reviews the previous literature on product evolution and ABSMs for product evolution. As previous research has rarely considered system-based approaches for identifying the evolutionary patterns of products, the ecosystem of product evolution is defined, and the evolutionary patterns of products are then addressed. Furthermore, by systematically analyzing the previous use of simulation models for product evolution, the simulation techniques and the agents that need to be taken into consideration are defined, and research questions regarding product evolution studies are presented.

The next two chapters propose operational definitions of the phenomena and examine their occurrence. Chapter 3 focuses on the three evolutionary patterns (i.e. exaptation, genetic information transfer, and episodic change), which lead to industrial change. In Chapter 4, the driving forces of episodic change, which causes industry-level changes, are conceptualized on the basis of episodic events in the field of biology, which are interpreted as the result of the accumulation of changes in technologies, products, and the industrial environment.

Chapter 5 illustrates the results of a simulation that was conducted to investigate the impact of agents' capabilities on the emergence of changes in the industrial environment. Agents' capabilities are defined as the innovation experience of firms and the purchasing capability of consumers. This chapter identifies aspects of the industrial and market setting that may hasten the emergence of episodic change, and these findings can be used to derive industrial and market policy.

Finally, Chapter 6 concludes this study. It draws implications for research into product evolution and innovation and industrial policy from a new perspective. Based on a review of the research results presented in earlier chapters, limitations and future directions are discussed.

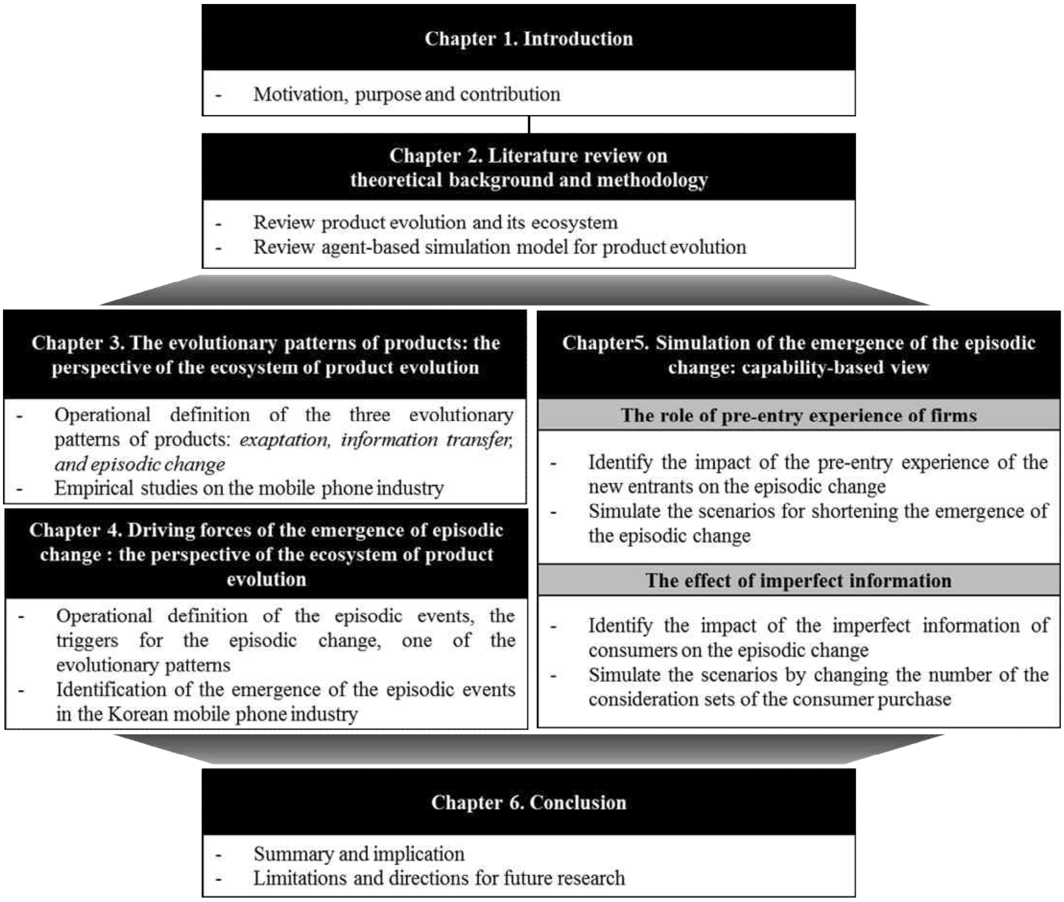


Figure 1 Research outline

Chapter 2. Literature review on theoretical background and methodology

2.1 Definition of the product evolution

2.1.1 Concepts of evolutionary theory

Since *The Origin of Species* (1859), numerous biological studies have focused on the logics for the biological evolution and the principal concepts that support the logics. Previous research has proposed that the patterns in the biological evolution is applicable to the product evolution (Basalla, 1988; Butler, 1872; Gilfillan, 1935; Petroski, 1992). The early studies proposes that the Darwinism is directly applied to the explanation on the product evolution by the generalization (Baldwin, 1896a, 1896b; Butler, 1872), arguing that the product evolves as the same way as the biological organisms.

Since the mid-1900s, however, researchers of product evolution have begun to recognize the difference between two evolutions. They focused on the core of the Darwinian process — variation, selection, and retention — with little modifications. The most representative argument is universal Darwinism, which is the logic applied to the social and cultural evolution by generalizing Darwinism (D. Campbell, 1965; Dawkins, 1983; Lewontin, 1970). One of the most well-known concepts is the meme, a concept of gene in the social and cultural evolution in order to consider the phenomenon that human-made cultural heritage is transferred to the next generation by variation, selection, and retention (Dawkins, 1983). Following the concepts of social and cultural evolution, Basalla (1988) defines the evolutionary principles by dividing them into four concepts— diversity, continuity, novelty, and selection— based on Darwinian process. Petroski (1992) suggests that products evolve through the interaction between technology and culture by introducing concepts of genetic transfer and selection in biological evolution.

Strictly speaking, evolution researchers are grouped into the schools of universal Darwinism such as Dawkins (1976) and Dennett (1995) and Hull's (1988) general evolutionary theory (Nelson, 2007). The former uses the concept of *meme* to investigate the changes in the perspective of the cultural evolution whereas the latter does not explore the cultural evolution issues. Despite the difference between two research groups, both share the inheritance dynamics of accumulated knowledge being transferred to the next generation.

To sum up, previous research makes the consensus on the use of the concepts of the carrier and the replicator that contain the essential information to generate the descendants. The core of the generation of new entities is the variation, selection and retention process that help to explain the emergence and the survival of new products. Therefore, this paper defines the carriers that contain the genetic information and explore the variation, selection, and retention process by analogizing the logics of the biological evolution.

2.1.1.1 The concept of the gene

Evolution means a process in which a biological group changes the characteristics of a whole group and generates new species by accumulating information on genetic variation that occurred over multi-generations (Gould, 2002). Genetic variation leads to biological evolution. Likewise, the concept of a gene can be adopted for artifact evolution. The gene in artifact evolution, however, is defined at different levels.

Identification of the causal factor of retention in artifacts is the baseline for defining genes in artifacts. Although previous researchers commonly share the view that the gene that causes variation evolves in response to changes in the environment, they define the causes of genesis using different perspectives. Nelson and Winter (1982) argue that artifacts originate with the expression of routines of firms, whereas Arthur (2009), Dawkins (2006), and Mokyr (2000) suggest that artifacts are generated due to social norms. The gap between these arguments is merely on the levels of analysis, but the basic concepts that are inferred are similar to those in Mokyr (2003), which extends the concept of knowledge to technique and routine.

The range of this study is to analyze changes of artifacts in the market where transactions of artifacts take place. Therefore, as per the definition in Nelson and Winter (1982), the authors define the carries that contains genetic information as firms and consumers whose decision-making is considered to be genotypes. The artifact itself is defined as a phenotype produced according to the decisions of two agents. In other words, an entity is defined as an integrated system of the decision-making of agents and the technological characteristics of artifacts.

2.1.1.2 Variation process

Genes change due to crossbreeding or mutation in order to cope with environmental changes. Organisms reproduce fitter organisms by variation and try to retain their genes by this continuous process. Once mutation occurs during the variation process, proteins transform to cause a variation in the genetic character. The accumulation of these mutations diversifies genetic combinations in a genetic cluster. Thus, this mutation is likely to be expressed in the future process of retention

The basic mechanisms of variation in biology and artifacts are alike. However, in artifact evolution, individual learning and social learning effectuate new genetic variation, thereby making the variation process in artifact evolution directional (Jablonka, 2003; Jablonka & Ziman, 2003). According to Jablonka (2003), variation is caused due to mutual learning between individuals and organizations. This mechanism is similar to that described in March (1991). March (1991) expresses fitness as a combination of capability and knowledge of individuals. This process can be seen as innovation that occurs by interaction between members and an organization. Thus, variation indicates both genotypic and phenotypic variation that occurred in a wide range from simple changes to innovation.

To summarize the definition of genes in this research, the interaction between firms and consumers causes innovation or variation in artifact evolution. In other words, artifacts contain the interaction between individual consumers and members in firms. Thus, this research illustrates the variation process with the changes in phenotypes – artifacts – that result from the changes in genotypes – decision-making of firms and consumers.

2.1.1.3 Selection and retention process

Selection is divided into the internal selection that occurs during the genetic combination process and the external selection by the environmental fitness. Internal selection, first introduced by Whyte (1964), determines whether a mutation in the genetic combination emerges. The features of an organism are altered by the result of the internal selection and the mutant goes through the external selection. External selection means that an adaptive organism encounters several colliding constraints with the environment and changes its features by the adaptation (S. A. Kauffman & Macready, 1995). Consequently, the survivors are likely to have the relatively higher fitness level, which are chosen randomly due to the blindness of the both selection mechanisms (Campbell, 1965).

In the product evolution, the internal selection is regarded as an internal decision-making process of a firm. In the internal selection process, a firm controls the emergence of mutations through the decision-making process such as Cooper (1994)'s stage-gate model (Ziman, 2003). Numerous studies have discussed the factors such as routines and capability of a firm that affect the internal selection process (Nelson & Winter, 1982; Rivkin, 2000; Teece, Pisano, & Shuen, 1997). The external selection is defined as a process led by consumers' purchase. A produce purchased by the majority of consumers has the highest fitness level in the market. Previous research on the external selection focuses on the consumer's purchase behavior and the structure of consumer networks (Adner & Levinthal, 2001; E. Lee, Lee, & Lee, 2006; Querbes & Frenken, 2017), .

Previous researches rarely consider both constructional selection and environmental selection. Although several researches consider both selections together (Ma & Nakamori, 2005), these researches focus only on decision-making and the performance of agents, and not on the artifacts. Thus, both selections need to be taken into consideration, along with the role of the artifacts played as the interface between firms and consumers.

Retention means that the fittest genes survived by the internal selection are inherited to the descendants. The previous discussions that mainly focus on the variation and selection process are expanded by Campbell (1960) that introduces the concept of selective retention.

Numerous studies on the product evolution exploit the concept of the retention. Gavetti and Levinthal (2000) argues that the retention changes the routines of agents by accumulating the experiential wisdom through the past activities. Zollo and Winter (2002) also considers that the retention process is discovered while knowledge of the agents is generated and accumulated. Thus, the retention is defined as the process that continuous changes of the genes—routines and changes the decision-making of firms and consumers.

2.1.2 The ecosystem of the product evolution

2.1.2.1 Definition of the product

The product plays a role as the interface that consumers and firms interact in the market (Frenken, 2006) and has a significant impact on the sustainable growth of firms. Products released by diverse firms compete in the market and firms adopt the product purchased by the majority of consumers. The continuous interaction between the two agents emerges the dominant design that consists of the combination of the selected design features of the product (J. M. Utterback & Abernathy, 1975) and contributes to the development of the descendant products by the retention (Ma & Nakamori, 2005).

In order to understand the evolutionary process of products, the boundary of the product should be defined. Numerous studies have analyzed the evolution of products such as Basalla (1988), Petroski (1992), Fontana and Nesta (2009) and Andriani, Ali, and Mastrogiorgio (2017). Among them, few studies use the quantitative analysis, but they consider the product as the product technology such as LAN (Fontana & Nesta, 2009)and science-based product such as the medicine (Andriani et al., 2017). The former is likely to be analyzed by the research on the technological evolution and the latter is dealt with by the research on the evolution of the knowledge. Among the numerous studies, Adomavicius, Bockstedt, Gupta, and Kauffman (2007) defines the technologies in the technology ecosystem and categorizes them into three groups on the basis of their role: component role, support and infrastructure role, and product and application role. The component role technologies compose the product and application role technologies, and support and infrastructure role technologies do not comprise the product and application role technologies as they are exogenously generated by the other agents (Adomavicius et al., 2007). The product and application role technology corresponds to the product purchased by the end users, and thus, this study considers the product as the final goods playing the application role.

The product has been defined as the two distinguishing concepts: product model and product category. The product model is the set of the technological characteristics and each product model has distinct by the same value of technological characteristics such as iPhone 3GS 8GB and iPhone 4 with 8GB, which is purchased by individual consumers. The product category consists of individual product models characterized by having the same technological characteristics but not exactly the same value. Thus, a product in this study refers to a product model that belongs to a product category.

2.1.2.2 Product evolutionary process

Product evolution in this study is distinguished from the technological evolution and knowledge evolution that has been discussed in previous research such as Basalla (1988) and Kivi, Smura, and Töyli (2012). To begin with the knowledge evolution, the driving force is the emergence of new knowledge. Knowledge is generated by the Schumpeterian recombination process and follows the patterns shown in the random network model (Erdos & Renyi, 1960) and scientific collaboration network (Barabási et al., 2002). Due to the fact that knowledge is created by inventors, the evolutionary process of the knowledge is the iterative process of recombination and adoption of the knowledge by the inventors using the knowledge discovered in the past (Petruzzelli & Savino, 2014).

The emergence of a new technology in the technological evolution is led by the combination of existing technologies or knowledge. Because the new technology is generated by the unpredictable process, innovation emerged in the process is regarded as the serendipitous innovation (Aharonson & Schilling, 2016). Technology is adopted by firms as the technology is a component of the product and likely to evolve to improve the performance (Fontana, 2011; Kivi et al., 2012). Due to the role of firms in both knowledge evolution and technological evolution, the direction of both artifacts is likely to be predicted, which is the distinguishing property from the product evolution.

Product evolution follows the variation, selection, and retention process of Campbell (1960). The variation is the process that economic agents intentionally create a variety of products through trial-and-error (Mokyr, 2003). Firms set up the new product development strategy considering the response of consumers on products released in the past. Firms search the market for supporting the new product development strategy and adopt the strategy for taking an advantage against the competitors. In this process, firms release new products by using their upgraded technological capability. After the launch of the new products, firms undergo the selection process. To successfully diffuse their products, they employ the promotion strategy and differentiate the pricing strategy. A consumer purchases a product by considering both price and quality of products. Furthermore, the neighboring consumers have a significant impact on the purchase behavior of a consumer due to the interaction among them. The purchase of consumers determines the survival of products and affects the performance of firms. A firm is likely to cease releasing a product hardly selected by consumers while a product selected by the majority of consumers is likely to contribute to the future product.

Figure 2 shows the ecosystem where the product evolves. Firms and consumers are regarded as carriers who contain the genotypes of the product. At time t, firms release products in the market based on their decision-making routines and offer the information on their decision-making to consumers. Consumers utilize their capability in purchasing products and transfer the market information by means of purchase behavior. Firms develop and release new products at time t+1 based on the market information. Thus, the genetic information contained by the two carriers is exchanged through the production and the purchase, leading to the genetic variation in series.

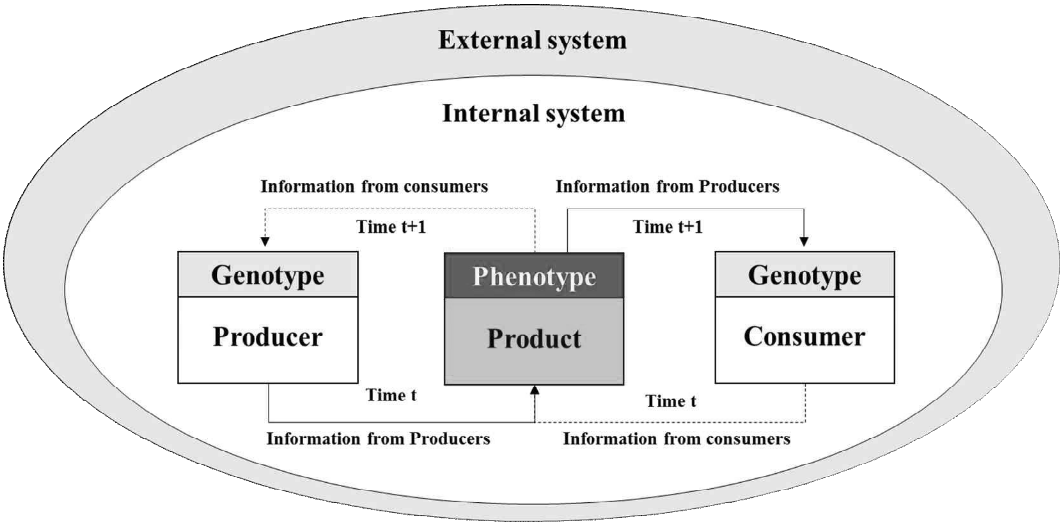


Figure 2 Systemic view of product evolution

To summarize, the product evolution is composed of a set of complex process where firms and consumers interact in the environment. If the patterns in the evolutionary process is able to be identified and replicated, the short-term changes occurred in the environment and its component can be predicted.

2.1.3 Evolutionary patterns of product

This section presents a systematic review of the evolutionary patterns that occur in the ecosystem of product evolution. The evolutionary patterns can be categorized into three: patterns in the variation process, patterns in the selection and retention process, and patterns in environmental change. As product evolution is composed of technological change, product change, and changes in firms and industries, the evolutionary patterns are investigated at these different levels of change. Previous arguments about evolutionary patterns, ranging from the Schumpeterian recombination of knowledge (Schumpeter, 1934) to the nine evolutionary patterns proposed by Wagner and Rosen (2014), are categorized by their relatedness to each evolutionary process.

2.1.3.1 Patterns in the variation process

One of the most representative evolutionary patterns is the emergence of trajectories (Dosi, 1982), which are formed by interactions between firms and consumers (Frenken, 2000). Trajectories can be divided into technological trajectories and product trajectories. The concept of the technological trajectory focuses on changing patterns of the technological characteristics, and is defined as the development path of technology for problem-solving (Dosi, 1982; Hameri, 1996). The product trajectory is defined as the pattern determined by the product strategy when investigated in terms of the traits of products (Wi, 2006). Comparing these two concepts, it can be seen that the technological trajectory is related to changes in technological characteristics, whereas the product trajectory is subject to a firm’s decision-making process in response to technological and market changes.

Second, combinatorial innovation is an important trait of the variation process (Yoo, Boland, Lyytinen, & Majchrzak, 2012). The concept of combinatorial innovation refers to methods of configuring components in different ways (Nylén & Holmström, 2015; Obstfeld, 2005; A. Wagner & Rosen, 2014). It is based on the trial-and-error approach to maximize the performance of products by combining modules from existing technologies (Scaringella, 2016). It differs from the concept of recombination defined by Schumpeter (1934), which focuses on knowledge recombination that causes technological changes to occur. Combinatorial innovation can be observed in the Korean mobile phone industry; for example, the Vega No. 5 released by Pantech was developed by combining the high battery capacity of the Optimus Black from LG and the large display size of the Nexus S from Samsung. Another example of combinatorial innovation is GPS technology, which calculates the user's coordinates using the time in which a signal is delivered to and from at least four satellites. It was invented by combining satellite technology, chipset, radar transmission technology, and transmitter technology. Thus, a new product category can emerge from combinatorial innovation with a variety of purposes and methods of combination.

Third, trial-and-error is an important process for developing improved products, as product evolution determines the level of fitness in a rugged landscape (S. Kauffman & Levin, 1987; Ziman, 2003). Trial-and-error refers to the repetitive process of variation and selection among products by other agents in the same product category (A. Wagner & Rosen, 2014). In this view, the variation process is an adaptive process similar to a hill-climbing pattern, as the fitness landscape is generally unpredictable (S. Kauffman & Levin, 1987). This evolutionary pattern usually operates through a learning process in which the new product development strategy is updated (Heylighen, 2007; Vaghely & Julien, 2010). The most important factor of this evolutionary pattern is that a product is improved by numerous agents as they interact with each other, and the result of new product development can be used by other agents in the industry (A. Wagner & Rosen, 2014). For example, the patent system helps agents share product knowledge in the form of documents, preventing that knowledge from becoming obsolete (Petruzzelli & Savino, 2014). A representative product demonstrating this evolutionary pattern is the lightbulb developed by Edison, which was the result of over 6,000 experiments to invent and adopt a suitable filament (A. Wagner & Rosen, 2014).

Unlike the evolutionary patterns described above, an unexpected result of the product innovation occurs through the exaptation process. Exaptation is defined as "characters, evolved for other usage (or for no function at all), and later 'coopted' for their current role" (Gould & Vrba, 1982). In product evolution, even though the inventor proposes the initial intended usage of technological characteristics or products, they are used for solving other problems, leading to the creation of new niches. Representative examples include the emergence of Viagra, exapted from sildenafil for erectile dysfunction (Andriani, 2017), and the change in the use of the cake pan, which turned into the frisbee (a toy) (Andriani et al., 2017). Another example is the microwave oven, which contains technology initially developed for radar (A. Wagner & Rosen, 2014). In recent years, the role of exaptation in the variation process has been highlighted by numerous researchers (Andriani & Cattani, 2016). Exaptation plays a role in niche construction at a different level (Dew & Sarasvathy, 2016). Furthermore, it is applicable to explain serendipitous innovations (Andriani, 2017), as it is not predictable.

Despite the importance of exaptation, previous studies have focused on the emergence of new instances of exaptation at the technology level. They have given examples and case studies of technology-based products that consist of a small number of technologies, such as medicine (Andriani et al., 2017; A. Wagner & Rosen, 2014). Therefore, the process of exaptation in complex products, which occurs through changes in their function, needs to be investigated in greater depth.

2.1.3.2 Patterns in the selection and retention process

Following a technological trajectory, a new product emerges as a form of descent with modification, which means that everything new comes from a previously released product. The parent-child relationship characterizes descent with modification, and therefore products with this relationship show similar technological characteristics and performance (A. Wagner & Rosen, 2014). An example of this evolutionary pattern is the emergence of the programming language Python, which evolved from Fortran (A. Wagner & Rosen, 2014). Even though the languages are not completely the same, the development of Python occurred through the accumulation of features of previously developed programming languages. Products and technologies are considered to evolve with continuous small modifications, as their lineages illustrate (G. P. Wagner, 2015), leading to non-linear patterns in their trajectories (Castaldi et al., 2009).

To complement the Darwinian theory of vertical inheritance, previous research has identified horizontal information transfer as a critical force in evolution, but this mechanism was unknown to early researchers such as Basalla (Carignani, Cattani, & Zaina, 2019). Horizontal information transfer occurs when two pieces of genetic information from different entities are combined, and in recent years, it has been pointed out that this concept helps to trace the origin of radical innovations that emerge by the transfer of functional modules across distinct technological trajectories (Carignani et al., 2019). Carignani et al. (2019) identified the occurrence of horizontal information transfer in the case of the turbojet, which led to revolutionary changes in military, civil, and general aviation, by analogizing genetic information to knowledge and technological expertise. Thus, horizontal gene transfer helps to create a new path within the product category through the selection and retention process.

If a product is not selected and is destined to exit from the market, it can do so through two modes: extinction and replacement (Wagner & Rosen, 2014). Extinction means that the product is no longer released to the market. Even if an extinct product is re-launched to the market, it is different from the original product. In contrast, replacement means that a new product replaces an existing product due to technological improvements or changes in demand. Extinction is likely to reduce the level and the number of technological characteristics by decreasing product diversity, whereas replacement increases the level of technological characteristics without changing product diversity, leading to an increase in the average fitness level of products.

Among the products that go through selection pressure, the dominant design is determined, which leads to a change in the number of agents (J. M. Utterback &

Abernathy, 1975). The dominant design is considered to be a specific path along an industry's design hierarchy (J. Utterback & Suarez, 1993). The dominant design is composed of stable core components, and numerous studies have identified dominant designs in different industries (Murmann & Frenken, 2006). Due to these characteristics of the dominant design, it represents a conceptual design framework for developing a new product. Examples of the components constituting the dominant design in the mobile phone industry are vibration alerts, a clock, and games (Koski & Kretschmer, 2007). The dominant design emerges as products adapt in the market after the introduction of a radical innovation. Once the dominant design of the product category is determined, descendants are developed following that path, and each firm establishes a new product development strategy with the goal of beating the competition, leading to the emergence of the product trajectory.

On occasion, a product is released containing redundant traits that are no longer effective, in a phenomenon known as skeuomorphism (Petroski, 1992). This happens due to resistance against internal change, which refers to the path dependency in product design. An example of this pattern is provided by plastic buckets that resemble buckets made of weaving reeds (Basalla, 1988). Riveted jeans are another example of skeuomorphism, as rivets were invented to keep jeans from being torn, but the denim in modern jeans is durable enough not to be torn. Therefore, the selection and retention process does not always operate in the direction that improves the fitness level of products.

2.1.3.3 Patterns occurring while the environmental change

Technology forms a paradigm based on its characteristics and develops along specific trajectories that depend on the technological paradigm (Dosi, 1982). A technological paradigm is a criterion for the evaluation of alternative solutions (Dosi, 1982); this concept is similar to that of the scientific paradigm (Kuhn, 1962), and it can be defined as a framework of recognition that technology experts share (Constant, 1980). A global optimal solution to a technological problem is difficult to identify owing to numerous constraints such as regional and industrial characteristics. As a result, technological development is a cumulative process that depends on the technological paradigm and emerges from technological trajectories. If the technological paradigm shifts because of the emergence of a new technological source, technological trajectories also change, meaning that the path of technological development will show complicated patterns as technological progress along technological trajectories changes, and changes in the technological paradigm overlap due to the emergence of the new source (Dosi & Nelson, 2010).

In product evolution, the concept of the paradigm can be defined as the product paradigm, which creates product concepts (Orihata & Watanabe, 2000b). A paradigm shift occurs in response to an innovation that initiates the construction of a new paradigm (Kuhn, 1962; Orihata & Watanabe, 2000b). A representative example is the passport-size video camera, which follows the traditional product paradigm of miniaturization (Orihata

& Watanabe, 2000b). A change in the product paradigm indicates that an environmental change has taken place, led by the emergence of a new way of understanding the concept of products by consumers, which in turn results in industrial changes and changes in the decision-making routines of firms (Orihata & Watanabe, 2000b).

Along with paradigm shifts, episodic changes are also significant, as they cause industrial change. Episodic change is defined as the phenomenon of radical change occurring in response to certain events (Boero, 1996). Episodic change is related to the punctuation in that both concepts relate to radical and rare events such as avalanches and catastrophes (Blackburn, 1998; Volkenstein & Livshits, 1989; Weick & Quinn, 1999). Episodic changes are infrequent, sometimes radical, and more likely to be experienced intensively (Gilley, McMillan, & Gilley, 2009). An example of an episodic change in product evolution is the industrial revolution, which seems to have occurred between systems in stable states (Gersick, 1991; A. Wagner & Rosen, 2014). The repetitive release and purchase of new products are likely to lead to the emergence of an episodic change. In other words, before the emergence of an episodic change, the other evolutionary patterns are likely to be observed.

To sum up, evolutionary patterns can be investigated in a single product market, ranging from technological changes to industrial changes. Thus, these patterns are helpful for decision-makers as ways to analyze patterns in the ecosystem of product evolution and thereby to predict possible changes in the future.

2.2 Agent-based simulation model for product evolution

As most previous studies have limitations in identifying and predicting the dynamic changes that occur in response to various factors and agents' behavior because they use empirical data for ex-post analyses (Huenteler, Ossenbrink, Schmidt, & Hoffmann, 2016; Kivi et al., 2012; Orihata & Watanabe, 2000a; Otto & Wood, 1998; Payson, 1995, 1997; Shibata, Yano, & Kodama, 2005; Sood & Tellis, 2005; Swann, 2001; Windrum, Diaz, & Filiou, 2009), the ABSM approach has been adopted to predict the evolutionary patterns that occur within a system. The ABSM approach seeks to analyze emergent phenomena in a complex system by considering the interactions between heterogeneous and autonomous agents (Kiesling, Günther, Stummer, & Wakolbinger, 2012). It has been widely used in the social sciences, as it suggests macro-level dynamics driven by components at the micro-level (Bargigli & Tedeschi, 2013; Fioretti, 2013; Garcia, 2005; Kiesling et al., 2012; Rand & Rust, 2011; Wall, 2016).

To develop a new ABSM for product evolution, a review is conducted of the existing ABSMs that focus on the variation, selection, and retention processes, as previous studies have reviewed ABSMs more broadly depending on their research objectives (Abar, Theodoropoulos, Lemarinier, & O'Hare, 2017; Garcia, 2005; Gómez-Cruz, Loaiza Saa, & Ortega Hurtado, 2017; Kiesling et al., 2012; Macal, 2016; Macal & North, 2010; Rand & Rust, 2011; Wall, 2016; H. Zhang & Vorobeychik, 2017). Among previous studies, Garcia (2005) and Kiesling et al. (2012) are representative of research considering the variation and selection processes, respectively. First, Garcia (2005) divided the topics addressed by ABSMs into the diffusion of products, organizational strategy that leads to product variation, and knowledge spillover and knowledge creation for supporting variation, and analyzed the characteristics of the models. However, as that study focused on the factors that contribute to successful product innovation activities, it did not meaningfully take into account the evolutionary patterns of products. Kiesling et al. (2012) analyzed only studies on the diffusion of innovations, focusing on the selection process of products. Thus, both studies only discussed ABSMs for product evolution partially; for this reason, the scope of the review of previous research needs to be extended, and previous ABSMs linking these two processes must be investigated in order to develop an ABSM for product evolution.

Therefore, this section further investigates the definition of agents, simulation techniques, and the objectives of simulation models, extending Garcia (2005) and Kiesling et al. (2012). The output of the review proposes a direction for developing a new ABSM to analyze the evolutionary patterns of products caused by changes in the agents and the environment.

The reviewed papers were collected from Scopus and Google Scholar with the keywords “agent-based”, “multi-agent”, “product innovation”, and “product evolution” and contained either a proposal for a new model or a conceptual analysis of the product variation and selection process. Models of organizational structure or organizational innovation, as well as studies on the empirical application of the models, were excluded as previous review papers have already investigated these issues in detail. In addition, studies on organizational theory, such as March (1991), and on knowledge or technological evolution were also excluded as they were only indirectly related to product evolution. The number of papers after the refinement of the search was 63.

The collected papers were classified into three groups, as shown in **Figure 3**. The first type (12 papers; roughly 16 percent of the papers) consisted of models considering the decision-making process for new product development and new product release. The second type (41 papers; roughly 65 percent) included models of the selection process, in which the survival of products after release is determined by agents. The last type (12 papers; roughly 16 percent) consisted of studies presenting a holistic view of product evolution that considered product variation, selection, and the transfer process, as well as studies on product dynamics that focused on the market longevity of products, the technological progress of products, and the competitive pressure generated by products.

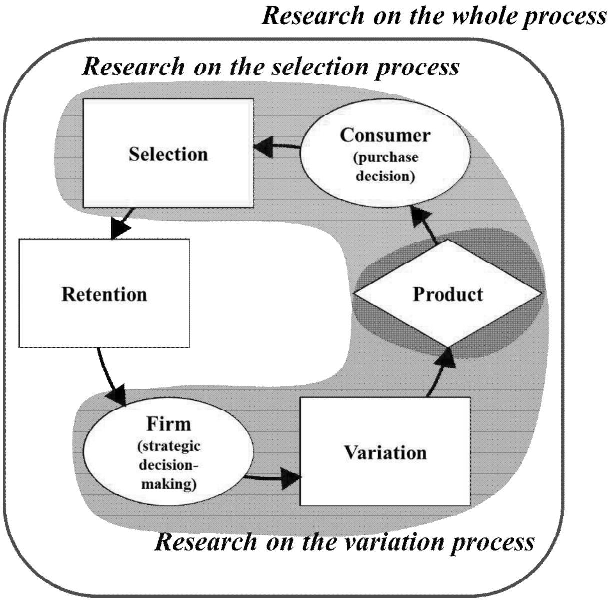


Figure 3 Categorization of the models

2.2.1 Models for the variation process

ABSMs of the variation process have developed from the network model of Barabási et al. (2002) to the ABSM-based NK model of Ganco (2017) through diversifying the simulation technique and the core factors. Table 1 shows the agents, simulation techniques, research purpose, and core factors considered in the previous models. Each model considers factors affecting the variation process and the dynamics of the product changes.

Most previous research has defined agents as firms and consumers. A firm releases new products, leading to changes in the technological characteristics of products and an increase in product diversity. Barabási et al. (2002) analyzed the emergence of new features caused by a network between scientists. Albino, Carbonara, and Giannoccaro (2006) classified firms into leaders and followers who generate variation in products. They defined the roles of suppliers, who directly affect new product development, and infrastructure suppliers, who indirectly contribute to new product development by using the concept of the industrial district, and investigated the patterns of the emergence of products depending on the structure of the industrial district. Villani, Bonacini, Ferrari, Serra, and Lane (2007) also identified the patterns of emergence, defining agents as firms and consumers, and especially focused on the exaptation of products, which happens because existing features are adopted by firms in a new form, causing changes in consumers' evaluation of products. Pyka, Gilbert, and Ahrweiler (2009) also defined agents as firms—manufacturers and suppliers—and consumers. In their model, firms use their knowledge to improve their innovation performance and to increase sales volume. Firms also purchase raw materials and complex inputs from suppliers in the form of the intermediate goods. In these models, it is assumed that a consumer purchases a product released into the market.

Meanwhile, several models defined agents only as firms (Antonelli & Ferraris, 2011; Ganco, 2017; König, Battiston, Napoletano, & Schweitzer, 2011; Lin & Wei, 2018; Oyama, Learmonth, & Chao, 2015). Antonelli and Ferarris (2011) showed patterns in the improvement of knowledge generated by the innovation activities of firms. König et al. (2011) modeled collaboration between firms that tend to collaborate with other firms that have common technological competencies. Beckenbach, Daskalakis, and Hofmann

(2012) defined the novelty-creating behaviors of heterogeneous firms as attributes of firms and investigated the changes in the patterns of product innovation depending on firms' attributes. Oyama et al. (2015) developed a model to show changes in a firm's new product development activities depending on the relationship between product features, taking into account the complexity of products. In line with the previous models, Lin and Wei (2018) also modeled the impact of innovation intermediaries in a network space consisting of diverse firms on product innovation. Finally, Garas and Lapatinas (2017) also defined agents as firms that release new products by considering demand and consumers who purchase products launched in the market, and focused on the variation process by considering the demands and market potential of products. To summarize, previous models of the variation process have mostly defined agents as firms and consumers, but they limited the role of consumers and the interactions between them.

Table 1 Models for the variation process of products

Research	Objective	Simulation technique	Agent
Barabási et al. (2002)	Capture scientific collaboration network's time evolution	Network simulation Monte Carlo simulation	Scientists
Albino et al. (2006)	Address how new innovation processes emerge, how, when and where they evolve in industrial districts in terms of learning and R&D investment behavior	Agent-based model	Firms (leader/follower) Suppliers
Villani et al. (2007)	Propose a model by which radical innovations are created by a process of 'exaptation'	Feedback model between innovation and functionality	Producer User
Pyka et al. (2009)	Present a framework for modeling learning competence in firms to improve the understanding of managing innovation	Agent-based model	Firms Consumers Suppliers
Zhong and Ozdemir (2010)	Explore how interaction structure among a group of actors affects the speed at which the group can collectively innovate	Genetic algorithm Network model	Firms Consumers
Antonelli and Ferraris (2011)	Identify emerging property of innovation	Agent-based model	Firms

Research	Objective	Simulation technique	Agent
König et al. (2011)	Investigate heterogeneous recombination of firms' technological competencies	Network model	Firms
Beckenbach et al. (2012)	Identify the obstacles for novelty creation and the effect of individual routine and sticky demand on innovation	Agent-based model	Firms
Oyama et al. (2015)	Complementary versus conflicting dependencies/ predominantly incremental design changes to components in evolutionary new product development process	NK model	Individuals
Garas and Lapatinas (2017)	Address the effect of consumers' social networks on their consumption decisions and on firms' process of developing new characteristics for their products	Monte Carlo simulation	Firms Consumers
Ganco (2017)	Revisit the question of whether the relationship between performance and complexity	NK model	Firms
Lin and Wei (2018)	Investigate the effect of innovation intermediary on knowledge transfer and innovation process in networked systems	Network model	Firms

2.2.2 Models for the selection process

Simulation studies of the selection process of products have developed from research into the bandwagon effect (Abrahamson & Rosenkopf, 1997) to research into consumer targeting (Hu, Lin, Qian, & Sun, 2018) and brand value (H. Lee, Lim, Lee, & Kim, 2018). Table 2 summarizes the ABSMs developed for the product selection process.

Previous models can be divided into three categories according to the definition of the ABSM, based on whether the agents are firms, consumers, or both. First, the models that define firms as agents focus on the constructional selection of firms. They investigate the impact of decision-making processes on the launch of products into the market. Abrahamson and Rosenkopf (1997) showed that the pressure of the bandwagon effect occurred through the interactions between numerous firms, which determined the selection of products. They suggested that the bandwagon effect would change depending on whether the innovation experience of firms is positive or negative. Ma, Grubler, and Nakamori (2009) also defined agents as firms that specifically adopt new products for the future variation process to generate final goods. As a result, firms in these studies are defined as the subjects of the selection process, which determines the survival of intermediate goods and is when plans are made for new product release.

Most studies on the product selection process have been based on interactions between consumers. These studies have applied numerous simulation techniques, such as network models to depict general interactions, genetic algorithms, and cellular automata (Goldenberg, Libai, & Muller, 2010; Guseo & Guidolin, 2010; S. T. Kim, Hong, & Kim, 2014; Ma et al., 2009). The most widely used technique is the network model, which visualizes the interactions between the agents involved in the system. Abrahamson and Rosenkopf (1997), who defined agents as firms, modeled the influence of a firm that first adopts a new product on others that consider doing so. Meanwhile, most studies that have defined agents as consumers have introduced the network model to define interaction mechanisms among consumers. Each study has adopted the model by changing the network structure or the relationship between consumers depending on the research objective. For example, Duan and Chen (2007) constructed a model using discrete dynamic state network simulation for the consumer’s choice to identify the impact of product quality and the network externality of products on consumers’ purchases.

Among the studies that did not apply a network model, Ma et al. (2009) modeled the effects of firms' risk-taking behavior and their tendencies when introducing technologies for new product development. Although Schramm, Trainor, Shanker, and Hu (2010) considered the patterns in which products are purchased by consumers, they compared the importance of two factors: brand value and product quality. Tao Zhang and Zhang (2007) investigated the impact of economic policies on the choices of different consumer groups. They modeled the decision-making of consumers and excluded interactions between consumer groups because it distinguished the purchases made by different consumer groups. Roozmand et al. (2011) simulated the changing patterns of consumers’ choices depending the characteristics of the system to which the consumers belonged and the locations of consumers with different cultures. Other models of the selection process were based on a network model because they concentrated on relationships between consumers.

The purpose of most previous research has been to identify factors affecting the diffusion of products. Simulation studies on diffusion as a result of the product selection have defined agents as consumers and introduced the network model to replicate network formation and endogenous interactions between consumers. Furthermore, previous research on firms' strategy has investigated the impact of various strategies on consumers' choices, including promotion strategy (Delre, Jager, & Janssen, 2007; Hu et al., 2018), pricing strategy (W. Chen, Liu, & Xu, 2018; Schramm et al., 2010), product manufacturing strategy (Negahban et al., 2014), and pricing and entry strategy (K. Lee, Lee, & Kim, 2014). In addition, previous research has considered the structure of the consumer network and the consumer's capability. Delre, Jager, Bijmolt, and Janssen (2007) and Delre, Jager, Bijmolt, and Janssen (2010) examined how individual consumers' preferences and experiences with social influence affected their purchasing behavior. Several models have been developed to examine the impact of consumers' capability on product selection, considering various types of networks depending on the connectivity between consumers (Choi, Kim, & Lee, 2010), the adoption threshold and innovativeness of consumers (Bohlmann, Calantone, & Zhao, 2010), and their social status and responsibility needs (Roozmand et al., 2011). Furthermore, van Eck, Jager, and Leeflang (2011) divided consumers into opinion leaders and non-opinion leaders according to the influence of individual consumers in the network, and discussed the impact of opinion leaders on product selection. Shinde, Haghnevis, Janssen, Runger, and

Janakiram (2013) investigated product selection and proliferation by considering consumers' risk-taking propensity as a major factor. Stummer, Kiesling, Günther, and Vetschera (2015) considered the decision-making process when consumers repurchase products, and Wolf, Schröder, Neumann, and de Haan (2015) analyzed the impact of emotional coherence on the decision-making process. The rest of the research has investigated patterns of the diffusion of product innovation and competition in different information regimes, in response to changes in the social environment (Jiang, Ma, Shang, & Chau, 2014; Laciana & Oteiza-Aguirre, 2014; Laciana, Rovere, & Podestá, 2013; Przybyła, Sznajd-Weron, & Weron, 2014; Smaldino, Janssen, Hillis, & Bednar, 2017), resulting from changes in the social network structure caused by controlling the amount of information (Pegoretti, Rentocchini, & Vittucci Marzetti, 2012), and based on the impact of market policy on the selection process (Kangur, Jager, Verbrugge, & Bockarjova, 2017).

To summarize, previous research has focused on the diffusion of products by investigating consumers' choices and purchasing behavior. Most previous studies have defined agents as consumers, used the network simulation technique, and adopted key factors affecting the consumer network.

Table 2 Models for the selection process of products

Research	**Objective**	**Simulation technique**	**Agent**
Abrahamson and Rosenkopf (1997)	Investigate the emergence of the bandwagon effect	Network simulation	Firms
Adner and Levinthal (2001)	Analyze product and process innovation in technology life cycle	Agent-based model	Firms Consumers
Adner (2002)	Investigate the emergence of technology disruption by demand condition	Agent-based model	Firms Consumers
Lee (2006)	Investigate the diffusion patterns of products under the consumer network model	Network model	Consumers
Delre, Jager, Bijmolt, et al. (2007)	Investigate the impact of promotion strategies on the diffusion of products	Network model	Consumers
Delre, Jager, and Janssen (2007)	Show how the social structures and the heterogeneity of the consumers significantly determine the shape and speed of the diffusion by using ABM	Network model	Consumers

Research	Objective	Simulation technique	Agent
Tao Zhang and Zhang (2007)	Evaluate the influence of governmental economic policies on business, and to improve companies' marketing performance in a competitive market by achieving an in-depth understanding of the psychology of consumers and the sociology of consumer groups or networks.	Agent-based purchase decision-making model	Consumers
Duan and Chen (2007)	Investigate the impact of the network externality on the selection and penetration of products, comparing the quality vs. installed base	Discrete dynamic state network dynamics simulation	Consumers
Guseo and Guidolin (2009)	Investigate the selection and penetration of products considering communication network	Cellular automata	Consumers
Ma et al. (2009)	Present a stylized model of technology adoptions for sustainable development under the three potentially most important “stylized facts”: increasing returns to adoption, uncertainty, and heterogeneous agents following diverse technology development and adoption strategies	Simple genetic algorithm	Firms
Schramm et al. (2010)	Develop an agent-based diffusion model with consumer and brand agents	Agent-based model	Firms (Brand) Consumers

Research	**Objective**	**Simulation technique**	**Agent**
Goldenberg et al. (2010)	Analyze the impact of the chilling effects in a consumer network on the selection process	Cellular automata	Consumers
Choi et al. (2010)	Investigate the patterns of diffusion	Network model	Consumers
Bohlmann et al. (2010)	Analyze the market network heterogeneity	Agent-based network simulation	Consumers
Delre et al. (2010)	Formalize different network structures and examine the impacts of the market characteristics on the innovation diffusion	Network model	Consumers
Guseo and Guidolin (2010)	Model the impact of direct network externality that depress sales for long periods and delay full benefits through a multiplicative dynamic market potential driven by a latent individual threshold	Cellular automata	Consumers
Lin and Li (2010)	Investigate the selection in scale free network (knowledge innovation and diffusion process)	Network simulation	Economic agents
Roozmand et al. (2011)	Investigate system-level resulting behavior of consumers based on culture, personality and human needs	Agent-based model	Consumers

Research	Objective	Simulation technique	Agent
van Eck et al. (2011)	Investigate the critical role that opinion leaders (or influentials) play in the adoption process of new products	Network model	Consumers
Pegoretti et al. (2012)	Investigate how the structure of social networks affects innovation diffusion and competition under different information regimes	Network model	Consumers
Shinde et al. (2013)	Create a framework that allows us to simulate and analyze the effect of multiple business scenarios on the adoption behavior of a group of technology products	Network model	Consumers
Laciana et al. (2013)	Analyze individual innovation diffusion and adoption patterns	Network model	Consumers
Kim et al. (2014)	Develop an agent-based artificial market, which is a product diffusion model that can forecast diffusion amounts (or market shares) of competing brand-level products	Genetic algorithm	Consumers
Jiang et al. (2014)	Explore the dynamic evolutionary process of knowledge sharing among users of the social commerce	Network model	Consumers
Lee et al. (2014)	Observe how consumer agents behave as the product life cycle and the degree of sensitivity on social influence	Network model	Consumers

Research	Objective	Simulation technique	Agent
	change		
Negahban et al. (2014)	Analyze the performance of different production planning strategies under various levels of volume flexibility and consumer social network structures	Network model	Firms Consumers
Laciana and Oteiza-Aguirre (2014)	Explore the selection and penetration of products in a competing environment	Network model	Consumers
Przybyła et al. (2014)	Understand how new ideas, products or behaviors spread throughout the society in time	Network model	Consumers
Szymczyk and Kaminski (2014)	Identify factors influencing the saturation level and the speed of innovation adaptation in the artificial population	Network model	Consumers
Stummer et al. (2015)	Present a model that is based on empirical data in the context of an actual case study and extends previous models in several directions	Network model	Consumers
Brouillat (2015)	Investigate the interplay between technological change and product life span in extended industrial dynamics	Network simulation Genetic algorithm	Firms Consumers
Wolf et al.	Suggest agent-based model by considering the role of	Artificial neural	Consumers

Research	Objective	Simulation technique	Agent
(2015)	emotion in human decision-making and communication	network model	
		Network model	
Heinrich (2016)	Propose a simple catastrophe theory model of technological change with network externalities and reevaluates the value of such a model by adding an agent-based micro layer	Network model	Firms
Xiao and Han (2016)	Introduce a novel approach of forecasting new product diffusion with ABMs	Hidden influence network model	Consumers
Günther (2016)	Investigate the diffusion of new products from multiple successive technology generations	Network model	Consumers
Kangur (2017)	Explore how policies may interact with consumer behavior over long time period	Social network	Consumers
Smaldino et al. (2017)	Investigate the dynamics of adoption and consider the role of structural factors such as demographic skew and communication scale on population-level outcomes	Network model	Consumers
Negahban (2017)	Introduce a new consumer decision-making model where each agent uses a neural network to evaluate word-of-mouth and predict her utility prior to adoption a new product based on her experiences in the past	Neural network	Consumers

Research	Objective	Simulation technique	Agent
H. Lee et al. (2018)	Simulate product diffusion through multi- agent simulation (MAS) and determine product specifications that can maximize future sales by adapting ordinal optimization	Network model	Firms Consumers
Hu et al. (2018)	Show that proposed consumer groups can be a promising target, depending on how they are targeted	Network model	Consumers
W. Chen et al. (2018)	Price Q-learning mechanism for perishable products that considers uncertain demand and customer preferences in a competitive multi-agent retailer market	Multi-agent simulation Q-learning algorithm	Firms

2.2.3 Models for whole evolutionary process

Various simulation techniques have been applied to model the whole evolutionary process in numerous studies such as Sommer and Loch (2004) and Querbes and Frenken (2017). The agents defined in these studies are both firms and consumers. The role of firms is to generate new variations and to release products into the market, while consumers purchase products depending on their preferences, leading to the selection and retention of product features. Unlike studies focusing on the selection process of products, consumers' behavior is limited and interactions between consumers are rarely considered. This approach simulates the survival of firms as a result of the repetitive evolutionary processes from new product development to the selection process.

Simulation models for the whole evolutionary process have tended to focus on the variation process, rather than on the selection process. These models have employed numerous techniques to construct the variation process, such as genetic algorithms (Cartier, 2004; Lim, Bentley, & Ishikawa, 2016; Ohori & Takahashi, 2012; Querbes & Frenken, 2017; Sommer & Loch, 2004), the NK model (Ma & Nakamori, 2005; Zhong & Ozdemir, 2010), and the network model (Korzinov & Savin, 2017). Genetic algorithms are used to model the emergence of mutations in products through recombination. The NK model helps to implement the emergence of products through variation in products in a complex system. Finally, studies using the network model describe the relationships among the technological characteristics with which various products are equipped. In other words, genetic algorithms are useful for studying variation as a simple recombination process, the NK model is a technique suitable for understanding the properties of products as entities engaged in a complex system, and networks are used to consider the relationships between component technologies and the products that are developed.

First, Sommer and Loch (2004) show the process that a firm adapts as it goes through the trial-and-error under the ions of unforeseeable uncertainty, which means that the output from the adaptation process could be regarded as the result of the product innovation. They set up the cost of the variation process and the complexity of the product as core variables and conducted a simulation by categorizing patterns of selection into that which occurs in environments where products are tested perfectly and that which occurs in environments where products cannot be perfectly tested. Cartier (2004) investigated the selection process according to the intensity of selective pressure, assuming the attribute of the firm's innovation as the mutation rate. Ma and Nakamori (2005) explored the performance of firms that varied with each scenario setting by considering the mutation rate, crossover rate, entry timing, and imperfection of consumers' information. Windrum and Birchenhall (2005) distinguished the invention phase from the innovation phase, and argued that the conditions under which later technology can overcome the network externality are formed in the course of the technological succession resulting from successful diffusion of the innovation. Wersching (2010) investigated the conditions in which market attributes and technological environments promote innovation. He considered major issues such as the conditions that cause technological development in the industry, the impact of competition in innovative industries, the relationship between innovation and market structure, the role of knowledge spillover, and the influence of internal and external learning on technological development. Marengo and Valente (2010) analyzed the evolution of industry by investigating the variation process of products by considering the type of pricing strategies, the complexity of the technological space, the search strategy of firms, and the ease of imitation. Ohori and Takahashi (2012) studied the selection and the formation of standards in consideration of the number of the characteristics of products, the number of standards, the coordination period of standards, and the market portion of the de facto standard. Korzinov and Savin (2017) constructed star network structures and core-periphery structures, and investigated the emergence of general purpose technology (GPT) by categorizing technological links into potential links, visible links, and discovered links. Querbes and Frenken (2017) compared first-movers and late-movers to identify successful firms in an environment with increasing complexity. They derived a pattern in which the type of products becomes diversified by analyzing changes in the fitness level concomitant with differences in mutation frequency and the average fitness and similarity of products in accordance with an increase in the product complexity.

In summary, these studies have mainly focused on product variation. Most of them have adopted the NK model and genetic algorithms. Thus, it is considered that they do not fully consider consumers' behavior as an important factor in the evolutionary process of products.

Table 3 Models for the integration of the variation and selection process

Research	Objective	Simulation technique	Agent
Goldenberg and Efroni (2001)	Propose market dynamics model regulating competition between innovators	Cellular automata	Firms Consumers
Sommer and Loch (2004)	Investigate the impact of the trial-and-error learning and selectionism	NK model	Firms Consumers
Cartier (2004)	Transformation and selection of products in two different firms	Genetic algorithm	Firms Consumers
Ma and Nakamori (2005)	Simulate the technological innovation by adopting the concept of the product evolution	NK model Genetic algorithm	Firms Consumers
Windrum and Birchenhall (2005)	Examine the conditions under which technological successions can occur in the presence of network externalities	Multi-agent simulation	Firms Consumers
Wersching (2010)	Examine technological regimes and the role of knowledge spillovers for innovation	Agent-based model	Firms Consumers
Marengo and Valente (2010)	Analyze how the complexity of the product space, the strategies that firms follow to search this space either innovating or imitating, and the differentiation of consumers' preference interact to determine the structure and evolutions of the industry	NK model	Firms Consumers

Research	Objective	Simulation technique	Agent
Ohori and Takahashi (2012)	Provide a computational market model with technological competitions among standards	Genetic algorithm	Firms Consumers
Korzinov and Savin (2017)	Investigate the condition of the emergence of the GPT	Network simulation	Firms Consumers
Querbes and Frenken (2017)	Compare search strategies between firms and consumers in complex products	Generalized NK model	Consumers

2.3 Research questions on the product evolution

Previous theoretical research on product evolution has raised questions that help to overcome the limitations of previous research and to extend the current issues. First, an analysis of product evolution at the system level is needed. Most previous studies have investigated evolutionary patterns from the perspective of technological innovations. As they focused on technological changes, the role of the product as an interface between firms and consumers has hardly been taken into consideration. Second, a quantitative analysis of the evolutionary patterns of products should be developed. Previous research has posited evolutionary patterns qualitatively by giving several anecdotal examples. Even though some studies have proposed quantitative indices, they have likewise focused on changes at the technological level. Third, the driving forces of evolutionary patterns are necessary to be investigated to predict short-term environmental changes. Previous research has lacked suggestions regarding scenarios that hasten the emergence of environmental changes. As they help firms take the lead to cope with environmental changes, the driving forces caused by interactions between agents are important. Based on these needs for further research, the following research questions arise:

(1) What drives evolutionary patterns in the ecosystem of product evolution?

(2) How is product evolution distinguished from technological evolution?

(3) When do evolutionary patterns emerge and how can they be quantitatively measured?

(4) Which evolutionary pattern drives significant changes in both the environment and agents?

(5) How do agents contribute to the emergence of the product ecosystem?

This study attempts to derive answers for all questions partially. In Chapter 3 and Chapter 4, evolutionary patterns are operationally defined in order to investigate quantitative evidences. In Chapter 5, a novel ABSM is applied in order to simulate the role of agents in the emergence of environmental changes.

Chapter 3. The evolutionary patterns of products: the perspective of the ecosystem of product evolution

3.1 Introduction

As technology changes dramatically and new products are launched faster than in the past, it is becoming difficult to predict the patterns of product changes. Numerous studies have suggested forecasting methods, including the Delphi technique (Y. Y. Cho et al., 1991; Rowe & Wright, 1999) technology roadmaps (Y. Cho, Yoon, & Kim, 2016; da Silveira Junior, Vasconcellos, Vasconcellos Guedes, Costa, & Guedes, 2018; Jin, Jeong, & Yoon, 2014; Phaal, 2004), and patent trends and network analysis (R. S. Campbell, 1983; Chang, 2012; Daim et al., 2006). Previous studies have focused on analytical techniques and methodologies. Recently, the importance of evolutionary principles has been highlighted in order to analyze socio-technical changes in sustainable ecosystems (Ayala, 2010; Phillips & Su, 2009), which helps to investigate the patterns of product innovation and its subsequent effects.

Although previous research has proposed novel approaches to investigate the evolutionary patterns of products, those approaches have the following two limitations. First, they lack a consideration of whether the evolutionary logic of biological organisms can be applied to the evolutionary process of products. The evolutionary approach discussed in the previous empirical research was essentially borrowed to illustrate the dynamics of product change. Consequently, discussions on the applicability of the logic of biological evolution to product evolution have been limited. Second, the applicability of evolutionary principles needs more cases, since previous studies have analyzed science-based products such as medications (Andriani et al., 2017). Even though scientific knowledge and technologies evolve following evolutionary processes, the agents and factors affecting those evolutionary patterns should be distinguished from those involved in product evolution due to how interactions between the agents are defined. More specifically, products have evolved in a more complex environment, which leads to the distinction between patterns in technological evolution and product evolution.

From the brief review of the previous literature, the following questions are derived: How can evolutionary principles be applied to complex products? How can evolutionary principles be applied to forecasting issues? To answer these questions, this study aims to investigate the three evolutionary patterns that occur in the mobile phone industry, which is among the fastest-changing industries worldwide. First, an operational definition of the three evolutionary patterns is proposed, which can be calculated using product specification data and product market data. Second, the metrics for the evolutionary patterns are applied to the case of the Korean mobile phone market between 2004 and 2013.

The results confirm that stylized facts are discovered in the innovation process of mobile phones, indicating that evolutionary principles are helpful to explain the dynamics in product innovation. Product innovation happens when a new product becomes more complicated as newly adopted features from other industry are successful for adaptation. Second, the evolutionary change of products occurs as a result of genetic information transfer among firms and between firms and consumers, which shows the importance of interactions between the decision-making routines of firms and consumers. Third, new product categories, which lead the processes of industrial change (B. Bayus, 1994; B. L. Bayus, 1998) and have at least one distinguishing technological characteristic, seem to emerge abruptly, but their emergence is caused by incrementally accumulated changes, followed by radical innovations. Through this demonstration of the applicability of three evolutionary principles via a case study of the Korean mobile phone industry, this study helps researchers, firms, and governments to cope with the industrial changes by supporting the forecasting of the dynamics of product innovation.

The rest of this chapter is organized as follows. Section 3.2 proposes the operational definition of the three evolutionary patterns. Section 3.3 illustrates the data and presents the results. Section 3.4 concludes this chapter with further discussion and outlines its contributions.

3.2 Stylized facts in the evolutionary process

The evolutionary process is considered to be at the core of product evolution. Numerous researchers have attempted to characterize the evolution of complex systems, including artificial systems, through the concept of variation-selection-retention (Aldrich et al., 2008; Schubert, 2014). In the meantime, previous research in the field of biology has analogized product evolution with biological evolution by subdividing the evolutionary process into detailed processes and distinguishing differences between them (A. Wagner & Rosen, 2014). A. Wagner and Rosen (2014) proposed nine stylized facts of product evolution from the perspective of a biologist: trial and error within populations, extinction and replacement, descent with modification, horizontal information transfer, combinatorial innovation, exaptation, ecosystem engineering, episodic change, and multiples and singletons. Even though they use numerous examples to support those stylized facts, their analysis has limitations in that they gathered anecdotal evidence from various products and thereby lacked an explanation of the dynamics of product evolution.

This study defines the following three stylized facts related to the evolutionary process: exaptation, genetic information transfer, and episodic change. Exaptation occurs relatively infrequently. Genetic information transfer helps to explain the internal and external selection process, which is linked to the variation process in descendants. Finally, episodic changes are related to environmental changes, which lead to changes in industries and markets.

3.2.1 Exaptation

Exaptation means that currently useful features were not generated in a direction that was adapted to their current role, but instead are considered to be the result of adaptation to their current function (Gould, 1991; Gould & Vrba, 1982). Bird feathers are one of the most representative examples of exaptation. Although feathers were initially used for insulation, their use changed as they came to be used in flying (Gould & Vrba, 1982). Another example are bones, which have several functions, such as support/protection and storage/homeostasis (Gould & Vrba, 1982). By considering these phenomena, exaptation has covered a major blind spot of Darwinism.

In research on product evolution, exaptation is significant but rarely considered, even though it is a special pattern in the variation process (Mokyr, 1997). Some researchers have newly defined exaptation by considering the context of product evolution. Desouza, Awazu, and Ramaprasad (2007) and other researchers have categorized types of exaptation (Andriani & Carignani, 2014; Andriani & Cohen, 2013). Exaptation in studies of technological evolution is categorized into three types: internal exaptation, external exaptation, and radical exaptation (Andriani & Carignani, 2014). Andriani and Carignani (2014) distinguished these modes in terms of changes in function and architecture. Products are likely to obtain different functions while evolving by exaptation. Thus, they posit that the modes of exaptation are radical exaptation and external exaptation.

Case studies on exaptation have also been performed; one of the most well-known examples is the microwave oven (Andriani & Cohen, 2013; A. Wagner & Rosen, 2014). The technology adopted in the microwave oven was originally developed to be used for radar technology, but later, it was applied to traditional ovens and developed into the current product. Gillette’s safety razor, Marsilid (Andriani & Carignani, 2014), and Post-it Notes (Garud, Gehman, & Giuliani, 2016) are other examples of exaptation. Each example was categorized and defined as a different sort of exaptation, according to the classification criteria suggested by each researcher.

By simplifying the existing definition of exaptation, this research defines exaptation as the phenomenon in which a new type of product is recognized due to the introduction of a new feature. We define exaptation as the emergence of a new type of product that consumers perceive and accept as a newly created niche of products.

Stylized fact 1. Exaptation can occur in the process of product evolution, and it creates a new type of product.

3.2.2 Genetic information transfer

Genetic information transfer affects the selection and retention process. The most well-known evolutionary principle is that descendants inherit mutated and modified deoxyribonucleic acid (DNA) from their parental group (A. Wagner & Rosen, 2014). The genes of parents are transmitted to their offspring in most organisms, except for unicellular organisms that breed through asexual reproduction (Amábile-Cuevas & Chicurel, 1993; Jain, Rivera, & Lake, 1999). In general, the former pattern reflects vertical transfer, and the latter represents horizontal information transfer.

Products evolve through both vertical and horizontal information transfer. Vertical information transfer means that products change through the generations. Representative examples of vertical information transfer are the evolution of the Ford Model T into the Prius and the Wright brothers' Flyer into the Boeing 787 (A. Wagner & Rosen, 2014). While the Ford Model T has evolved into the Prius, firms and consumers have transferred their decision-making routines continuously. The decision-making routines of consumers are shown by the purchase of products. Firms acquire information on consumer decision-making routines and then update their decision-making, which affects the development and introduction of the next generation of products. The exchange of information between these two groups of agents has caused the Ford Model T to evolve into the Prius.

Horizontal information transfer, in contrast, occurs when firms generate new products by considering other kinds of products or competitors' products. This is similar to the combinatorial innovation process (Arthur, 2009) since it is identical to a firm's process of developing new products by recombining existing products. An example of this process is the generation of the BASIC programming language, which involved a combinatorial process of Fortran and ALGOL (Solé et al., 2013).

Vertical information transfer is useful for describing aspects of the new product development process, as it also considers both supply-side and demand-side innovation. Horizontal information transfer is prevalent, and it is therefore helpful for explaining the new product development process in which firms share their knowledge with other firms. Thus, both horizontal and vertical information transfer occur through interactions between product genes—the decision-making routines of firms and consumers.

Stylized fact 2. Product evolution occurs not only through vertical information transfer between producers and consumers, but also through horizontal information transfer among producers.

3.2.3 Episodic change

Darwinism and punctuated equilibrium are distinguished in terms of their perspectives on understanding the process of the emergence of new species. Darwinism considers the emergence of new species to be the result of gradual changes. However, this framework has limitations in that it is difficult to explain epistasis and the absence of fossils that show gradual changes (Eldredge & Gould, 1972; Gould & Eldredge, 1977). In contrast, punctuated equilibrium complements this limitation of Darwinism by considering the emergence of new species as an abrupt appearance of a new type of entity through speciation.

The difference between Darwinism and punctuated equilibrium is that Darwinism insists on gradualism, whereas punctuated equilibrium focuses on radicalism. Both perspectives have been investigated to identify the evolutionary patterns of products. Early researchers considered an “invention” to be the emergence of a new species, as it is the result of gradual and cumulative changes (Basalla, 1988; Gilfillan, 1935; Usher, 1954). Mokyr (1990), however, asserted that feverishly radical changes happen when a long-term stagnation of gradual changes occurs. Following these studies, researchers focused on product innovation have argued that product evolution tends to follow both gradualism and radicalism by categorizing innovation into incremental innovation and radical innovation (Levinthal, 1998). In recent years, both radical and incremental changes have been combined to explain large-scale evolution by substituting radical change with the term ‘episodic change’ (Valverde & Solé, 2015; A. Wagner & Rosen, 2014).

To summarize, previous researchers have considered gradualism and punctuated equilibrium as either bisected concepts or as having a systematic relationship. Strictly speaking, however, it is not clear when an episodic change occurs and how it can be identified. By considering patterns of episodic change, this study defines the evolutionary patterns of products to be the results of episodic change caused by the accumulation of small changes, based on gradualism.

Stylized fact 3. The evolutionary dynamics of products follow gradualism, and episodic change occurs as a result of accumulated, gradual changes.

3.3 Metrics for identifying stylized facts on product evolution

3.3.1 A metric for exaptation in product

Exaptation is defined as the emergence of a new product category i that consumers accept as a product category with different functions, as Andriani and Carignani (2014) observed exaptation by analyzing whether the performance of the products and modules that comprised the existing architecture had changed due to newly introduced features.

Andriani et al. (2017) suggested the only measure of exaptation, which calculates the occurrence ratio of exaptation. They investigated the unintended usage of medications and counted the number of occurrences of unintentional changes in the pharmaceutical industry. The key concept defining exaptation is how users recognize the products. Thus, in order to identify the exaptation EX_i by a new technological characteristic i in the product market, we define exaptation in the product market by referring to the emergence of a new product category i with a new technological characteristic c_i in Wikipedia, which indicates the consumer's perception cp_i of the generation of a new product category i with a different function from the original function, as in Eq. (1).

$$EX_i = \begin{cases} 1, & c_i > 0, \quad cp_i = 1 \\ 0, & otherwise \end{cases} . \qquad (1)$$

3.3.2 A metric for genetic information transfer

Genetic information transfer is determined by analyzing whether genetic information is exchanged between the decision-making routines of firms and consumers or between firms, as the genes of products are defined as the routines of firms and consumers, and the technological characteristics and functions are regarded as the phenotype, which is determined by the genes. The former pattern represents vertical information transfer, and the latter represents horizontal information transfer. Vertical information transfer can be measured by comparing firms' pricing with consumers' preferences. Price information is used to consider a firm's routine regardless of technological characteristics, and it is used as a proxy for the pricing strategy, one of the decision-making results based on a firm's routine. To analyze how their decision-making interact, we suggest vertical information transfer VIT_t at time t as the correlation between the consumer rating CR_j of a product model and the average price p_j of each product model j as follows:

$$VIT_t = \frac{\sum (CR_j - \overline{CR})(p_j - \overline{p})}{\sqrt{\sum (CR_j - \overline{CR})^2 \sum (p_j - \overline{p})^2}} \quad \cdots\cdots (2)$$

The benchmark for *VIT* is presumed to be 0.6, which can be interpreted as meaning that these two variables show a correlation. A VIT_t higher than 0.6 can be interpreted as indicating that a product reflects the vertical transfer of genetic information, meaning that the two factors have a linear correlation. In contrast, if VIT_t is negative, the transferred information can be interpreted as not being reflected in the evolutionary process based on the intention of carriers. This happens because firms do not accept the information on evaluations that consumers pass to firms, and consequently firms launch new products outside of that trajectory. A positive correlation between the two agents implies that the decision-making of firms and consumers is likely to show synergies, according to which the price becomes higher and consumers evaluate the product more favorably. In contrast, a negative correlation implies that firms are likely to release maladaptive products due misunderstandings about consumers' decision-making, which cause firms to launch new products away from their trajectory.

Horizontal information transfer is shown by the innovation and imitation strategies of firms. Imitation is generated by the exchange of decision-making routines between firms, which reduces the diversity of products. Innovation, in contrast, increases the diversity of the products as firms develop new products that are different from existing products. Thus, horizontal information transfer HIT_t at time *t* can be calculated by the fluctuation in the number of product models, referred to the diversity of the products PD_t at time *t*, as follows:

$$HIT_t = PD_t - PD_{t-1} \quad \text{(3)}$$

3.3.3 A metric for episodic change

The concept of the phase transition in thermodynamics can be modified to describe episodic change. In research on network theory, the percolation threshold is applied to identify a phase transition where the pattern of a specific phenomenon changes (Achlioptas, D'Souza, & Spencer, 2009; Holme & Newman, 2006). In the product market, the market undergoes a phase transition through changes in product categories. This research considers the point of phase transition to be the change from the market with an existing product category to a new market with an emerging product category. The market share of products shows their fitness level, and thereby the sum of market share s_{it} in a product category *i* that consists of product model *j* represents the fitness level of a product category *i* as follows:

$$S_{it} = \sum_{j=0}^{j=J} S_{jit}, \qquad j \in i \tag{4}$$

If the market share s_{kt} of the existing product category k at time *t* is higher than s_{it} of the emerging product category *i* at time *t*, the product market has not changed. Once s_{it} exceeds s_{kt}, the product market becomes a new market. Thus, the percolation threshold—the point of episodic change EC_t— can be defined as the intersection between the sales volume of the existing product category and the emerging product category as follows:

$$EC_t = \begin{cases} 1, & d_{ikt} d_{ikt-1} < 0 \\ 0, & otherwise \end{cases}, \tag{5}$$

$$d_{ikt} = s_{kt} - s_{it}. \tag{6}$$

This research suggests metrics for analyzing each stylized fact to support the evolutionary principles of products as summarized in Table 4.

Table 4 Metric for analyzing stylized facts

Stylized fact	Metric	Operational definition
Exaptation	$EX_i = \begin{cases} 1, & c_i > 0, \quad cp_i = 1 \\ 0, & otherwise \end{cases}$	The emergence of a new type of product by introducing a new feature
Genetic information transfer	Vertical information transfer: $VIT_t = \dfrac{\sum (CR_j - \overline{CR})(p_j - \overline{p})}{\sqrt{\sum (CR_j - \overline{CR})^2 \sum (p_j - \overline{p})^2}}$	Interaction of decision-making between firms and consumers
	Horizontal information transfer: $HIT_t = PD_t - PD_{t-1}$	Interaction of decision-making routines between firms
Episodic change	$EC_t = \begin{cases} 1, & d_{ikt} d_{ikt-1} < 0 \\ 0, & otherwise \end{cases}$	Phenomenon in which the market share of new products exceeds that of existing products

3.4 Case of the mobile phone industry

3.4.1 Data

This section presents an investigation of evolutionary patterns in the Korean mobile phone market, as mobile phones are one of the most widespread and rapidly changing products in an IT-based society (Wirtz, Mathieu, & Schilke, 2007). In the mobile phone industry, numerous catastrophic changes have been observed in short time periods due to its rapid variation cycles; this pattern is similar to the characteristics of Drosophila (fruit fly), whose ten-day-longevity and large chromosomes make it a useful organism for investigating biological evolution in the laboratory (O'Connell, 1992). In Korea, domestic firms, represented by Samsung and LG, have increased the competitiveness of the mobile phone industry by utilizing the Korean mobile phone market as a testing ground and thereby gathering information on consumers, which provides relatively larger 'chromosomes' than other markets. Thus, changes in firms' and consumers' decision-making routines in response to market changes appear clearly in the Korean market.

For this research, sales data, specification data, and consumers' rating data for each model were collected. The sales data was provided by GfK (Gesellschaft für Konsumforschung) Korea, including information on 1,282 observations from 2004 to 2013. As numerous technological characteristics were adopted frequently during this period, it offers a reasonable context for investigating the evolutionary patterns in the mobile phone market. These scanner data have been used for panel analysis of consumers and market pricing (Ioannidis & Silver, 1999, 2003; Kivi et al., 2012; Klingebiel & Joseph, 2016; Silver, 2000; Thiele & Weiss, 2003). The scanner data contain sales volume, sales value in dollars, and manufacturer information; the average price of each mobile phone model is calculated by dividing sales value by sales volume.

Table 5 Description of collected features

Mobile phone features	Description	Unit
Telecommunication technology	Name of technology used for cellular communication	
Display	Physical size of the screen	Inch
Application Processor Chipset (AP chipset)	Performance of the main chipset of a smartphone, which executes the operating system	Gigahertz (GHz)
Camera pixel	Resolution of the camera	Million mega pixels
Random Access Memory (RAM)	Amount of main memory, to which read and write operations can be directed	Gigabyte (GB)
Read-Only Memory (ROM)	Amount of non-volatile read-only data storage	Gigabyte (GB)
Battery	Amount of electric charge	Ampere-hour
Volume	Case size described through three dimensions of the smartphone	cm^3
Weight	Weight of the smartphone	100g
MPEG-1 Audio Layer-3 (MP3)	MP3 technology support	
Touch	Existence of a touch screen	
Digital multimedia broadcasting (DMB)	A digital radio transmission technology for sending multimedia	
Bluetooth	Existence of Bluetooth technology	
Global Positioning System (GPS)	Existence of GPS hardware	
Smartphone OS	Name of system software of a smartphone (e.g., iOS, Android)	
Wi-Fi	Existence of Wi-Fi technology	

The data on technological characteristics was gathered from the official websites of manufacturers and representative online shopping malls, *Danawa* (http://www.danawa.com) and *Cetizen* (http://cetizen.com), which sell and review digital gadgets. Among the numerous technological characteristics of mobile phones, the choice of features to collect was based on previous studies analyzing the mobile phone industry (Dewenter, Haucap, Luther, & Rötzel, 2007; Garcia-swartz & Garcia-vicente, 2015; Kivi et al., 2012; H. Lee et al., 2018; Riikonen, Smura, Kivi, & Töyli, 2013). The collected features are described in Table 5. We also collected the average consumer ratings from Cetizen as consumer evaluation data. Consumer ratings were used to consider the decision-making routines of consumers, which helped to analyze the genetic information transfer that occurred in the selection and retention process. Finally, perceptions of changes in mobile phones were determined by the presence of definitions of various types of mobile phones such as 'camera phone', 'touchphone', and 'smartphone' in Wikipedia.

3.4.2 Results

Early mobile phones, which operated using the first-generation telecommunications network, were just considered to be portable telephones. However, numerous technological characteristics, such as MP3, GPS, DMB, Bluetooth, touch, Wi-Fi, and OSs, were introduced and adapted to the mobile phone market. **Figure 4** illustrates the timeline of the introduction of new features and their adoption rate. From the second half of 2004, MP3 and GPS began to be introduced in earnest, and DMB, touch, and Bluetooth were installed afterward. It also shows that the adoption rate of OSs dramatically increased in the first half of 2009. The adoption of these new features fundamentally changed the meaning of the term 'mobile phone'.

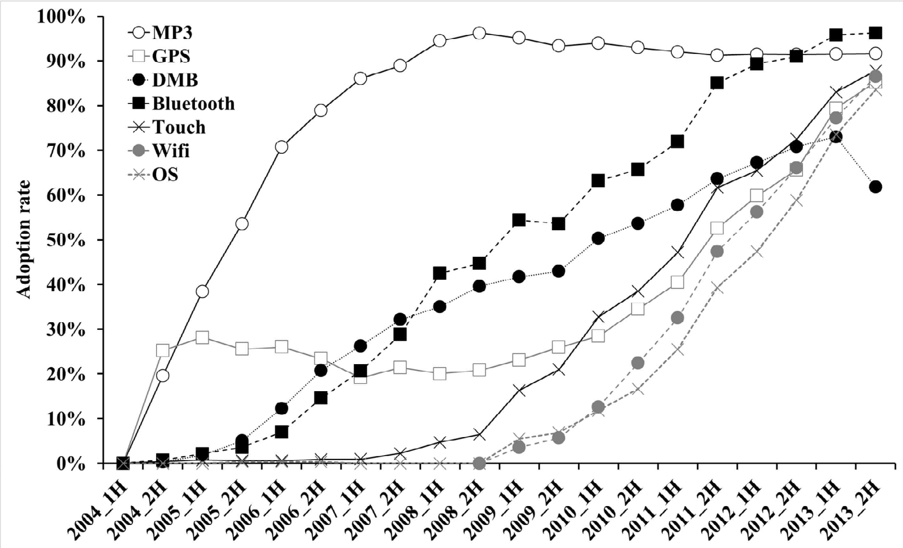


Figure 4 Adoption rate of new features in mobile phones

Table 6 presents the introduction of new features and the occurrence of their exaptation. In Wikipedia, a mobile phone is defined as "a telephone based on a cellular radio system which can cover a wide area without any physical connection to a network. Cameras, which have achieved an 100 percent adoption rate, were introduced in the early 2000s. Mobile phones moved into the new category of camera phones with the introduction of the camera feature. Even though DMB, Bluetooth, and touch were all introduced in the second half of 2004, the only one of those features that created a new category was touch. In other words, the touch feature was the only one of those three features that resulted in exaptation of mobile phones. In the first half of 2009, OSs started to be adopted in mobile phones, creating the new category of smartphones. To summarize, the introduction of cameras, touch, and OSs was the driving force behind exaptation in the evolutionary process of mobile phones.

Table 6 Introduction of functions and exaptation

New category i	**Camera**	**Touch**	**DMB**	**Bluetooth**	**GPS**	**MP3**	**OS**
EX_i	1	1	0	0	0	0	1

The average VIT_t during this entire period was 0.6053. Dividing the period into two—before and after the phase transition— during the first period, the average VIT_t was notably high, reaching 0.8418. In contrast, it became strongly negative (at about -0.9768) during the second period. This means that information transfer between firms and consumers actively occurred, but since the phase transition point, firms might have misperceived the information that consumers delivered and launched mobile phones separate from the trajectory. If this trend continues, firms will release maladaptive mobile phones, for which survival is difficult in the mobile phone market.

Horizontal information transfer is shown in **Figure 5** through an analysis of the diversity of mobile phones. The diversity of mobile phones has gradually decreased, which indicates that genetic information transfer between firms has occurred. As seen in Table 7, the fluctuation of the diversity was high until the phase transition point. HIT_t increased for about one year and then decreased the following year. Since the phase transition point, diversity steadily decreased except for the first half of 2013, when HIT_t had a negative sign. In other words, genetic information transfer between firms happened irregularly before the phase transition point but increased gradually after the phase transition point.

To summarize, the genetic information transfer that takes place in biological evolution also occurs in product evolution. Specifically, we captured both vertical information transfer and horizontal information transfer of the third stylized fact by using the metric suggested in this research.

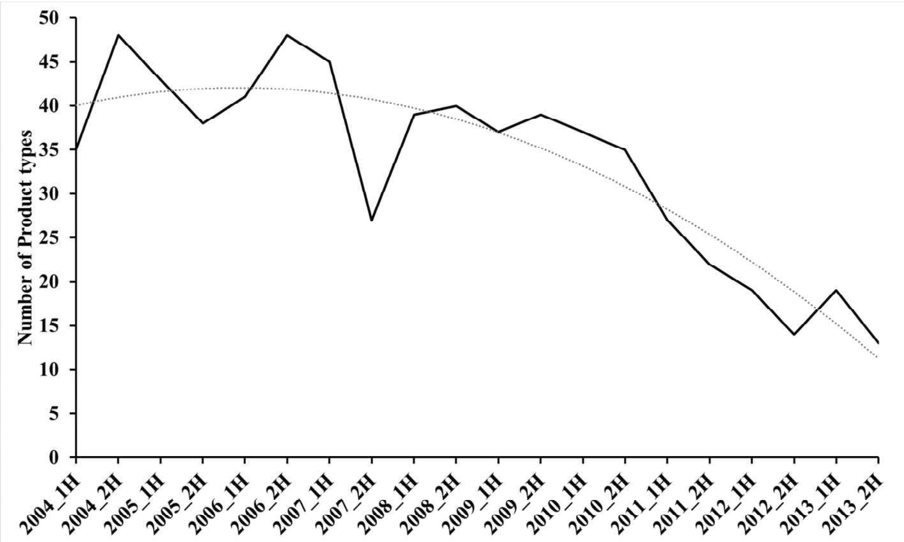


Figure 5 Trends of product diversity

Table 7 Trends of horizontal information transfer

Time	2004 1H	2004 2H	2005 1H	2005 2H	2006 1H	2006 2H	2007 1H	2007 2H	2008 1H	2008 2H
HIT_t	-	13	-5	-5	3	7	-3	-18	12	1

Time	2009 1H	2009 2H	2010 1H	2010 2H	2011 1H	2011 2H	2012 1H	2012 2H	2013 1H	2013 2H
HIT_t	-3	2	-2	-2	-8	-5	-3	-5	5	-6

The mobile phone market can be divided into the era of the feature phone and that of the smartphone. The point of episodic change demonstrates the distinction between the two eras. Table 8 shows the emergence of episodic change using Eq. (3). The episodic change in the mobile phone industry occurred in the first half of 2011. Before the first half of 2009, the market share of smartphones was insignificant, at less than 1 percent. Then, the smartphone market share started to increase from about 2 percent, and the gap in the market share between the two product categories became smaller. During the first half of 2011, the market share of smartphones exceeded that of feature phones, and the smartphone became dominant afterwards. Thus, we confirm that stylized fact 1, episodic change, also emerges in product evolution.

Table 8 Episodic change through the market share of feature phone and smartphone

Time	2004 H1	2004 H2	2005 H1	2005 H2	2006 H1	2006 H2	2007 H1	2007 H2	2008 H1	2008 H2
d_{ikt} (%)	99.99	100	100	99.98	99.99	99.98	100	100	100	100
EC_t	0	0	0	0	0	0	0	0	0	0

Time	2009 H1	2009 H2	2010 H1	2010 H2	2011 H1	2011 H2	2012 H1	2012 H2	2013 H1	2013 H2
d_{ikt} (%)	97.85	94.28	73.51	17.48	-33.84	-63.37	-78.06	-84.21	-87.55	-88.28
EC_t	0	0	0	0	1	0	0	0	0	0

Figure 6 helps to understand the dynamics of this episodic change by illustrating the timing of the introduction of mobile phone OSs and their market share. It shows that a phase transition—the episodic change— in the mobile phone market occurred in the first half of 2011. Before the phase transition point, numerous OSs had preceded smartphone OSs, such as Palm OS. Even though Palm OS was already introduced before the first half of 2004, its impact was insignificant to the transition away from the feature phone era. Windows Mobile OS was introduced to support the development of smartphones. From the second half of 2008, an early version of smartphones with Windows Mobile OS installed arose, which lasted until iPhones with iOS installed were introduced in the second half of 2009. Although Symbian was proposed prior to iOS, its influence was not distinguishable in the market. As the iPhone held a more successful position compared to

former smartphones, smartphones with Android OS and RIM OS installed started to be introduced. Android achieved huge success in the second half of 2010, and the sales volume of smartphones with Android OS exceeded that of feature phones in the first half of 2011. To summarize, OSs were gradually developed and launched in the mobile phone market since the Palm OS, and the feature phone market was converted to the smartphone market through an episodic change between the second half of 2010 and the first half of 2011.

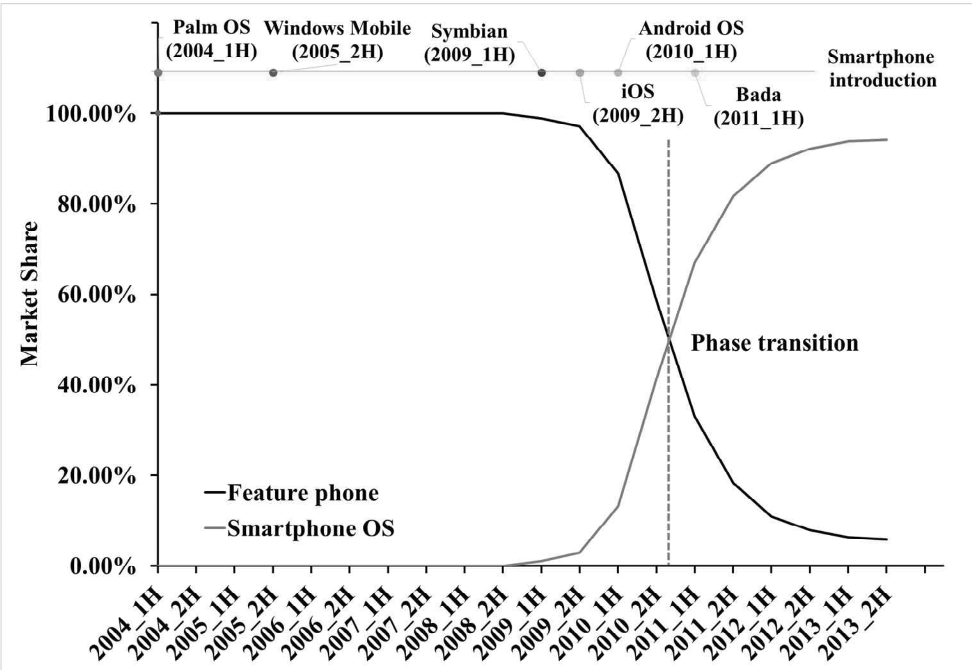


Figure 6 Introduction and market share of smartphone OSs

3.5 Sub-conclusion

The research presents in this chapter confirms that product evolution and biological evolution have quite similar characteristics in many respects. The phenomena of episodic change, exaptation, genetic variation, and environmental change led by variation in biology are seen in the mobile phone market as well. The reason for these similarities is that both evolutionary processes occur owing to the interaction between entities within a certain system.

The major difference between biological evolution and product evolution is that the intention of entities in product evolution is to intervene in the evolutionary process. Because biological evolution is characterized by blindness in the variation process, the intention of entities does not affect the evolutionary process. In contrast, the evolutionary process of products is driven by the intentions of firms and consumers. To begin with, considering the first stylized fact, the increasing number of smartphone manufacturers leads to an episodic change in the mobile phone market. While exaptation, the second stylized fact, leads to the introduction and diffusion of new features, in this case, the intention of entities is engaged, since this process happens via the decision-making of firms and new features were not introduced randomly. In addition, intention is a relevant factor during the process of genetic information transfer. This is because when firms ignore information from the decision-making routines of consumers when they produce new products, firms make decisions with their own intentions regardless of genetic information transfer.

Likewise, product evolution is directed by the intention of entities, since the decision-making routines of firms and consumers are defined as the analogue of genes. Thus, product evolution is relatively predictable, and the direction of product evolution is determined by the strong intention of entities in the evolutionary system of products. The strong intention of entities mostly corresponds to firms' strategy or government policy. Firms lead product evolution by making their products the core of evolution through intensive investment of their capital in research and development (R&D) and marketing. The government increases the survivability of domestic products through government R&D or construction of a new environment by searching for a new market. Eventually, firms or the government must have more powerful motives than competitors in order to lead product evolution. At this point, it is necessary to create a new niche through aggressive investment. Marsilid and Post-it Notes are examples of exaptation that creates new niches. Firms need to update their decision-making routines by accepting the decision-making routines of consumers after exaptation occurs. These updated decision-making routines affect the launch of next-generation products. In this process, firms are able to obtain an opportunity to achieve leadership in the new niche. Thus, the government is recommended to support firms in the creation of new niches through exaptation.

This research reinterprets product evolution through an analogy with evolutionary principles in biology. Except for the intentions of entities, it is considered that products and biological organisms have common evolutionary principles. In addition to the three stylized facts investigated in this research, more stylized facts observed in biological evolution can be identified in product evolution. Thus, it is possible to forecast product innovation using evolutionary principles. Analyzing a series of changes such as variation in entities and the successional change of the environment helps firms predict and determine the most suitable timing to try to cope with environmental changes and to survive in an uncertain environment. In other words, firms can predict changes in the industry in which they are involved and analyze their fate.

This research builds on existing studies in the literature that present anecdotal evidence on product evolution by investigating the evolution of products using the technological characteristics and market data of mobile phones. The existing literature has documented the evolutionary patterns of each feature with which mobile phones are equipped, rather than considering the patterns of mobile phones themselves and their environment. In order to understand industrial change, the evolutionary patterns of products in the industry needs to be observed. By suggesting a research framework to investigate the evolutionary patterns of products, this research will help firms establish new product development and marketing strategies and will assist policy-makers in deploying industrial policy by providing an approach to analyzing the industrial environment.

The generalizability of this study is limited since it focused on the Korean mobile phone market. To generalize the applicability of general evolutionary principles, further research needs to show the evolutionary patterns in the mobile phone market in other countries and in other product markets. By generalizing evolutionary principles, this study helps firms build scenarios for product roadmaps and new product development strategies.

Chapter 4. Driving forces of the emergence of episodic change: the perspective of the ecosystem of product evolution

4.1 Introduction

Product innovation is caused by the recombination of existing products (Schumpeter, 1934) and is distinguished by incremental innovation and radical innovation depending on the level of newness compared to existing products (OECD/Eurostat, 2005). New products are mostly the result of incremental innovations, reflecting slight changes compared to existing products, while changes in the industrial environment emerge in the market as the result of radical innovations that appear to differ significantly from existing products (Davies, 1997). This phenomenon is one of the stylized facts observed in the evolutionary process of products through the accumulation of two types of innovation (Orihata & Watanabe, 2000a). The enormous environmental changes due to this phenomenon are defined as episodic change, which includes the concept of punctuation (A. Wagner & Rosen, 2014; Weick & Quinn, 1999).

One of the most representative examples of an episodic change in biology is the Cambrian explosion (Wallace, 2014), which involved a large-scale episode of punctuated equilibrium that occurred 500 million years ago. The mechanism of episodic change is compounded by short-term punctuation between long-term periods of stasis (Weick &

Quinn, 1999). Episodic changes in product evolution include changes not only in technological characteristics, but also changes at multiple levels (Lyytinen & Newman, 2008), which result in system-level changes to the point of upheaval. One of the most well-known examples of episodic changes in product evolution is the inclusion of an electrical telegraph in a semaphore (Mokyr, 1990).

Episodic change helps to explain the dynamics of an industry by considering the components of the industry and their relationships. It is a phenomenon that occurs due to cumulative changes at the technology, product, and industry levels, compared to radical innovations, which focus on the birth of a completely novel product or business (Chandy & Tellis, 2000), and disruptive innovations, which emerge by creating new demand through the expansion of demand to a niche (Christensen, 1997b). Thus, the concept of episodic change enables the emergence of industrial change to be anticipated by understanding the driving factors that have been accumulated before the punctuation.

The driving force of episodic change is defined as episodic events (Boero, 1996). The concept of episodic events is used in biology, but previous studies on product innovation have also attempted to define episodic events in terms of disruptive technology (Christensen, 1997a, 1997b), architectural innovation (R. M. Henderson & Clark, 1990), and breakthrough innovation (Frenken, Van Oort, & Verburg, 2007). These previous studies have qualitatively defined episodic events as a result of the product portfolio diversification of existing firms and new entrants or changes in consumers' preferences, leading to the creation of new demand (Adner & Levinthal, 2002; Chandy & Tellis, 2000;

Levinthal, 1998; J. M. Utterback & Abernathy, 1975).

This study proposes quantitative indicators for episodic events, which are defined as the following three sequential events through a modification of the description suggested by Boero (1996): 1) technological change as the introduction of new technological characteristics, 2) product speciation as the emergence of a new product category, and 3) producer change as the release of a new product included in the new product category by both an existing firm and a new entrant. Technological change is defined as a marginal increase in the number of technological characteristics that compose products. Product speciation is a phenomenon in which products belonging to a new product category are released in succession. The last indicator, producer change, is determined by whether an existing firm and a new entrant release products in the new product category in the same time period. Each indicator represents a change in the physical technology, the product selection environment, and the strategy of firms, respectively, similar to the concept of phase transition in economic growth (Beinhocker, 2006).

In this study, we used data for products released in the Korean mobile phone market between 2004 and 2013 to investigate the episodic events that occurred before the episodic change, and to compare the properties of the products before and after the occurrence of the episodic change. This study is expected to help policy-makers identify suitable directions of industrial policy to trigger episodic changes in products through quantified precursors.

This chapter is composed as follows. Section 4.2 reviews previous studies on radical innovation and disruptive innovation to distinguish the concepts of episodic change and episodic events. Section 4.3 proposes indicators for episodic events. Section 4.4 identifies the occurrence of episodic changes in the Korean mobile phone market by applying the indicators and examines the evolutionary patterns during the emergence of the episodic change. Section 4.5 concludes with a discussion of the contributions and limitations of this chapter, followed by a presentation of future research questions.

4.2 Episodic change as the perspective of the ecosystem of product evolution

4.2.1 Episodic events as the driving force of episodic change

Episodic change emerges by episodic events—episodes that comprise normal flows of relative events and the birth of a novel entity (Boero, 1996). Episodic events have a huge impact on the environment, such as natural calamities (Griffin & Prakash, 2014) followed by incremental adaptation (Lyytinen & Newman, 2008), and occur through interactions between concurrent processes, from which unpredictable and dynamic changing outcomes emerge (Boero, 1996).

In biology, episodic events are mainly identified by the following four historical events: a change in the composition of the species in biological communities, a change in the features of species by speciation or extinction, an environmental change where species survive, and a change in the ratio of the species (Boero, 1996). The first episodic event is a change in the species composition of biological communities due to immigration of exotic species or local distinction by emigration or terminal extinction. The second episodic event is defined as a change in the features of species due to extinction by speciation or to fragmentation by allopatric or sympatric speciation. The third episodic event occurs in the environment, such as climate change due to shifts in season occurrence or changes in the features of seasons. El Niño is an example, in that it causes increases in temperature that lead to local extinction (Glynn & de Weerdt, 1991). The last event is a change in the contribution of the species to the biomass of the community due to rare species becoming abundant or to abundant species becoming rare.

Previous research on industrial dynamics and economic development (Avnimelech & Teubal, 2006; Dutrénit & Teubal, 2011) has characterized the pre-emergence phase, which is similar to episodic events (Dutrénit & Teubal, 2011). The pre-emergence phase consists of the inventions and innovations that define a new product category and a standard product configuration, and the successful transition to the emergence phase is led by the 'scaling up' of mutational innovations (Dutrénit & Teubal, 2011), resulting in the introduction of new entrants. Economic development is also similar to the patterns of episodic change, as it is the result of accumulated changes (Beinhocker, 2006).

4.2.2 Comparison between radical change, disruptive change, and episodic change

The most important and fundamental event is the emergence of a new technological change, especially radical innovation and disruptive innovation. Radical innovation, a major factor in product evolution, causes industrial and business changes (Coccia, 2016). Radical product innovation leads to the emergence of an entirely new product (Coccia, 2016; Ettlie & Rubenstein, 1987). Disruptive innovation is considered to be a similar phenomenon to radical innovation. New customers participate in the new market as the technological level improves, leading to niche creation (Christensen, Raynor, & McDonald, 2015). Despite the fact that both radical innovation and disruptive innovation are likely to lead to industrial change, these are only regarded as the one of the triggers for industrial change; therefore, previous research has focused on identifying which products should be considered to be the result of either radical innovation or disruptive innovation and analyzing the phenomena that occur after the emergence of these innovations.

Although both radical innovation and disruptive innovation generate high market uncertainty, the mechanisms are different. Radical innovation creates new demands by launching a novel product that has not yet existed (Leifer, O ’connor, & Rice, 2001). Disruptive innovation creates a new niche market regardless of technological superiority, or attracts non-users in the existing market into the new market by satisfying new demands (Christensen, 1997b). An example of radical innovation is the quartz watch, which was developed by adopting the semiconductor and the Swatch, thereby converting the concept of the watch from timepiece to jewelry (Verganti, 2008). A representative example of disruptive innovation is the 3.5 inch floppy disk, which attracted non-users into a new market by making the disk smaller than the previously existing 5.25 inch floppy disk (Christensen & Rosenbloom, 1995). Both radical innovation and disruptive innovation are considered to be driving forces for the emergence of radical change and disruptive change, respectively.

Previous research has attempted to propose criteria for investigating the emergence of these innovations. Whether an innovation is radical is determined by whether a new product is composed of a substantially different core technology from the existing core technology and provides substantially higher benefits to consumers (Chandy & Tellis, 1998). The emergence of a new trajectory to evaluate the performance of products and new niches is considered to be the key criterion for determining whether an innovation is disruptive (Christensen et al., 2015). Thus, both are determined by qualitative criteria.

Table 9 shows the differences among episodic change, radical change, and disruptive change. Episodic change is considered to be a result that occurs while products evolve, and therefore it is investigated from the perspective of analyzing a complex system. It is caused by numerous infrequent events, which include changes in the product category at the micro-level and subsequent changes in the industrial environment where products are engaged. Based on these innovations, the characteristics of products in the ecosystem of product evolution become diversified. Episodic change also emerges by divergence led by a growing misalignment between an inertial deep structure and perceived environmental demands (Weick & Quinn, 1999), which means that the interactions occurring in the ecosystem of product evolution are also considered to be major drivers (Lyytinen &

Newman, 2008). Thus, episodic change is ignited by technological innovations due to radical and disruptive innovations, and then the sequential change in environmental factors causes an episodic change in the form of episodic events, which may be used to identify the change quantitatively.

Table 9 Comparison between radical change, disruptive change and episodic change

	Radical change	**Disruptive change**	**Episodic change**
Trigger	Radical innovation: a product/service and process with unprecedented performance or unknown features that significantly affect existing market (Leifer et al., 2001)	Disruptive innovation: a change in the process of creating a product/service while a smaller can challenge incumbent businesses with fewer resources—disruption (Christensen, 1997b; Christensen et al., 2015)	Episode: an infrequent event intentionally caused in short-term (Weick & Quinn, 1999)
Example	Swatch (Verganti, 2008)	3.5 inch floppy disk (Christensen, 1997) Apple's iPhone (Christensen et al., 2015)	Evolution of books from paper to e-book (A. Wagner & Rosen, 2014)
Feature	Substantially different core technology and higher consumer benefits (Chandy & Tellis, 1998)	Creation of new market by bridging new features to consumers (Christensen, 1997b)	Composition of the episodes such as invention and scaling-up, and industrial change during the pre-emergence phase of new industry

4.3 Indicators for identifying episodic change

The first event is related to changes in the product category. The product category can be considered as analogous to the species of the product (B. L. Bayus, 1998); thus, it is regarded as an indicator for identifying changes in the composition of an ecosystem due to the emergence of a new species. The second event involves changes in the features of the entities; therefore, an indicator for the second event is the presence of modifications in the composition of the technological characteristics. The third event is related to environmental change. It is analogized with changes in the decision-making of firms, and therefore changes in a firm's demography and new product development strategies can be considered as proxies. The fourth event, similar to the first event, corresponds to a change in the composition of a biological community after the emergence of an episodic change. Therefore, the first three episodic events are involved in the emergence of an episodic change.

In line with previous research, episodic events are considered as phenomena occurring in the pre-emergence phase of industrial change (Dutrénit & Teubal, 2011). Inventions and innovations, and the scaling-up of mutational innovations, are translated into technological change and product speciation, which causes episodic change (Dutrénit & Teubal, 2011). Catastrophic phenomena such as radical change and disruptive change cause changes in demand that are also interpreted as changes in the industrial ecosystem, or producer change.

4.3.1 Technological change and product innovation

One of the most significant events in the evolutionary process is the generation of a mutant as a result of genetic variation. A new entity genetically different from an existing entity increases species diversity. An existing product category k is defined as in Eq. (7), and an existing product model involved in the product category k, P_k, has the property shown in Eq. (8).

$$P_i = \{c_1, c_2, \cdots, c_k\}, \qquad k > 1, \quad \cdots\cdots (7)$$

$$N_{kT-1} N_{kT} > 0, \quad \cdots\cdots (8)$$

where N_{kT} is the population of the product category k at time T. Genotypic change in product evolution means the introduction of a new idea (Mokyr, 1990). The new idea is adopted as a form of a new technology, leading to product innovation (J. M. Utterback & Abernathy, 1975). Product innovation is regarded as a mutation different from an existing product, as previous research has defined the change in the genotype as the technological change comprising a product (Ma & Nakamori, 2005). Thus, the adoption of a new technological characteristics to a new product is the most significant event to focus on when investigating the emergence of a new product category and the environmental change that subsequently occurs. A new product category P_i is defined as in Eq. (9), and Eq. (10) describes the property of its population.

$$P_i = \{c_1, c_2, \cdots, c_k, \cdots, c_i\}, \quad i > k \tag{9}$$

$$\sum_{t=0}^{T-1} N_{it} = 0. \tag{10}$$

The first episodic event TC_t, a technological change due to the introduction of new technological characteristics, is defined as follows:

$$.TC_t = \begin{cases} TC_{t-1} + 1, & N_{it} > 0, \ \sum_{t=0}^{T-1} N_{it} = 0 \\ TC_{t-1}, & otherwise \end{cases}. \tag{11}$$

The products belonging to the initial product categories consist of K technological characteristics. A mutation occurs after the introduction of new technological characteristics, which can be considered as a one-shot mutation or can lead to later speciation. In this process, it is assumed that the number of the technological characteristics adopted in the products increases, which reflects the fact that mutations are irreversible and species cannot return to the their former genotype (Mokyr, 1991).

4.3.2 Product speciation

Speciation is a key event that occurs during the evolution of an organism by generating new genealogies (Schluter, 2009), which means that multiple generations survive in the environment. In biology, speciation occurs by genetic mutation, geographic isolation, or behavioral isolation, whereas product speciation emerges through the introduction of a new product with new technological characteristics. Thus, product speciation is distinguished from mutation because it launches innovative descendants. In other words, a mutation leading to subsequent products can be defined as the origin of product speciation.

Product speciation is defined as the second event in episodic change, through which a new product category emerges within an industry. The change in the population of the new product category is what distinguishes product speciation from mutation. When products with similar technological characteristics to those of a mutant product are launched after the introduction of the mutant product, product speciation has occurred. Thus, the emergence of the second episodic event, product speciation PS_t at time *t*, is defined as follows:

$$PS_t = \begin{cases} PS_{t-1} + 1 & , N_{it} N_{i(t+1)} > 0 \\ PS_{t-1} & , otherwise \end{cases}, \quad \cdots\cdots \quad (12)$$

where N_{it} denotes the number of products belonging to product category i released at t, and the product with technological characteristics i has not been released until $t-1$.

4.3.3 Producer change

Product speciation after the introduction of new technological characteristics means that a new market will be created. Previous studies have shown that a new entrant creates breakthrough product designs in the environment where product innovation occurs, while incumbents release new products by incremental innovation (Davis & Tomoda, 2018). Incumbents trigger the product speciation by introducing the mutation that becomes the origin of the product speciation (Chandy & Tellis, 2000; R. Henderson, 1993; Mitchell, 1991; Mitchell & Singh, 1993). In contrast, a new entrant has an advantage in instances of product speciation, as it is better able to adapt to the environment compared to the incumbents and can release new products belonging to the new product category (Bessant, 2005).

The entry of a new firm into an industry means that the output of product speciation is likely to emerge in that industry as the new entrant makes a strategic decision on its entry, implying expansion of the industry. The environmental change in the industry following product speciation is regarded as the concurrent release of the new products in the new product category. Therefore, the third episodic change, the producer change PC_t at time t, is defined as follows:

$$PC_t = \begin{cases} PC_{t-1} + 1, & N_{mit} N_{(m+1)it} > 0 \\ PC_{t-1}, & otherwise \end{cases}, \quad \cdots\cdots \quad (13)$$

Where N_{mit} and $N_{(m+1)it}$ released by the incumbent m and the new entrant $m+1$ are the population of the products belonging to the new product category i.

If PC_t becomes 1, episodic change is likely to occur. As an episodic change comprises product innovation, product speciation, and the industrial environmental change, this concept is useful for identifying the current stage in the industrial life cycle and predict the emergence of the industrial change.

4.4 Empirical analysis of the mobile phone industry

Among recent high-tech products, episodic change can be observed in the evolutionary process of mobile phones. The mobile phone market is characterized by a short product lifecycle, rapid changes in the technology and the environment, and widespread variety and high frequency of product innovation (Wirtz et al., 2007); thus, this framework is useful for identifying the patterns of innovation that occur during the evolutionary process.

Incremental innovation improves the technological characteristics of products, whereas radical innovation is defined as the introduction of novel technological characteristics into products (OECD/Eurostat, 2005). Examples of radical innovation occurring in the mobile phone market include the introduction of Bluetooth, Wi-Fi, Touch, and the smartphone OS. The most successful among these technologies was the smartphone OS, which led to the beginning of the smartphone industry. Apple's iPhone 3 was the product that made the biggest contribution to the transition from the feature phone market to the smartphone market. In the first half of 2009, before the launch of the iPhone 3, the Windows Mobile OS had already been adopted in smartphones, so considering the technological characteristics of the product, the iPhone 3 can hardly be regarded as the result of radical innovation. However, after the launch of the iPhone 3, the number of smartphones that adopted the Android OS increased abruptly, contributing to the emergence of the industry, as previous research has argued that Apple's iPhone yielded a disruptive innovation (Christensen et al., 2015).

Even though Apple's iPhone seems to have contributed to the emergence of a new industry, this analysis is the result of an ex-post investigation. Therefore, this section investigates the emergence of a new industry in light of episodic change by using the indicators for episodic events proposed in section 4.3.

4.4.1 Data

The data used in this study comprise the mobile phones launched in the Korean market from January 2004 to June 2013, including both feature phones and smartphones. The technological characteristics of mobile phones were gathered from the webpages of the manufacturers and websites with product reviews, such as www.Cetizen.com and www.OpenMobile.net, following the data collection regime of previous research (Dewenter et al., 2007; Kivi et al., 2012; Watanabe, Nakajima, & Ida, 2010). Compared to the dataset in Chapter 3, the present dataset was refined from 1,282 mobile phones by extracting the products containing the same technological characteristics. As the consumer ratings were not considered in this study, the number of mobile phones used in this study was reduced to 763.

Table 10 describes the characteristics of the mobile phones analyzed in this chapter. Their technological characteristics comprise the display, AP chipset, RAM, product volume and weight, battery performance, camera pixel, telecommunication technology, touch technology, DMB technology, Bluetooth technology, GPS technology, smartphone OS, Wi-Fi, and open platform of applications. Since all existing mobile phones are equipped with a screen, RAM, volume, weight, battery, ROM, and telecommunication technology, these characteristics were classified as existing characteristics. Furthermore, touch technology, camera pixel, MP3 technology, and GPS technology were introduced before 2004. In contrast, DMB, Bluetooth, smartphone OS, Wi-Fi technologies, and the open application platform were newly introduced technological characteristics after 2004. Therefore, TC and PS were confirmed using these characteristics. The last PC was defined as the entry of a new firm using the firm variable.

Table 10 Description of the variables

Variable	Description	Unit
Telecommunication technology	Name of technology used for cellular communication	
Display	Physical size of the screen	Inch
AP chipset	Performance of the main chipset of a smartphone, which executes the operating system	GHz
Camera pixel	Resolution of the camera	Million mega pixels
RAM	Amount of main memory, to which read and write operations can be directed	GB
Volume	Case size described through three dimensions of the smartphone	cm^3
Weight	Weight of the smartphone	100g
Battery	Amount of electric charge	Ampere-hour
ROM	Amount of non-volatile read-only data storage	GB
MP3	MP3 technology support	
Touch	Existence of a touch screen	
DMB	A digital radio transmission technology for sending multimedia	
Bluetooth	Existence of the Bluetooth technology	
GPS	Existence of GPS hardware	
Smartphone OS	Adoption of smartphone OS	
Wi-Fi	Adoption of Wi-Fi technology	
Open application platform	Adoption of open application platform	

4.4.2 Analytic framework

This study analyzes the pattern of episodic events in the mobile phone industry and examines the timing of the emergence of episodic changes by investigating the phenomena of technological change (TC), product speciation (PS), and producer change (PC). Through the analysis, the process of episodic change in the mobile phone industry is shown to be the result of the accumulation of changes that occurred in the evolutionary ecosystem.

In order to provide support for this phenomenon driven by the accumulation of the changes within the product evolution system, this study compares the complexity of the mobile phone models. The complexity of the mobile phones was calculated by modifying Shannon's entropy, which is an index used to investigate the diversity of entities in a system (Frenken, 2006; Wu, Huatuco, Frizelle, & Smart, 2013) as follows:

$$H = \sum_{i=1}^{n} p_i \log_2 \left(1/p_i\right) = -\sum_{i=1}^{n} p_i \log_2 p_i \text{ ,} \quad (14)$$

where p_i means the probability that the entity i exists.

p_i in Eq. (14) is replaced by the technological advancement c_{jk} of the technological characteristic k and product model j, assuming that firms tend to adopt the technologically superior product. To convert the technological characteristics of products into the adoption rate $adopt_{jk}$, the value of c_{jk} is normalized to values between 0 and 1 through max-min normalization, as follows:

$$adopt_{jk} = \frac{c_{jk} - \min(\mathbf{c}_k)}{\max(\mathbf{c}_k) - \min(\mathbf{c}_k)}. \qquad (15)$$

When $adopt_{jk}$ is 0.3678, the contribution of the characteristics is maximized, so $adopt_{jk}$ is multiplied by 0.3678 and the adjusted adoption rate of each characteristics $newadopt_{jk}$ is defined. Thus, the complexity H_j of the product model j increases as c_{jk} rises, and is defined as follows:

$$H_j = -\sum_{k=1}^{K} (newadopt_{jk}) \log(newadopt_{jk}). \qquad (16)$$

As a result, the entropy increases as the technological characteristics increase, but the trend of the increase diminishes.

To analyze changes in the mobile phone industry, the mobile phones were grouped using k-means clustering, which is a method of minimizing the variance by calculating the distance from the center of each cluster, based on the number of clusters. The number of clusters is defined by using the D-index calculation in the R program.

$$V = \sum_{k=1}^{k=K} \sum_{l \in S_k} \left| x_l - \mu_k \right|^2, \quad (17)$$

where μ_k is the center of cluster k, S_k indicates a product belonging to cluster k. S_k belongs to the nearest cluster μ_k by calculating the Euclidean distance, and μ_k is continuously updated by the center of mass of products engaged in cluster k until becoming stable.

4.4.3 Results

4.4.3.1 Emergence of episodic change in the Korean mobile phone industry

To identify episodic change in the mobile phone industry, the indicators proposed in Section 4.3 were used. The first indicator identifies changes in the adoption of new technological characteristics in the mobile phones. The second indicator confirms the timing of the emergence of PS. Finally, the last indicator shows the timing at which both incumbents and a new entrant release new products belonging to the new product category.

Table 11 shows the emergence of episodic events. First, the technological characteristics introduced in the mobile phone industry since 2004 were DMB, Bluetooth, smartphone OS, Wi-Fi, and the open application platform, which were introduced in the second half of 2004, the first half of 2005, the second half of 2005, the second half of

2007, and the second half of 2009, respectively. The cumulative number of TCs was 5 by the second half of 2009, the time when the last new technological characteristic was added.

Next, PS in the mobile phone industry has occurred four times. DMB technology triggered the first PS in the second half of 2004. The second PS emerged as a result of Bluetooth technology in the first half of 2005. The third PS occurred in response to the smartphone OS and the Wi-Fi technology. The smartphone OS was introduced in the second half of 2005, but subsequent products adopting a smartphone OS had not yet been released; therefore, this is regarded as a mutation. Subsequently, mobile phones adopting a smartphone OS appeared in the second half of 2007 and the first half of 2008, forming a new category of products with smartphone OSs. Wi-Fi technology also penetrated into the market in the second half of 2007, and subsequent products with Wi-Fi technology were launched in the first half of 2008, constituting a new product category. The last PS occurred in the second half of 2009 due to the continuing launch of products with an open application platform.

Finally, it appears that new firms entered the mobile phone industry in the first half of 2009 and the second half of 2009. During this period, both the new entrants and incumbents released new products belonging to new product categories with smartphone OSs and an open application platform. In other words, as different types of firms launched products in the new product category, PC_{2009H1} was 1 and PC_{2009H2} was 2. Therefore, episodic change can be seen to have occurred after the first half of 2009, when

TC_{2009H1} was 4, PS_{2009H1} was 3, and PC_{2009H1} was above 0.

Table 11 Emergence of the episodic events

Time (t)	TC_t	PS_t	PC_t
2004 H1	0	0	0
2004 H2	1 (DMB)	1 (DMB)	0
2005 H1	2 (Bluetooth)	2 (Bluetooth)	0
2005 H2	3 (OS)	2	0
2006 H1	3	2	0
2006 H2	3	2	0
2007 H1	3	2	0
2007 H2	4 (Wi-Fi)	3 (OS and Wi-Fi)	0
2008 H1	4	3	0
2008 H2	4	3	0
2009 H1	4	3	1 (HTC)
2009 H2	5 (Open platform)	4 (Open platform)	2 (Apple)

From the first half of 2004 to the time that the episodic change occurred, the introduction of new technological characteristics was relatively frequent, with a probability of about 42 percent. The occurrence rate of PS was about 33 percent. The probability of environmental change due to a new entrant was about 17 percent. To summarize, the introduction of new technological characteristics and the speciation of the existing product categories into new product categories were continuously attempted by existing firms, and episodic change emerged as new entrants gave signals about the emergence of a new industry and market, after which the incumbents coped with the industrial changes resulting from those signals.

Figure 7 shows the introduction of technologies and the emergence of new product categories. Products that consisted of existing technological characteristics occupied the majority until the first half of 2006, but since the second half of 2006, the number of mobile phones with Bluetooth increased. New product categories emerged due to the introduction of new technologies. In the first half of 2009, when the episodic change is thought to have occurred, it seems that mobile phones with Bluetooth and touch technology, those with Bluetooth only, and those with all four new technological characteristics were relatively equally produced. Since then, however, the population of mobile phones with the five new technological characteristics has increased, taking up a larger proportion than products belonging to other categories. These changes occurred slowly, but a shift of the major product category occurred from the existing product category to a new product category. The result indicates that before the episodic change, several episodic events with incremental changes led to the emergence of new products and new industries.

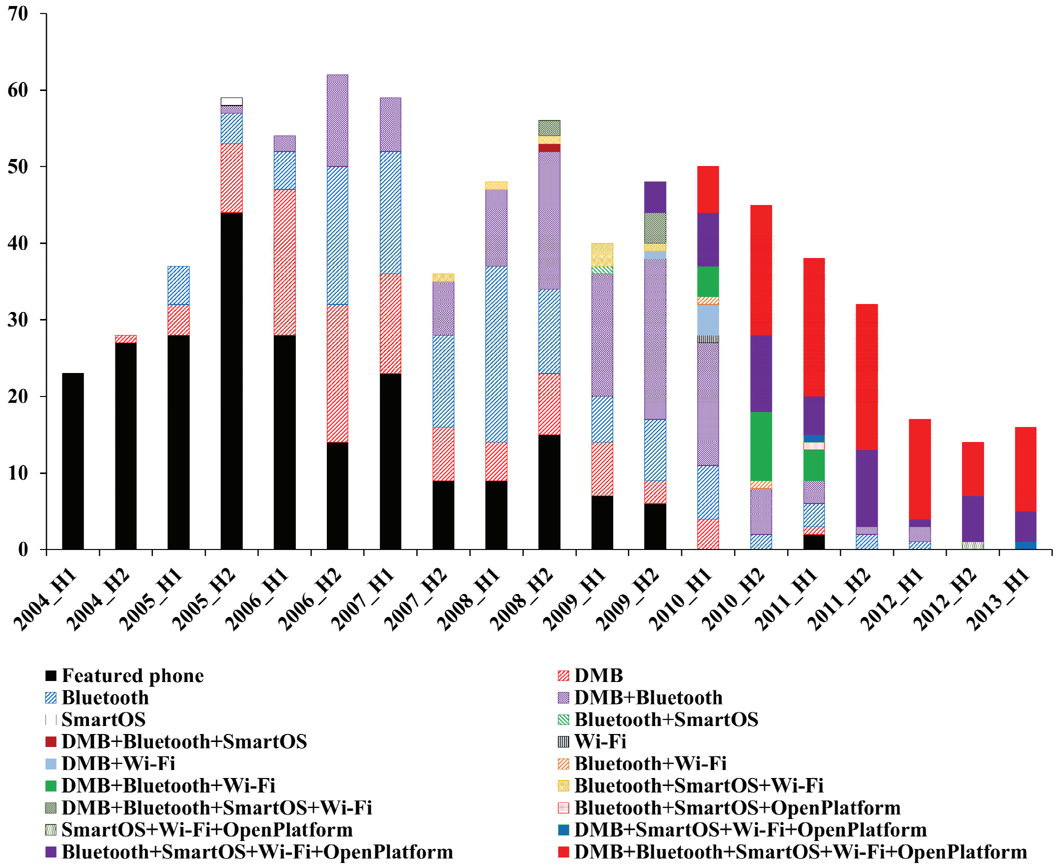


Figure 7 Technological change and emergence of new product category

Figure 8 shows the new products released by firms before the emergence of the episodic change. **Figure 8**-(a) briefly presents information on the change in the type of mobile phones from non-smartphone OSs to smartphone OSs. The number of types of mobile phones increased between the first half of 2004 and the second half of 2008, although a temporary decrease occurred in the second half of 2007. During this period, all products were released by incumbents, and the incumbents survived until the third episodic event emerged. In other words, the incumbents continuously released new products for survival before the episodic change occurred. **Figure 8**-(b) shows the number of products adopting new technological characteristics released by incumbents and new entrants. Before the episodic change, the incumbents continued to adopt new technological characteristics. In the second half of 2005, Curitel, the predecessor of Pantech, released a mobile phone with Windows Mobile OS. In the second half of 2007, it was found that Samsung, the incumbent, expanded PS by generating new product categories in which Wi-Fi and an OS were introduced. After the emergence of the third episodic event, incumbents such as LG and Nokia launched products belonging to new product categories, and the number of new entrants started to increase, which is a typical pattern of the emergence of a new industry. To summarize, these changes—the emergence of episodic events—led to the emergence of an episodic change with a high likelihood of creating a new industry.

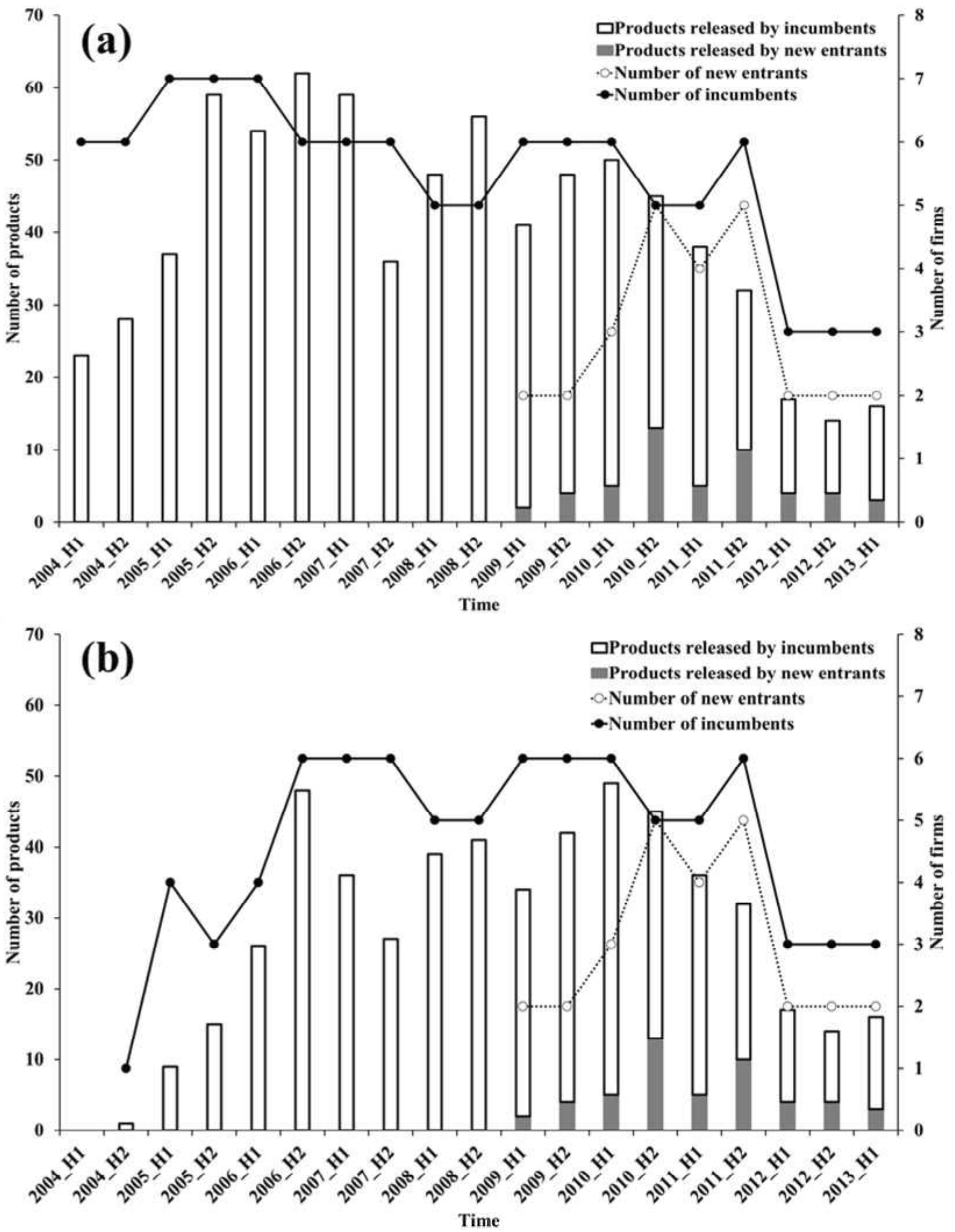


Figure 8 New product released according to the entry mode

4.4.3.2 Evolutionary patterns before episodic change

Figure 9 presents the result of k-means clustering using the calculated complexity of each product and the portion of each cluster per year. The average product complexity of Cluster 1, Cluster 2, and Cluster 3 were found to be 2.354, 3.779, and 7.070, respectively. The complexity of Cluster 2 was about 1.6 times higher than that of Cluster 1, and that of Cluster 3 was about 1.87 times higher than that of Cluster 2. Most mobile phones in 2004 were included in Cluster 1. Since then, the share of Cluster 2 had inclined, and mobile phones belonging to Cluster 3 were launched starting in 2008. Since the first PC occurred in 2009, numerous mobile phones belonging to Cluster 3 have been released, and the proportion of Cluster 3 increased by 77 percent in 2011, which is considered to be the period after the episodic change.

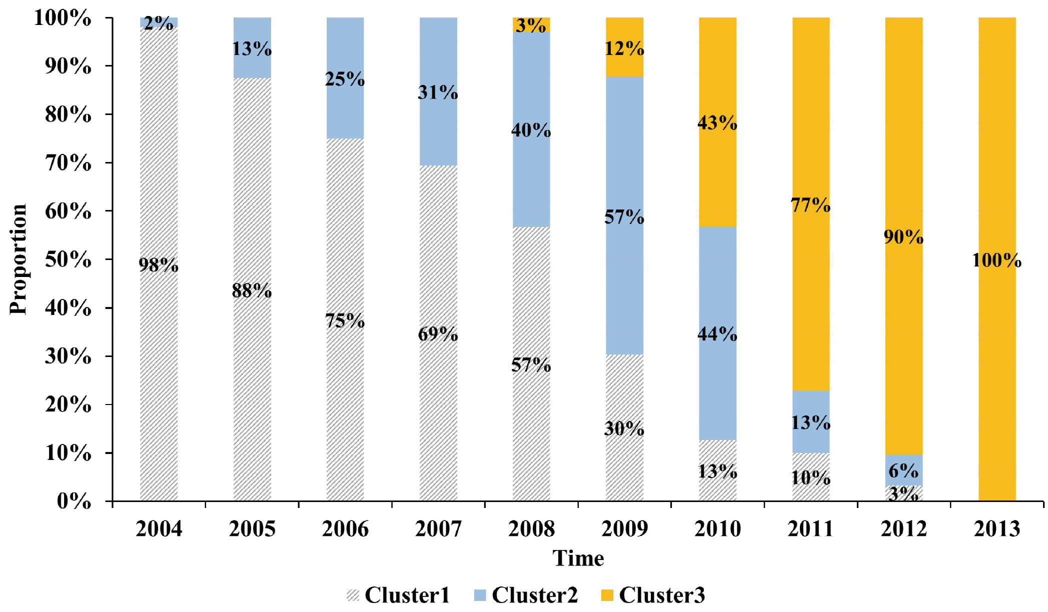


Figure 9 Change in the composition of clusters

Figure 10 shows trends in changes in product complexity. Product complexity increased slowly before the episodic change. However, after the episodic change, the slope increased rapidly. This can be attributed to the change in the technological characteristics adopted in the products of the corresponding cluster. Even if products with high product complexity were released before the episodic change, their contribution was not significant due to their small population. After the emergence of the episodic change, product complexity increased by about 10 percent more than the complexity of the existing feature phones. Until 2008, the complexity of the overall mobile phone industry could be represented by the complexity of feature phones, as the number of mobile phones with new technological characteristics was relatively small compared to the number of existing feature phones. Then, the number of feature phones released after the episodic change decreased and the proportion of smartphones in the mobile phone industry increased. In other words, the mobile phone industry may appear to have changed dramatically in response to the episodic change. However, a detailed analysis of the changes in the industry due to product changes shows that the changes in the mobile phone industry were caused by TCs before the episodic change, and the drivers of that change were accumulated by product innovation.

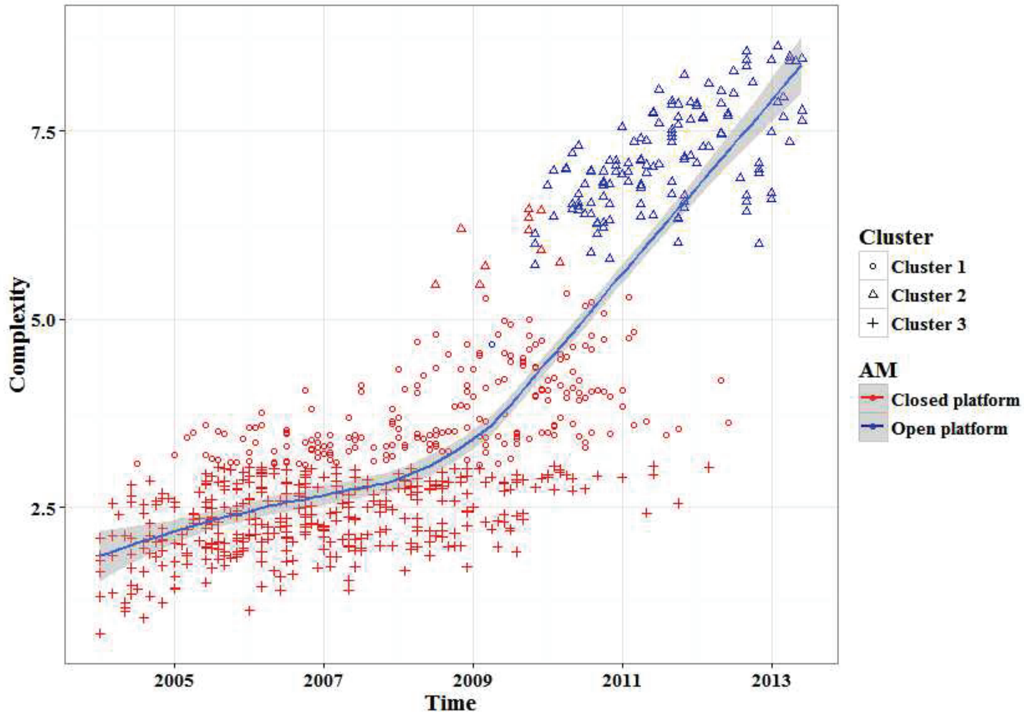


Figure 10 Trend of complexity change

4.4.3.3 Discussion

The episodic change in the Korean mobile phone industry is shown to have taken place after the first half of 2009. New products with a smartphone OS and those with the open application platform were launched by both incumbents and new entrants in the first half of 2009 and the second half of 2009, respectively, showing that both the smartphone OS and the open application platform were key to the emergence of the episodic change. The trends of product complexity in the Korean mobile phone industry also show that the episodic change occurred immediately after 2009.

As shown in **Figure 7**, the open application platform played a crucial role in the emergence of the episodic change. A product with a smartphone OS was first introduced in 2005 by adopting Windows Mobile 2003 Second Edition for Smartphone. Following it, numerous incumbents released new products with Window Mobile OS (Windows Mobile 6.0, Windows Mobile 6.1, and Windows Mobile 6.5). Despite the fact that products with Window Mobile OS were called smartphones, they did not have a significant impact on the Korean mobile phone industry. When new products with an open application platform, such as the iPhone 3GS, were first introduced in the second half of 2009, incumbents and the following new entrants adopted the open application platform, leading to a significant increase in the product complexity. As a result, Apple, which launched the iPhone 3GS with an open application platform, is considered to be the pioneer of the smartphone era, as discussed by Christensen et al. (2015).

In addition to the role of the new entrant, Apple, the incumbents also contributed to the emergence of the episodic change. The incumbents launched new products with new technological characteristics. In the Korean mobile phone market, mobile phones with DMB technology were introduced starting in the second half of 2004. Curitel first launched PH-1000V, a mobile phone with DMB technology, and even after the episodic change, incumbents continued to release products with DMB technology. Furthermore, several mobile phones with Bluetooth technology, such as the KF1000 by LG, the SPH-V6900 by Samsung, and the PH-S6000 by Curitel, were also introduced beforehand. Following these TCs and the PS, Curitel launched the PH-S8000T, the first smartphone with Windows Mobile 2003 Second Edition for Smartphone, and Samsung released the SCHM620 with both Wi-Fi technology and a smartphone OS. These products are considered to be triggers of the episodic change, as they contributed to the speciation of products. Even after Apple entered the market by introducing the iPhone3GS with its open application platform, the incumbents released new products by combining the technological characteristics they had adopted with the open application platform. Thus, the continuous trials of the incumbents formed the cornerstone of the emergence of the episodic change.

4.5 Sub-conclusion

This study quantifies the changes in the environment due to the introduction of new technological characteristics, product speciation caused by the emergence of a new product category, and the entry of new firms in order to identify an episodic change. The quantified indicators are applied to explain an instance of episodic change in the Korean mobile phone market. It demonstrates the importance of the introduction of iPhone, which has been referred to as disruptive innovation by Christensen et al. (2015). Thus, the indicators proposed in this study can contribute to analyses of the emergence of episodic changes.

This study also contributes to the analysis of episodic events and the environmental changes before an episodic change. After the accumulation of technological changes, and sequential product speciation events in response to those changes, episodic change occurred through new entrants that promote the environmental change in the industry. Therefore, it can be considered that the episodic change is caused by the accumulation of earlier events. Furthermore, incumbents continued their efforts to generate new species before the entry of new firms. Radical innovations in products occur due to continuous product innovation by the incumbents, but it seems that new entrants make a greater contribution to product innovation that leads to product speciation, because the emergence of a new industrial environment and the resulting changes in the market occur in response to new entrants. Thus, this study will help government policy-makers to establish industrial policies on new growth engines by creating a new industry, and the findings of this research lead to the proposal that the government should encourage firms that have been involved in another industry and can launch new products in a new product category to enter a new industry.

The limitations of the research described in this chapter are that it does not take into account the attributes of the new entrants. In reality, most new entrants have advantages over existing ones because they enter the industry with factors that can lead to success. However, the attributes of the new entrants analyzed herein are difficult to quantitatively measure and analyze. Thus, future research will need to consider the attributes of the new entrants that affect episodic change.

Chapter 5. Simulation of the emergence of the episodic change: capability-based view

5.1 Introduction

A new industry emerges due to the introduction of new products by firms' innovation activity (Cefis & Marsili, 2005) and changes in consumers' purchasing behavior. The introduction of a new technology and a new product category changes firms' new product development strategy, leading to the emergence of a new industry. The consumers' purchasing behavior is determined by their capability to acquire information on the product models. Thus, in order to investigate the patterns that occur when an episodic change emerges, changes in firms' capabilities and consumers' capabilities need to be taken into consideration.

Firms' capabilities are differentiated by type. Firms in an industry can be divided into incumbents and new entrants, which in turn are classified as start-ups and diversifying firms. Start-ups are by definition non-experienced firms, whereas a diversifying firm has experience in its previous industry, which is referred to as pre-entry experience. Thus, the firms with prior experience in industry are incumbents and diversifying firms.

The capabilities of firms affect their decision-making on innovation activity. Previous research has distinguished between innovation capability and imitation capability (Beckenbach et al., 2012; Rivkin, 2000). Imitation capability is manifested by the development of products that are intended to be the same as the target product, and innovation capability contributes to the development of new products that are different from existing products. As this study focuses on the interaction between firms and consumers, an alternative concept to imitation and innovation capability needs to be adopted, namely implementation capability and design capability, which are determined by firms' production experience (J. Lee, Baek, Maliphol, & Yeon, 2019).

In addition to firms' capabilities, consumers' capabilities are also important in the emergence of a new industry as they determine the selection of products. Consumers purchase products among those in their consideration set while they participate in innovation processes (K. Kim & Altmann, 2013; K. Kim, Lee, & Altmann, 2015). If all consumers are able to fully acquire information on the product models, they are likely to purchase the product with the highest utility, leading to the winner-takes-all phenomenon (E. Lee et al., 2006). However, if consumers are affected by other consumers or constrained in gaining information on the product models, each consumer purchases a different product depending on his or her consideration set. In other words, the former phenomenon takes place in a perfect information regime, while the latter takes place in an imperfect information regime.

This study aims to identify the impact of the capabilities of firms and consumers on the emergence of episodic change. To investigate the impact of those capabilities, this chapter raises the following research questions:

(1) Which type of firms shorten the emergence of an episodic change?

(2) Does imperfect information of consumers on product models affect the timing of

the emergence of an episodic change?

The first research question engages with the impact of pre-entry experience, implementation capability, and design capability on the timing of the emergence of an episodic change. Each capability changes as firms experience the production of existing products and products with a new concept design, respectively. The second research question is related to comparing the information regimes.

This study uses an ABSM, which is useful for simulating the evolutionary process of products by considering the new product development and entry strategy of firms (Garcia, 2005). Furthermore, it helps to interpret the evolutionary patterns that occur through the interaction between firms and consumers. The model used in this study is based on that of Ma and Nakamori (2005), which is regarded as the initial model for product evolution. The simulation was conducted as shown in **Figure 11**. To validate the model, the performance of firms was first illustrated, and then the emergence of each episodic event that generates the episodic change was investigated. The results show the patterns of the emergence of an episodic change across various scenarios distinguished by agents' capabilities. The findings of the simulation are expected to contribute to proposals in the fields of industrial and market policy to hasten the emergence of episodic changes, which will help firms in various industries cope with dramatic environmental changes.

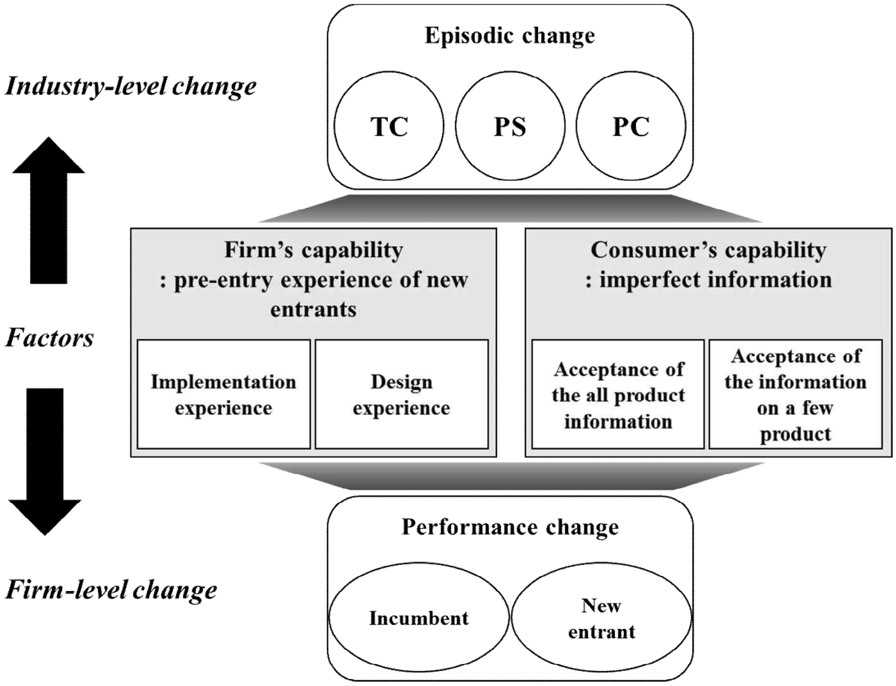


Figure 11 Conceptual framework of the research

The rest of this chapter is structured as follows. Section 5.2 reviews the role of the capabilities of firms and consumers in the emergence of an episodic change. Section 5.3 proposes an ABSM for product evolution, including the validation of the model. Section 5.5 concludes with the summary and implications of this study.

5.2 The role of pre-entry experience of firms and imperfect information of consumers on the emergence of episodic change

5.2.1 The role of pre-entry experience of firms on the episodic change

Episodic change is a phenomenon in which changes in product categories lead to changes in an industry. New product categories emerge due to the introduction of new technologies and episodic changes when both existing and new entrants launch products in a new product category.

New entrants can optimize their organization and information processing structure to exploit new designs (R. M. Henderson & Clark, 1990) because they are more flexible with new needs and new knowledge than existing firms. In contrast, existing companies take a long time to respond to these changes because they engage in new exploration activities based on the industry's built-in routines and capabilities. Previous studies have shown that radical changes are caused by new entrants and that new entrants can overcome the first-mover advantage as fast-followers (Lieberman & Montgomery, 1988). Existing companies introduce new technologies into their products and launch new products, creating many innovative products. They tend to produce products that can create new product categories through extensive trial and error. As a result, most new product categories emerge from existing companies.

New entrants enter the market by imitating existing products or by introducing entirely new products. Existing consumers are reluctant to accept entirely new products. As a result, new entrants that launch an entirely new product will fail. New entrants that have suffered failure for that reason instead launch products that are similar to those released by existing companies, based on imitation strategies. Products that are easy to imitate by new entrants are mature products in an existing industry, and these products follow a dominant design. If a new entrant creates a new product category that does not follow the dominant design of the existing firms' products, it can create a product that does not technically follow a lock-in architecture. At this time, if both existing and new entrants create products belonging to a new product category, the possibility of episodic change increases.

New entrants can more flexibly accommodate new needs and technical requirements than existing firms. Products belonging to the new product category are implemented as products capable of performing new functions by new entrants, and as a result, the trade-off relationship with the functions expressed by the combination of the technical properties of the product is changed.

The most useful theory for explaining these changes is the technical-service characteristics map proposed by Saviotti and Metcalfe (1984). This approach divides the composition of a product into technological and service characteristics. Technological characteristics are those that producers consider, and service attributes are those that consumers consider. Existing firms cause changes in technological characteristics, and new entrants lead to changes in service characteristics. When both existing firms and new entrants launch products belonging to a new product category, they introduce products with both technical and service characteristics that change as the episodic change occurs. Therefore, properties of the product change due to interactions between existing firms and the new entrant, resulting in an episodic change.

New entrants can be divided into diversifying firms and start-ups depending on their previous experience in industry. A diversifying firm is a company belonging to an existing industry that has accumulated competency and is trying to diversify its products into a new industry. A start-up can be regarded as a company that has no previous industry experience or embedded routines. Diversifying firms can exceed incumbents' advantage because they have complementary assets, such as marketing capabilities, built up in existing industries, but start-ups without pre-entry experience do not exceed the incumbents' advantage because they do not have those complementary assets (Teece, 1986). In contrast, some researchers have argued that start-ups have pre-entry experience in the form of founder knowledge (Agarwal, Echambadi, Franco, & Sarkar, 2004; Helfat & Lieberman, 2002). Prior studies have categorized companies from different perspectives, depending on the type of entry into existing markets, but share the point that pre-entry experience is important from a capability perspective. Pre-entry experience helps a firm adapt to technological change (P.-L. Chen, Williams, & Agarwal, 2012). Pre-entry experience is accumulated by trial-and-error in new product development, leading to an increase in the dynamic capability due to path-dependency (Teece et al., 1997). A diversifying firm is considered to have a higher dynamic capability than start-ups and is likely to decide what to develop and design and how to do it (Teece et al., 1997). A greater breadth of prior experience enables a firm to deal with technological uncertainty because it results in higher dynamic capability, which helps a firm to match technological and service characteristics (Roy & Cohen, 2015). Thus, a firm with a higher dynamic capability is likely to contribute to the new combination of two characteristics, which is defined as radical innovation.

Previous studies have investigated after the triggers of change such as radical innovations or disruptive innovations emerged. Firms' pre-entry experience plays an important role in their survival, and firms with pre-entry experience are more likely to survive than entirely new start-ups. Previous studies have suggested that radical innovation and disruptive innovation occur when new entrants enter an existing market. When heterogeneous firms enter into an industry, compared to the existing firms, they are subject to variation, resulting in innovation. However, previous studies have neglected concerns about the mechanism through which the pre-experience of new entrants creates an episodic event. Pre-experience includes the innovation capabilities of founders of diversifying firms and start-ups and their process of accumulating those capabilities. Implementation capability includes the pre-experience of releasing a product that imitates those produced by existing companies or applying only marginal changes, and this reflects new technical characteristics and design characteristics. The experience of creating products with new designs is considered to indicate that a firm has secured design capability (J. Lee et al., 2019).

New technological characteristics and design characteristics generate a product with a new concept design. A new concept design is a product that meets new demands and represents a different function from that of the existing product. Therefore, innovation activity can include both the addition of new technological characteristics and improvements in the trade-off relationship between technology and function. This improves both the technical and service characteristics in the technical-service characteristics map and redefines the relationship between them.

Both pre-entry experience and innovation experience in existing industries are important for building design capability. In this study, the effects of episodic change on the occurrence of a company with design capability accumulated from this experience are simulated.

5.2.2 Imperfect information and episodic change

Traditional economic theory has not substantially covered consumers' imperfect information (Smallwood & Conlisk, 1979). Oi (1973) assumed that consumers recognize all risk factors related to product use, while Goldberg (1974) argued that Oi's (1973) model is limited by its assumption of perfectly informed consumers, and this must be considered.

Imperfect information is bifurcated into imperfect information about price and quality, and imperfect information about the product itself. Although several studies have discussed imperfect information about prices (Hirshleifer, 1973; Lindsey-Mullikin &

Grewal, 2006; Rothschild, 1973; Salop, 1976; Stiglitz, 1979; Varian, 1980), they have mostly analyzed the macroscopic effects of imperfect information and are therefore limited in their considerations of product evolution.

Studies of imperfect product quality information have adopted diverse viewpoints. Courville and Hausman (1979) analyzed the economic effects of product liability when consumers are imperfectly informed about product quality, and product liability can be seen as a service characteristic (Saviotti & Metcalfe, 1984). Smallwood and Conlisk (1979) argued that imperfect information occurs due to continuous changes in product quality in the real world. Regarding the uncertainty of information about product quality, several studies have assumed an environment where consumers cannot access information about whether a product exists. Pegoretti et al. (2012), recently presumed that agents are not always informed about all products. Likewise, this study focuses on consumers' limited access to information.

Several attempts have been made to analyze the relationship between consumers' imperfect information and product diversity (Lancaster, 1979; Schwartz & Wilde, 1985; Wolinsky, 1984). Lancaster (1979) insisted that firms focus on price competition rather than product differentiation when consumers are imperfectly informed. In other words, limited information decelerates the process of product diversification. Although diversity in organisms tends to steadily increase, Wolinsky (1984) argued that the optimal level of diversity does exist in the market. When consumers are not fully informed, the optimal level of diversity decreases since this market condition restricts consumers' access to product information. According to Schwartz and Wilde (1985), firms change strategies according to consumers' preferences in a market of imperfect information, thereby changing the level of product evolution. This finding implies that when consumers are not fully informed, firms set non-competitive prices to enable flexible strategies. For example, when consumers prefer products with high quality, firms offer ideal products, whereas when consumers prefer products with low quality, firms use noncompetitive pricing.

Several studies have discussed the relationship between imperfect information and product diversity, and despite the notion that products are an interface connecting consumers and firms (Frenken, 2006), few studies have focused on the mechanisms of product evolution. As more products are released in the market, firms are likely to have more opportunities to develop new products by recombination. Thus, imperfect information can also affect the emergence of episodic events. Therefore, this study examines changes in the emerging patterns of episodic changes due to the lack of market information and its sequential impact on the performance of firms.

5.3 Model

ABSMs are used to derive changes in a complex system resulting from the interactions between agents in the environment (Macal, 2016; Macal & North, 2010). Agents are autonomous and heterogeneous, and they interact based on their behavioral patterns. Previous research on economic simulation has defined agents as firms, consumers, and public sector actors such as the government, generating emergent phenomena as a result of interactions and coevolution.

The model used in this study is based on that of Ma and Nakamori (2005), which implements technological innovation as an evolutionary process. Compared with the model of Ma and Nakamori (2005) as shown in Table 12, it identifies the cause of market monopolization and the cause of the local optimum in the market. However, it ignores the internal capabilities of firms and assumes that firms randomly generate products through exogenous technological change. In addition, both incremental and radical innovations are set to occur exogenously. Different firms are assumed to be heterogeneous based on random settings. The model proposed in this study posits that both incremental innovation and radical innovation are generated by the strategic decision-making of firms and that the survival of products is determined by the consideration sets of consumers.

Table 12 Comparison between Ma and Nakamori (2005) and the model in this study

	Ma and Nakamori (2005)	The suggested model
Agent	Homogeneous/Heterogeneous	Heterogeneous
Innovation mechanism	Random	Depending on the firm capability
Introduction of innovation	Exogenous	Endogenous
Innovation possibility	Unchanged	Changed based on firm capability
Firm capability	Not considered	Design experience and implementation experience
Firm entry	No entry	New entry

5.3.1 Overall framework

The overall structure of the model in this study is shown in **Figure 12**. First, the model characterizes the attributes of firms and consumers engaged in the product evolution system and assumes a set of technological knowledge that firms can utilize. Each firm is responsible for the variation process among the three evolutionary processes. In this process, the decision-making modes of a firm are assumed to be imitation, innovation, and routine modes, as suggested by Beckenbach et al. (2012). In the selection process, heterogeneous consumers purchase products based on their utility. They determine the retention of the products in the next generation, which means that the product that the majority of consumers purchase has a higher chance to be the dominant product. This model focuses on the environmental changes that occur in the product evolution system. Before a firm develops the next generation of a product, the new entrants, changes in the functions, and the relationship between the technological characteristics and the function of products are updated.

The simulation technique adopted in this model is a generalized NK model based on a genetic algorithm. Each technological characteristic is defined as a chromosome, a product is illustrated by a gene string, and the process of combining the gene strings is implemented by the genetic algorithm. The generalized NK model is used by defining the genotype-phenotype map. By combining the two techniques, the model only implements the variation and selection process of product evolution in order to construct a parsimonious model.

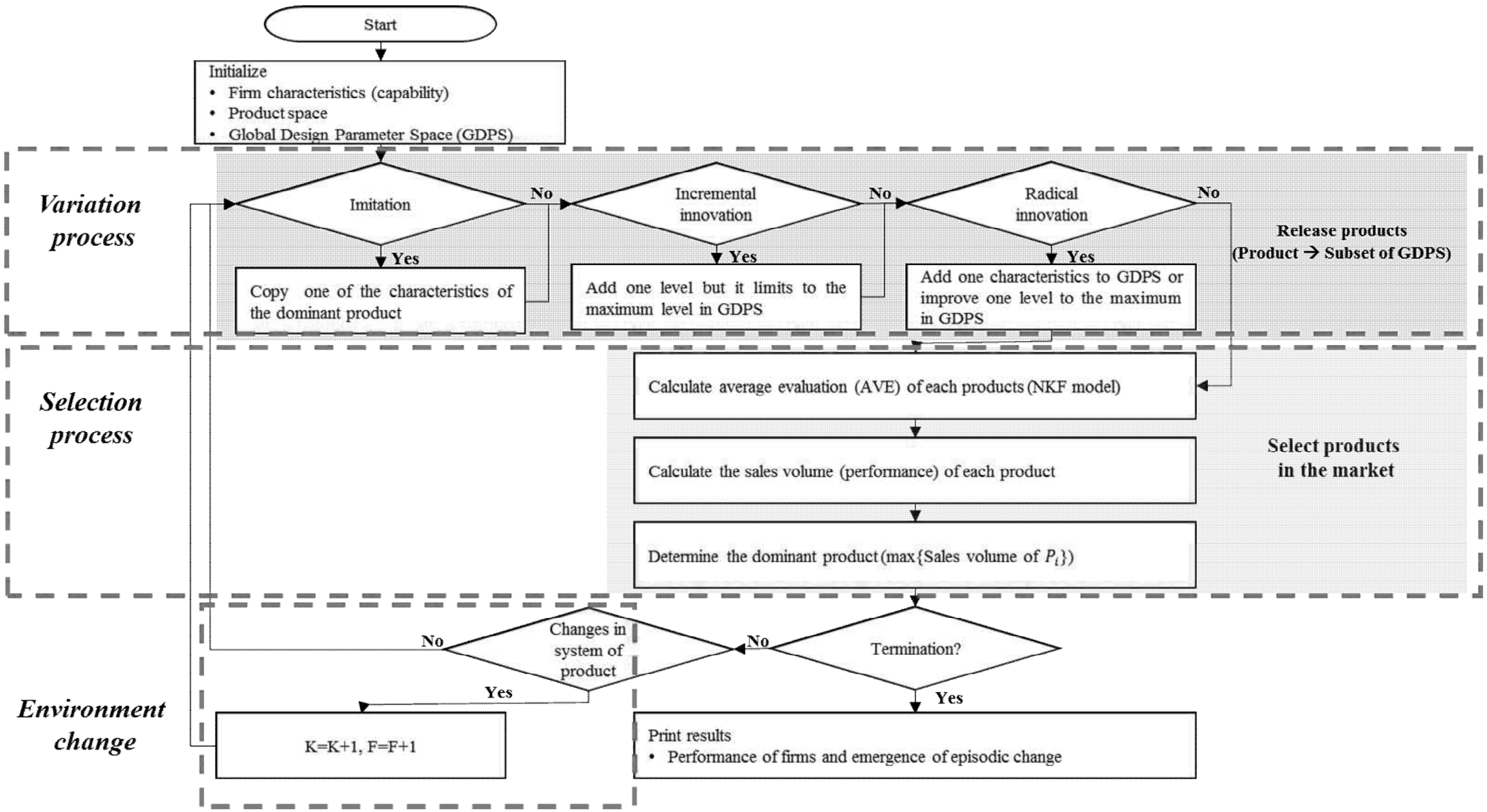


Figure 12 Flow chart of the model

5.3.2 Firms, consumers, and design parameter space-performance parameter space map

The agents in this model are defined as firms and consumers. Firms develop new products and introduce them to the market. The public sector is assumed to be an exogenous agent (Ting Zhang, Gensler, & Garcia, 2011) Each firm has an innovation routine, and the innovation routine is represented by the firm's innovation capability. The innovation capability of a firm is defined as its tendency to create a new product and to copy existing products, as discussed in previous research (Beckenbach et al., 2012).

The set of firms that exist in the industry is defined as:

$$\mathbf{M} = \{M_1, ..., M_m\}. \tag{18}$$

Firms release L types of products and the set of products $\mathbf{P_m}$ released by firm m is defined as follows:

$$\mathbf{P_m} = \{P_{m1}, ..., P_{mL}\}. \tag{19}$$

Products are composed of the technological characteristics that the firm can implement. The set of the technological characteristics that a firm has is referred to as the design parameter space (DPS), and the DPS is a subset of the general design parameter space (GDPS), which is the set of technological characteristics in the industry. The DPS of an existing firm m is randomly generated within the GDPS by a uniform pseudo-random distribution. A product P_{mj} that the firm m launches using k technological characteristics using the DPS_m of the firm m is defined as follows:

$$P_{mj} = \{\mathbf{c} \subset DPS_m \mid c_1, c_2, \cdots, c_k\} \quad \text{(20)}$$

Once a new technological characteristic i is introduced in the industry, the GDPS becomes improved. In turn, the DPS_m is updated, and a new product that adopts the technological characteristic i is defined as follows:

$$P_{mj} = \{\mathbf{c} \subset DPS_m \mid c_1, \cdots, c_k, \cdots, c_i\} \quad \text{(21)}$$

The performance of a product is represented by its combination of technological characteristics, and the fitness level in the environment is calculated based on the performance of the product. The performance of the product does not always increase linearly as the level of the technological characteristics increases. Considering the relationship between performance and technological characteristics, the DPS-PPS map is constructed using the concept of the genotype-phenotype map that shows the relationship between an organism's genes and its appearance. **Figure 13** is an example of the DPS-PPS map of a television, assuming that the television consists of two technological characteristics—display size and resolution with two quality levels—and that the PPS includes portability and visibility. An increase in the display size leads to better visibility, but lower portability. An increase in the display resolution improves visibility, but has no impact on portability. If the fitness level is calculated only using the technological characteristics, the fourth product is the fittest. However, taking the DPS-PPS relationship into consideration, the second product is likely to achieve the highest level of fitness, with 0.97 in an environment where portability is more important than visibility.

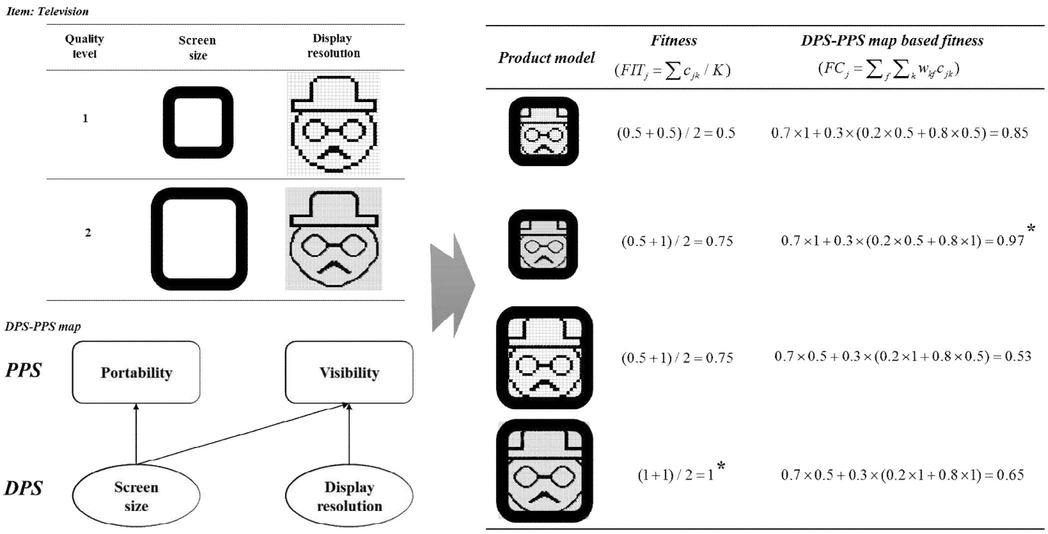


Figure 13 Example of the DPS-PPS map

The DPS-PPS map also includes the generalized NK model, which assumes that there are K relationships between the N components in the complex system simulation. The NK model of Kauffman (1993) is a special condition where the number of components and functions is equal (Querbes & Frenken, 2017). Ma and Nakamori (2005) introduced the logic that determines the performance of a product based on the combination of technological characteristics that make up the product design. Similarly, Querbes and Frenken (2017) conducted a simulation in a similar way, where consumers determine their purchase by considering the performance parameter (PP) of a product. Both of those studies applied an NK model to simulate the selection process.

The consumer group that purchases products considering the PPS is defined as follows:

$$\mathbf{B} = \left\{ B_1, \cdots, B_r \right\}, \qquad r = 1, \cdots, R \quad \cdots\cdots (22)$$

Consumers provide information on the design parameter (DP) and the PP for the products to be released in the next generation by evaluating and purchasing the products of firms. They evaluate the PPs with different preferences, and the preference set $\mathbf{Pref}_{B_r}$ considered by the individual consumer B_r is defined as follows:

$$\mathbf{Pref}_{B_r} = \left\{ pref_{1B_r}, \cdots, pref_{UB_r} \right\}, \qquad r = 1, \cdots, R\,, \quad \cdots\cdots (23)$$

subject to

$$\begin{cases} pref_{fC_r} \in [0,1], & f = 1,\cdots,U, \\ \sum_{f=1}^{U} pref_{fC_r} = 1. \end{cases} \qquad (24)$$

Consumers have different preferences depending on the PP. Due to the heterogeneity of consumers, their preferences are set differently using a uniform pseudo-random distribution.

To calculate the utility, the weighted average method is employed, and the utility E_{B_r} of each product is calculated as follows:

$$E_{B_r} = \sum_{f=1}^{U} pref_{fB_r} PP_f \qquad (25)$$

When a consumer purchases a product based on Eq. (25), a product chosen by the majority of consumers is likely to be released in its current form. Therefore, consumer choice is the driving force of the retention of products.

5.3.3 New product development process and environment changes

5.3.3.1 Variation process

The variation process is based on a genetic algorithm, and includes the process by which a product is generated by the combination of the firm's DPS. The gene string used in the genetic algorithm is the set of technological characteristics of the product. The new product is developed through a recombination process using the existing product. It is diversified depending on the firm's technology capability and innovation capability. If a firm has the both high technological capability and innovation capability, it is likely to develop a new product that is distinctive from existing products because it is easy for the firm to implement the technological characteristics adopted in the existing product. A firm with a high level of technological capability but a low innovation capability is likely to implement the technological characteristics of existing products and thereby release a product similar to existing products. A firm with lower technological capability and lower innovation capability tends to imitate existing products, but with a level of technological characteristics that is lower than those of existing products.

Firms establish a new product development strategy considering changes in the DP and PP. A firm employs one of the following three modes when establishing a new product development strategy among the three modes: (1) production of an existing product, (2) imitation of products released by other firms, or (3) the release of a new product that is distinctive from existing products (Beckenbach et al., 2012). **Figure 14** presents a flowchart of the decision-making process of a firm in the variation process. A firm first decides whether to perform imitation. It is presumed that a firm with the implementation experience accumulated by repeating product launches is likely to embark on the imitation process. The firm regards a product selected by the majority of consumers in the previous time period as the product to imitate—the dominant product—

and attempts to copy the design parameters. If possible, it imitates the level of the design parameters belonging to its DPS. If not, it introduces the design parameters from its DPS, adopting those that are the most similar to the design parameters of the dominant product.

A firm with high design experience attempts to innovate. A firm that imitates the dominant product is also likely to innovate to improve the level of the design parameters. Innovation is divided into incremental improvements of existing design parameters and changes in the GDPS, in which a new DP is introduced into the industry. Improvement of an existing DP leads to the increase in the depth of the GDPS if the value of this DP is the highest in the corresponding DP of the GDPS. Otherwise, the implementation experience of a firm increases because the previously discovered value of the DP is used for an incremental improvement. The change in the GDPS is caused by the adoption of a new DP, which adds a new DP to the GDPS. Each such change increases the number of the design parameters that can be adopted for products by one. The probability of the introduction of the new DP and its adoption for a product follows the Poisson distribution as used in Ciarli, Lorentz, Savona, and Valente (2010). The mean of the Poisson distribution changes as the experience of a firm increases.

An increase in the number of the design parameters also affects the PPs of the product. When a new DP is introduced, the DPS-PPS map is likely to be newly constructed (Ma & Nakamori, 2005) by updating the weight w_{kf}, implying the impact of the design parameters on the PPs. As a result, even if consumers' preferences do not change, the utility of the product changes as the value of the PPs changes with the introduction of technological characteristics.

A firm that neither imitates nor innovates releases the same products that it released in the previous time period. Thus, it does not meaningfully contribute to the change that occurs in the variation process, and consequently its experience is not accumulated.

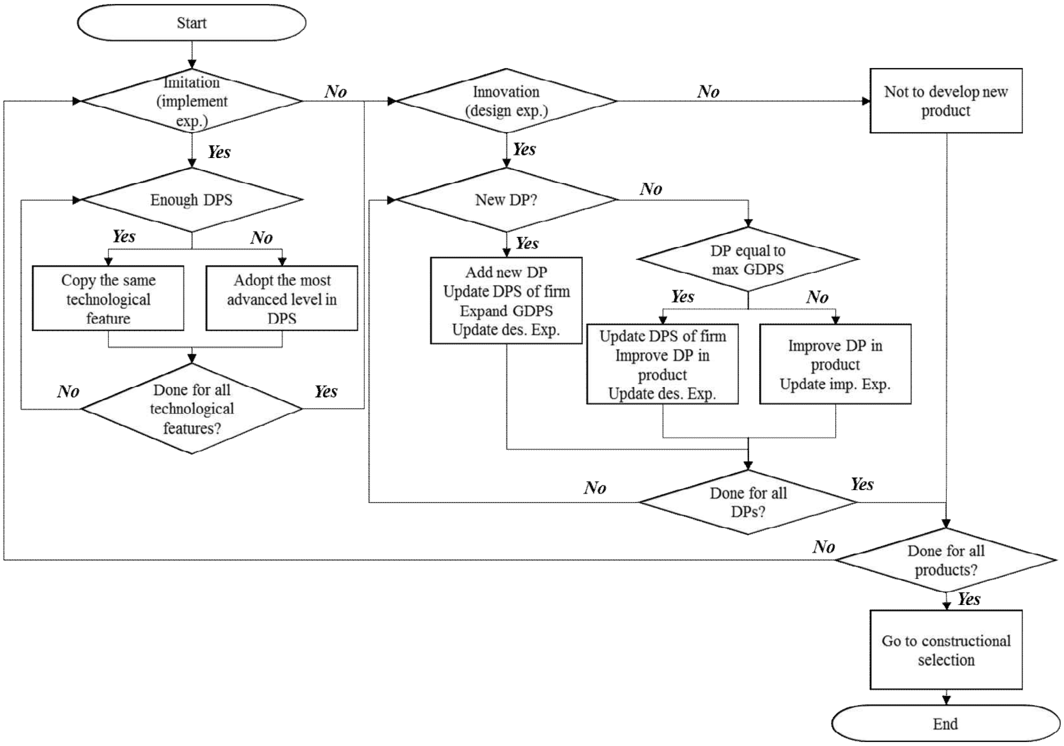


Figure 14 Decision-making process of a firm in the variation process

5.3.3.2 Selection and retention process

Figure 15 shows the selection and retention processes of this model. The selection process is divided into two types: internal selection (or constructional selection) and external selection (or environmental selection). The internal selection is the process of selecting a product to be released by a firm. The firm compares the demand for the product category to which the developed product belongs with the market size of the existing product category to which the previously launched product belongs, and decides to release a product with the higher demand. If a firm develops a product belonging to an existing product category, and there is no difference in demand, then it releases the product with the higher value of fitness. In contrast, if a developed product belongs to a different category, the firm compares the demand for both product categories and releases the product with the higher demand. In order to compare the demands between product categories, the change in demand is assumed to follow the diffusion curve of Bass (1969). The demand $MarketSize_{it}$ for a product category i at time t is defined as follows:

$$MarketSize_{it} = CMS(t) - CMS(t_i)\,, \qquad (26)$$

where t_i is the time that the product category i is first introduced into the market, and the market size accumulated $CMS(t)$ until the time t is defined as follows:

$$CMS(t) = \frac{1 - e^{-(\alpha+\beta)t}}{1 + \frac{\beta}{\alpha} e^{-(\alpha+\beta)t}}\,. \qquad (27)$$

A firm releases a developed product if it contains a newly introduced DP and the demand for it is higher than the demand for the previously released product, leading to product speciation because products including the newly introduced DP are continuously released.

External selection is related to the purchase of a new product based on consumers' utility. The utility of a product can be calculated by the following different methods: 1) purchasing a product closest to the ideal of a consumer, 2) purchasing a product with the best value of the PP among the lowest values of each PP, and 3) purchasing the product with the highest calculated utility (Ma & Nakamori, 2005). This model adopts the third of these methods. The utility of each product is calculated by Eq. (28) and the product with the highest utility is selected as described in Eq. (29).

$$E_{B_r P_{mj}} = \sum_{f=1}^{U} pref_{fB_r} PP_{P_{mj} f} \text{,} \quad (28)$$

$$Choice_{B_r} = max[P_{mj} \mid \mathbf{E}_{B_r P_{mj}}] \text{.} \quad (29)$$

The sales volume of each product P_{mj} is calculated by Eq. (30) and the performance of firm m is determined by Eq. (31).

$$Sales_{P_{mj}} = \sum_{choice_{B_r} = P_{mj}} , \tag{30}$$

$$Performance_m = \sum_{j=1}^{j=L} Sales_{P_{mj}} . \tag{31}$$

The product selected for the most consumers is determined to be the next generation of imitation products, which illustrates the retention process that occurs in the product evolution environment. This implies that the firm with the highest performance is most likely to survive in the environment of product evolution and that its decision-making routine indirectly affects that of other firms via its products.

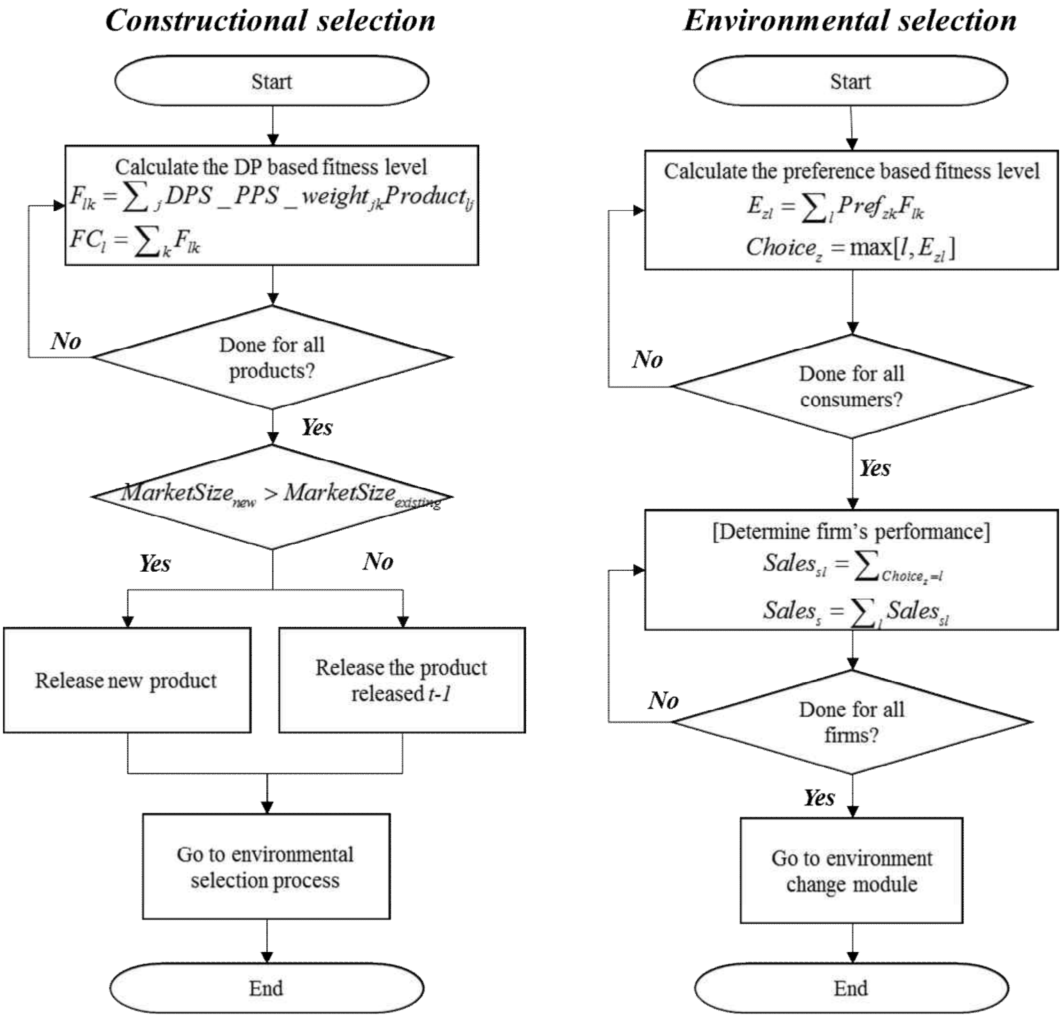


Figure 15 Selection and retention process

5.3.3.3 Environmental change

Figure 16 shows the environmental change process, including changes in the functions of products and the relationship between DPS and PPS. First, the number of functions is updated depending on the Poisson process with a mean value of 0.01. It also follows the probability of the emergence of a technological innovation, as a change in the function implies product innovation. Second, the DPS-PPS map and its weight also change as a new function is introduced. The mapping and weighing process are also the same as in the initial setting of the DPS-PPS map.

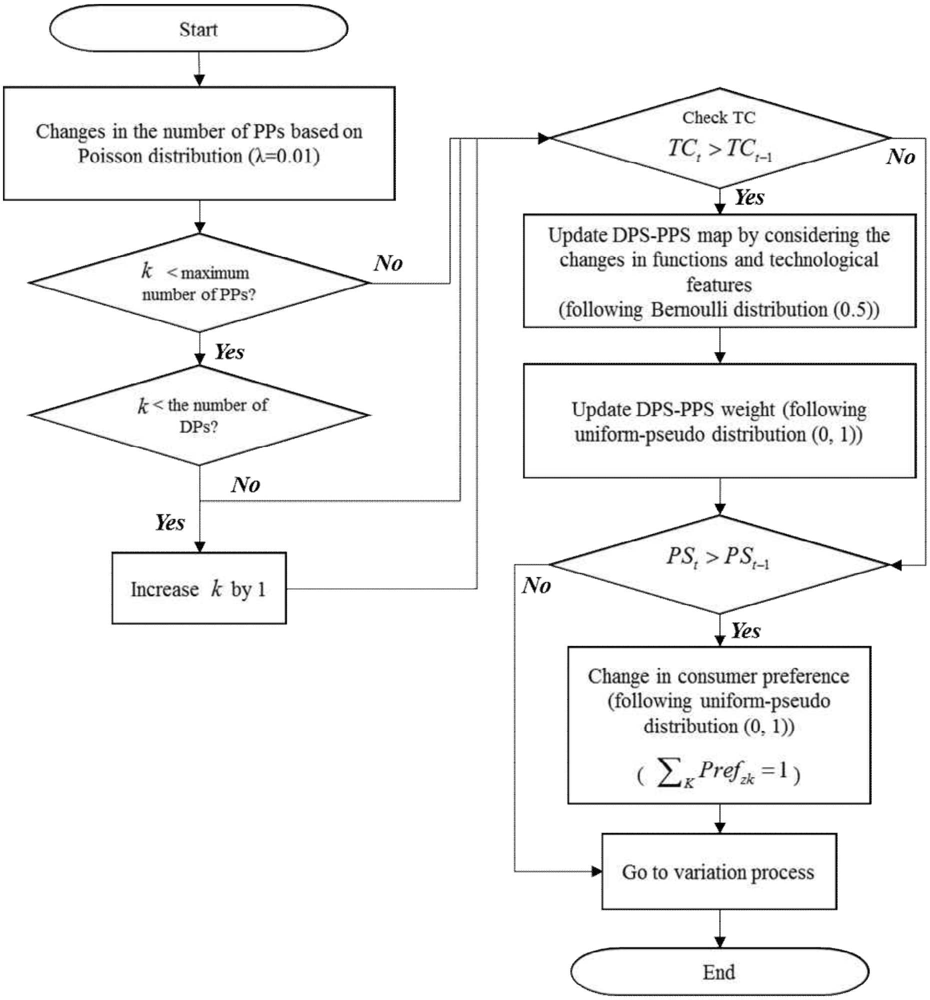


Figure 16 Flow chart for updating design parameters and DPS-PPS map

Figure 17 illustrates the entry of new firms. The entry of a new firm is another one of the main changes in the environment, and is also dependent on the Poisson process with a mean λ value of 0.02, indicating that a new entrant is expected to enter the market at time 50.

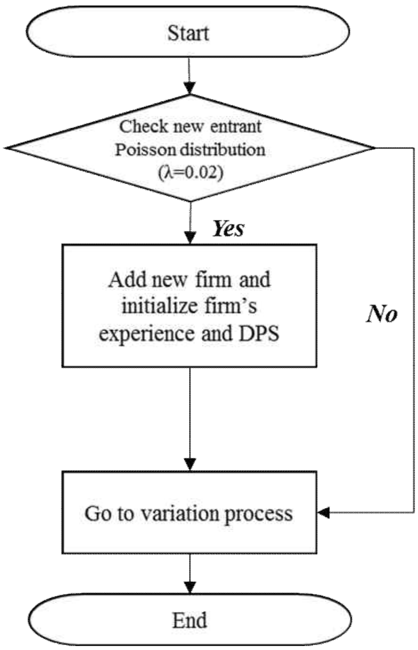
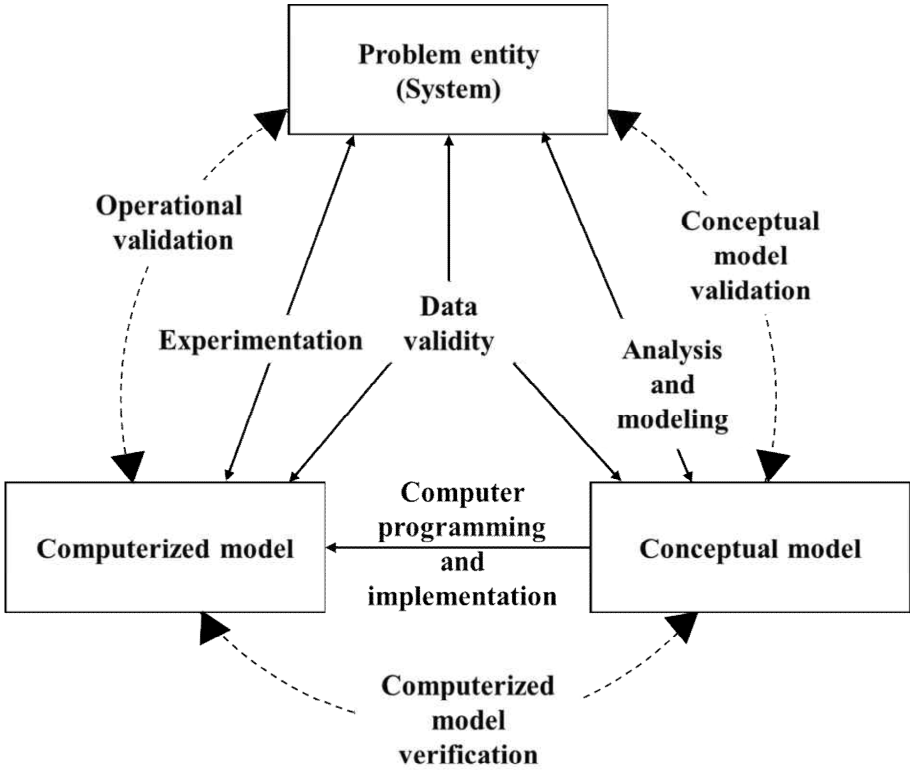


Figure 17 Flow chart for generating a new entrant

5.3.4 Validation of the model

The validation method for a theory-building simulation is distinguished from that for an empirical simulation, and the process is shown in **Figure 18**. First, an empirical simulation is validated following the process of structural validation, predictive validation, and replicative validation (Darvishi & Ahmadi, 2014). Structural validation confirms whether the simulation model can replicate the behavior of the real system. Predictive validation confirms whether the model can predict unobserved behavior. The last process, replicative validation, compares the simulation data with the real data. In economic simulations, GDP and GDP growth are used for the validation of the model (Kwon & Motohashi, 2017; Windrum, Fagiolo, & Moneta, 2007).



Source: Martis (2006)

Figure 18 Verification and validation process of the simulation modeling

The validation of a theory-building simulation is conducted by confirming whether the model produces a result similar to that of an existing model. Conceptual model validation is defined as confirming that the theories and assumptions of the conceptual model are correct (Yilmaz, 2006). It also contains a validation process that compares the implementation of the model and the specification, and the operational validity of the model (also referred to as its replicability) is compared to theory by graphical comparisons, confidence intervals, and hypothesis tests (Yilmaz, 2006).

Following the validation method for a theory-building simulation, the model in this study was validated by confirming that the model replicated theoretical findings through a comparison of the results with Ma and Nakamori (2005) and by confirming replication of the relevant phenomena (i.e., the emergence of episodic events).

The first stylized fact used for the validation was the first-mover advantage in the market and the catch-up of latecomers as the industry becomes mature (Lieberman & Montgomery, 1988). The first-mover advantage occurs due to consumers' lock-in to the products that they are exposed to initially. Combining the first-mover advantage with the positive feedback of Arthur (1989), the first-mover involved in an unchanged environment is likely to maintain the first-mover advantage due to positive feedback, resulting in monopolization of the market by the first-mover, as discussed by Ma and Nakamori (2005). Meanwhile, the latecomer has the chance to overcome the first-mover by technological innovation, which leads to the introduction of new products with higher utility, thereby neutralizing the first-mover advantage (Gal-Or, 1985). Thus, a monopolistic market becomes an oligopolistic market, and at last turns into a competitive market.

Stylized fact 1. Without innovation, the market becomes a monopoly of a single firm.

Stylized fact 2. With innovation, the market becomes competitive.

To compare the results of the model with those of previous models, consumers' heterogeneity was adopted. Ma and Nakamori (2005) showed that the heterogeneity of consumers makes the market competitive. Furthermore, they confirmed that imperfect information of consumers leads to a competitive market.

Stylized fact 3. If all consumers are heterogeneous, the market becomes competitive.

Stylized fact 4. If all consumers are heterogeneous and not fully informed on the types of products, the market becomes competitive.

The validation results presented in **Figure 19** graphically confirm that all four stylized facts are shown in our model, as in the previous model. The model shows that the market share among firms becomes divergent as firms cannot outperform the first mover without adopting new technological characteristics. However, if firms have the opportunity to develop and adopt new technological characteristics, they obtain some of the market share that the first mover had occupied. Next, a condition for the market becoming competitive is purchase by heterogeneous consumers who have imperfect information. As a firm is not likely to be affected by the repetitive purchases of consumers in the same consumer group, consumers are not locked-in to certain product models, leading to the formation of a competitive market.

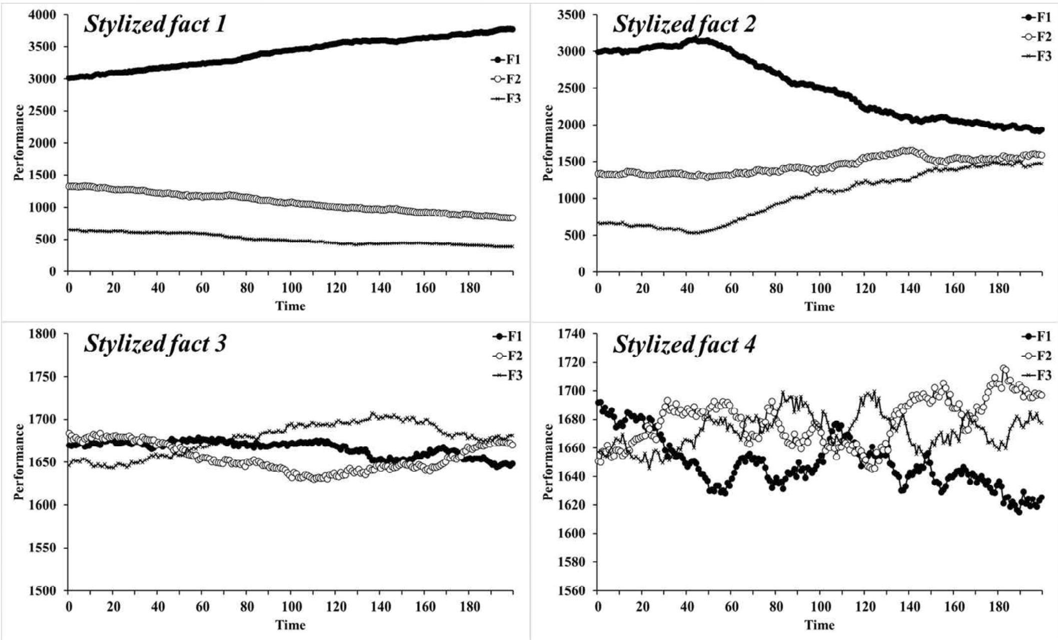


Figure 19 Validation results from the stylized facts

The patterns of the emergence of episodic events are shown. The following three scenarios were used for the validation process: (1) without either innovation or entry, (2) with innovation but without entry, and (3) with both innovation and entry. According to the definition of the episodic events and episodic change, the first and second episodic events are expected to be shown in the second and third scenarios, while the third episodic event is expected to occur only in the third scenario, leading to the emergence of the episodic change.

Figure 20 shows the results of a comparison of the emergence of the episodic events across the validation scenarios. In the first scenario, none of the changes occurred, which means that there was no possibility to change the industry. In the second and third scenarios, both technological change (TC) and product speciation (PS) occurred, but only the third scenario enabled the third episodic event to emerge. Therefore, episodic change occurred only in the case of scenario (3), which is in line with the empirical case study presented in Chapter 4.

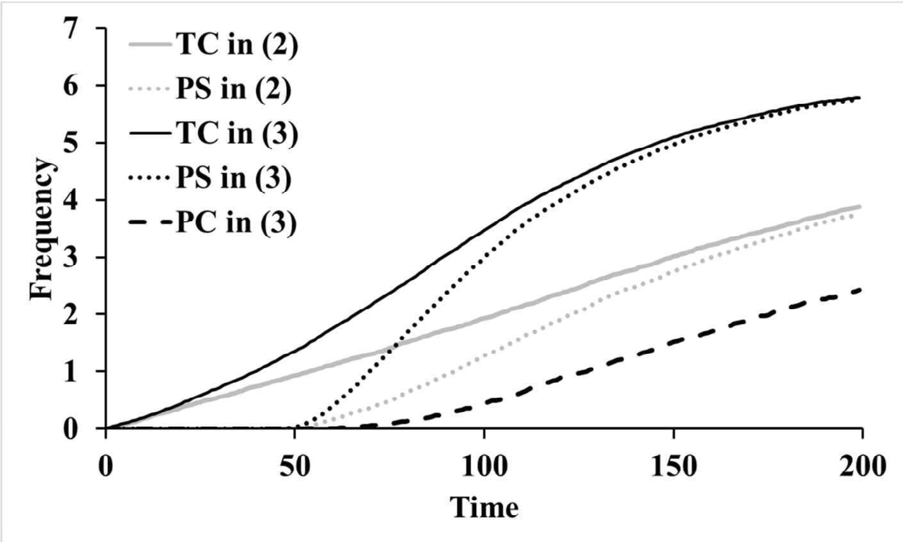


Figure 20 Comparison of the the episodic events across the validation scenarios

5.4 Simulation

5.4.1 Scenario and parameter setting

The scenarios are composed of three different control parameters, as outlined in Table 13: implementation experience of a new entrant, design experience of a new entrant, and information imperfection of product types that a consumer considers. During the simulation, firms enter into the new industry. The firms are either start-ups or diversifying firms who have experience in the previous industry. That experience is divided into two types: implementation experience and design experience. A start-up is presumed to have low experience in both, whereas a diversifying firm is likely to have high implementation experience but low design experience, low implementation experience but high design experience, or high experience in both. Furthermore, the scenarios are divided by the type of information that consumers have: perfect information and imperfect information. If a consumer is informed perfectly, the consumer is likely to consider all products in the market and purchase the product that delivers the highest utility. Otherwise, the consumer is likely to consider a few products and purchase the product that give the consumer the highest utility among them. The former scenario means that a product is selected by a global search algorithm, whereas the latter means that a product is purchased by a local search algorithm.

Table 13 Scenario setting

Scenario	Implementation experience	Design experience	Information type
SC1	Low	Low	Perfect
SC2	High	Low	Perfect
SC3	Low	High	Perfect
SC4	High	High	Perfect
SC5	Low	Low	Imperfect
SC6	High	Low	Imperfect
SC7	Low	High	Imperfect
SC8	High	High	Imperfect

The basic parameters and control parameters are set based on the settings in Ma and Nakamori's (2005) scenario. Most of the parameters are the same except for the number of the consumers, simulation time, and replications. In particular, the simulation time and the number of the replications are expanded to illustrate the robustness of the results by neutralizing the effects due to the randomness in the simulation model. The entry mode is determined by the Poisson random distribution with a mean value of 0.02, similar to the mutation rate in Ma and Nakamori (2005), as it is also considered to reflect the mutations that happen in the industrial environment.

The number of the experiences in the baseline setting is 1 and the experiences of the initial firms increase by about 2 at time 50. Thus, to distinguish the scenarios, a new entrant with high experience is assumed to have a value of 10 for experience, while the values of the other parameters are described in Table 14.

Each scenario is numerically set as follows:

- SC1: both implementation experience and design experience are 1.
- SC2: implementation experience is 10 and design experience is 1.
- SC3: implementation experience is 1 and design experience is 10.
- SC4: both implementation experience and design experience are 10.
- SC5: both implementation experience and design experience are 1, and a consumer considers only 3 products.
- SC6: implementation experience is 10 and design experience is 1, and a consumer considers only 3 products.
- SC7: implementation experience is 1 and design experience is 10, and a consumer considers only 3 products.
- SC8: both implementation experience and design experience are 10, and a consumer considers only 3 products.

The other simulation parameter is set as follows:

- The number of the initial firms is 3 and each firm produces 3 different product models.
- The number of initial technological characteristics in the in the industry is 3. It gradually increases by 8, having a positive relationship with the function of products.
- The initial number of functions that a product has is 3 and the number of

function increases by 8, which reflects the constraint in the NK model that the number of functions cannot exceed the number of technological characteristics.

- The entry of new firms is determined by the Poisson random distribution with a mean value of 0.02. It is assumed that the maximum number of new entrants is 3. The DPS of each new entrant is determined by the GDPS at the entry timing.
- Both design experience and implementation experience increase depending on the new product development activity of a firm, determining the direction of the future new product development.
- The number of consumers is 5,000. Each consumer is heterogeneous and makes the purchase decision every time.
- The simulation terminates at time 200, and the number of replications is 1,000, which is the minimum value at which further replications do not lead to change.

Table 14 Parameter setting

Parameter		Value
Number of initial firms (incumbents)		3
Initial number of design parameters		2
Maximum number of design parameters		8
Initial number of PPs		2
Maximum number of PPs		8
Number of products that each firm produces		3
Number of consumers		5,000
Entry parameter λ for the Poisson distribution		0.02
Size of consumers' consideration sets		3
Experience	Low	1
	High	10
Simulation time		200
Number of replications for each scenario		1,000

5.4.2 Simulation result 1: growth of performance of new entrants

Differences in performance among firms were investigated by changing the scenarios in the environment for the product evolution. Comparing the performance of firms in the perfect information regime and in the imperfect information regime, as shown in **Figure 21** to **Figure 24**, it can be seen that firms in the imperfect information regime tended to gain profits in the competitive market. A firm that launches superior products in the perfect information regime is likely to obtain more profits than other firms. In the imperfect information regime, however, such firms hardly achieve more profits as consumers' purchasing behavior is not driven towards purchasing more advanced products.

First, the performance of a new entrant depending on its pre-entry experience was compared across the scenarios under the perfect information regime. Both start-ups and diversifying firms with high implementation experience found it difficult to surpass the advantages of the incumbents, as shown in **Figure 21**. Start-ups lack the ability to combine their technological knowledge to create new products, as they do not have experience with combinations. They are likely to imitate existing products of the incumbents, but their DPSs are not well-accumulated to completely imitate them. As a result, start-ups release products belonging to the same product category as existing products, resulting in a low market share since they are not selected by consumers. A diversifying firm with high implementation experience is also likely to launch products belonging to the same product category as the existing products. It cannot afford to create products belonging to a new product category, leading to relatively low performance.

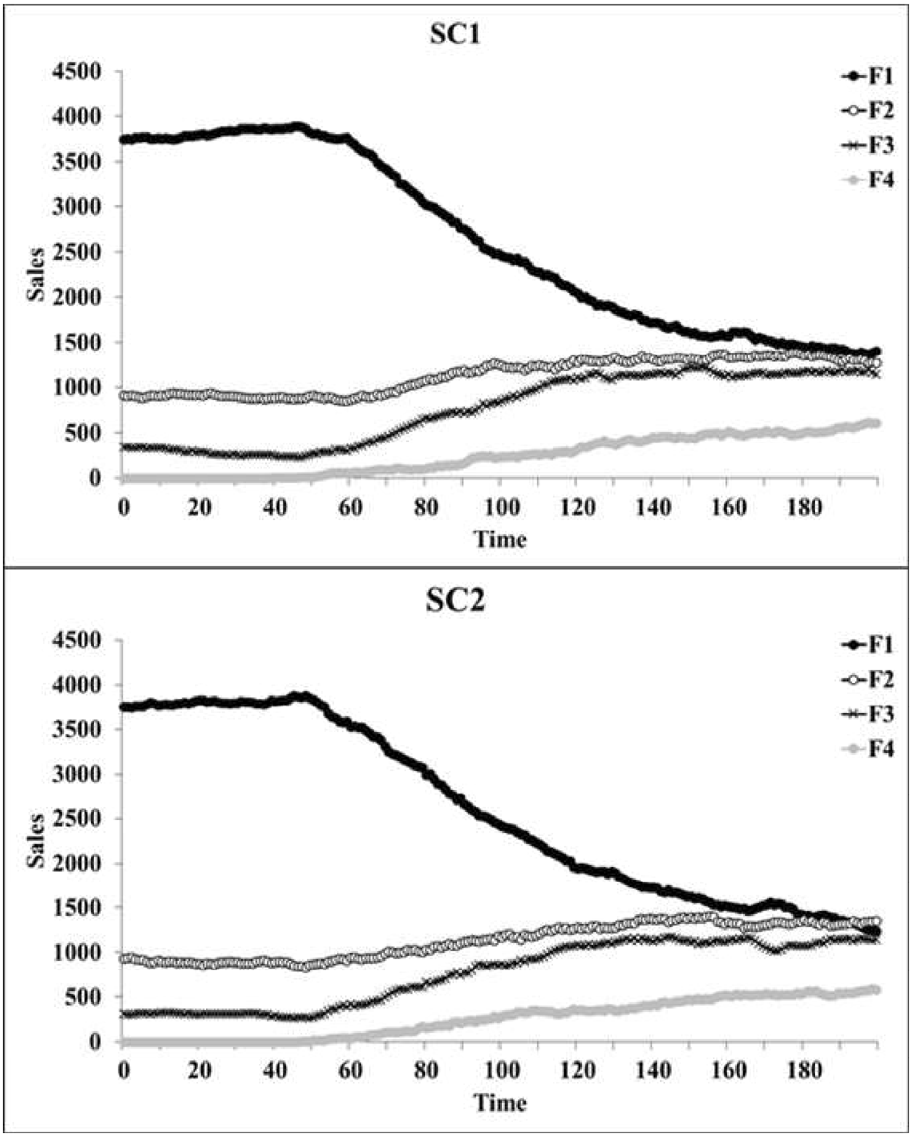


Figure 21 Performance of firms in SC1 and SC2

Figure 22 shows the performance of a diversifying firm with only high design experience and with both types of experience. First, a diversifying firm with high design experience tends to launch products belonging to new product categories, different from those of the incumbents, and thereby it exceeds the performance of the incumbents sooner, as it is likely to launch more advanced products. Even if it imitates the incumbent’s products at the stage of new product development, it improves the technological characteristics and releases products with superior functions than those of the incumbents. These products are selected by more consumers than products belonging to the same category as the incumbent's products due to their higher utility to consumers. A diversifying firm with both design experience and implementation experience maintains higher performance than the incumbents and is likely to adapt to the evolutionary environment. These findings indicate that implementation experience is ineffective for a diversifying firm to survive in a new industry.

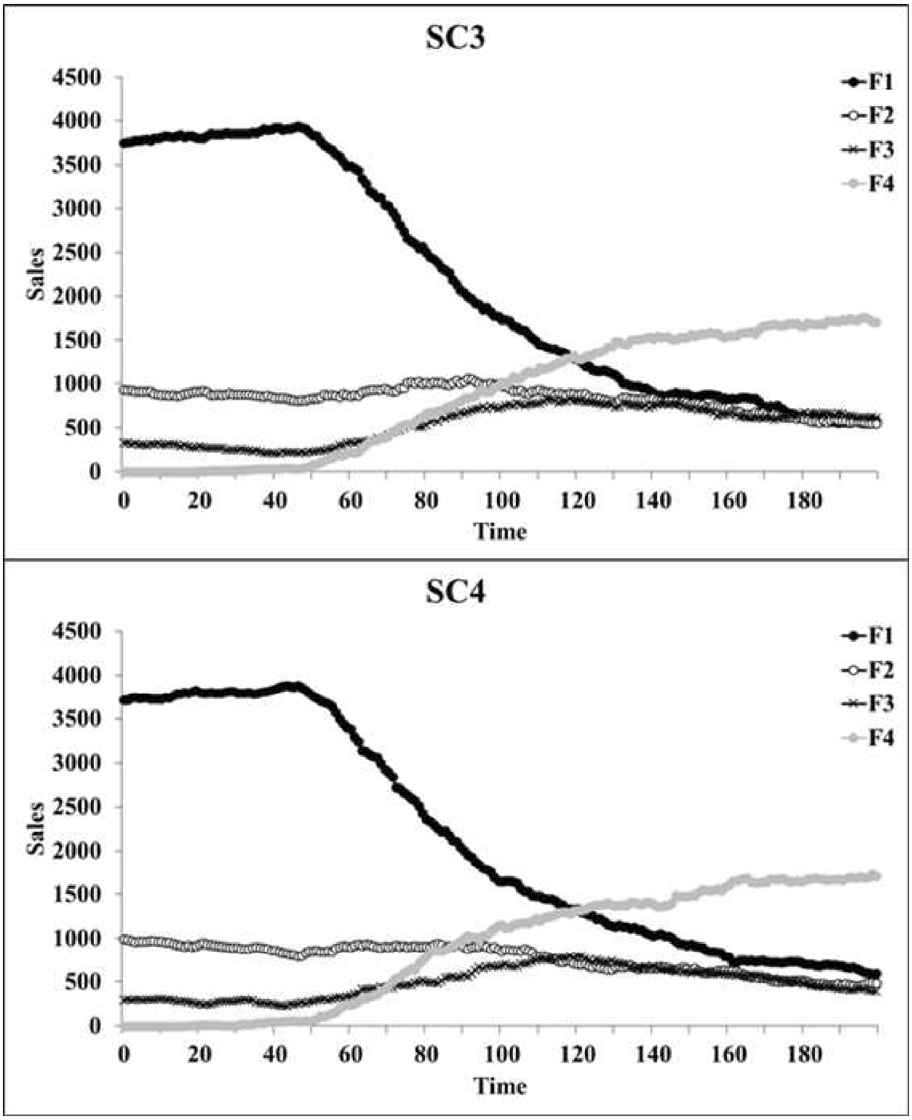


Figure 22 Performance of firms in SC3 and SC4

Figure 23 shows the change in the performance of a diversifying firm with only implementation experience and a start-up when information on the product models was imperfectly given to consumers. When consumers buy products considering only a limited number of products, they search for a local optimum rather than a global optimum of utility. Even if there is a difference in the functional fitness level between products in this regime, there is almost no difference between firms. A start-up and a diversifying firm with only high implementation experience are likely to gain market share while improving their products, but are unlikely to exceed the performance of the incumbents. Even if the winner cannot take all, they cannot afford to create new demand as they lack the ability to combine the existing design parameters. Thus, new demand is also created by the incumbents, which allows them to continue to occupy an advantageous position in the industry.

Figure 24 shows the performance of diversifying firms with high design experience. A diversifying firm with high design experience outperformed the incumbents. A diversifying firm with high levels of both types of experience is likely to utilize the DPS to create new combinations, thereby creating new demand. Even though implementation experience contributes to the launch of improved products compared to existing products, a diversifying firm with high design experience tries to launch new designs, rather than to release improved versions of existing products. Therefore, implementation experience also does not affect the performance of diversifying firms with high design experience under the imperfect information regime.

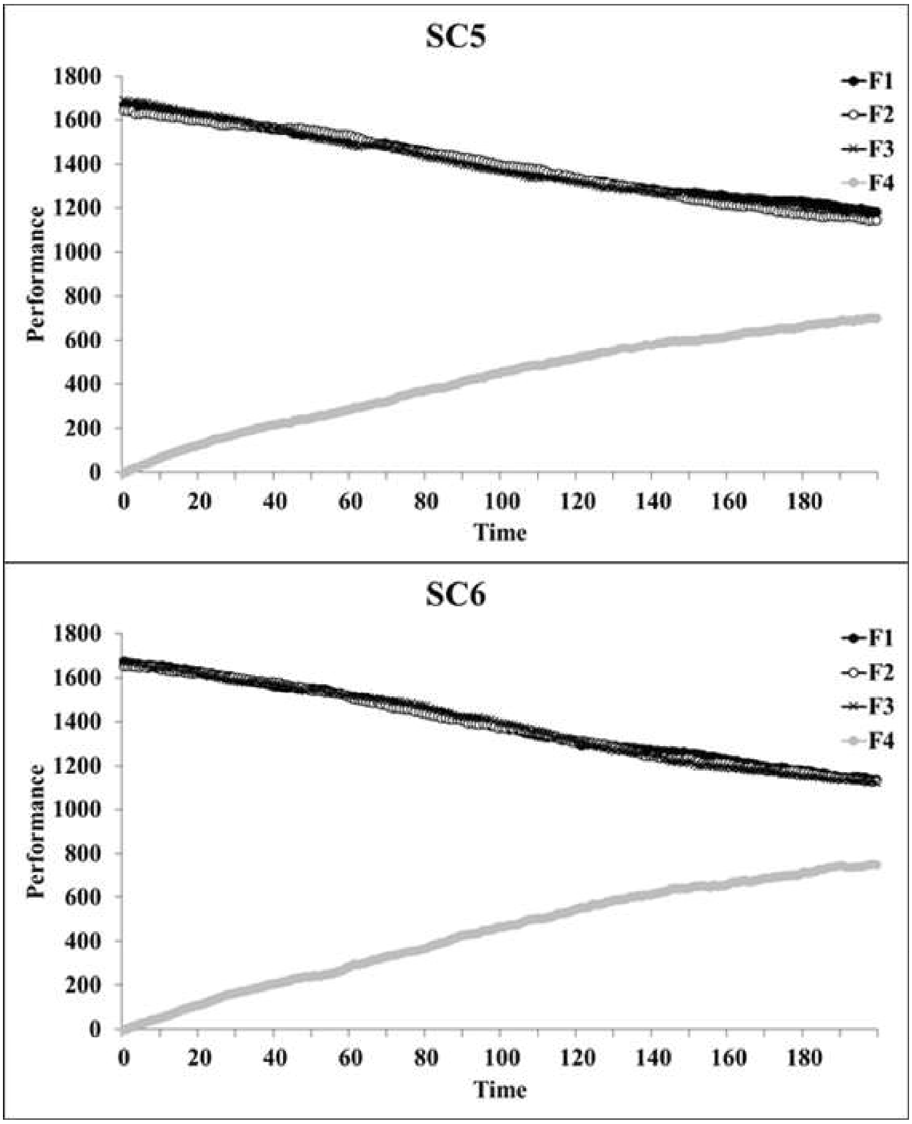


Figure 23 Performance of firms in SC5 and SC6

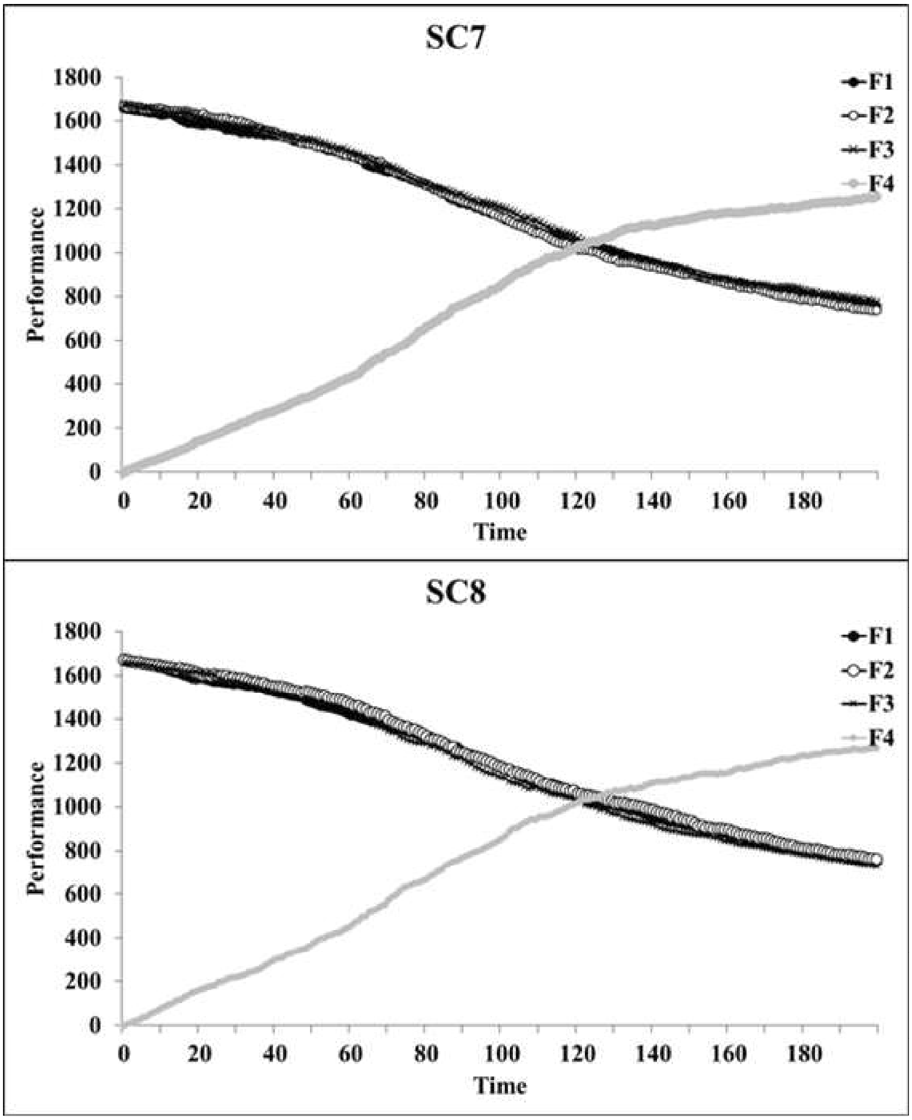


Figure 24 Performance of firms in SC7 and SC8

Figure 22 and **Figure 24** show different patterns in terms of when new entrants overtook the incumbents. A firm with high design experience in the perfect information regime successively overtook the existing firms. The performance of a diversifying firm exceeded that of the incumbents at times 70, 100, and 120 in SC3 and at times 70, 90, and 120 in SC4. The difference between the two scenarios was caused by the role of implementation experiences, which contribute to adaptation in the new environment by making profits that can be invested into new product development. Under the imperfect information regime, firms with high design experience displayed the same pattern, as shown in SC3 and SC4. Implementation experience made little contribution to overtaking the incumbents. In addition, a diversifying firm in the perfect information regime was likely to have higher performance, as it overtook all the incumbents at once compared to the pattern shown in the perfect information regime, where diversifying firms steadily surpassed the incumbents. Thus, comparing the changes in relative advantages, firms are highly likely to be encouraged in the perfect information regime, but the actual achievements of diversifying firms are higher in the imperfect information regime.

This result shows that the pre-entry experience has a significant impact on the performance of a firm, but this effect depends on the type of experience. Furthermore, these findings show that the winners cannot take all profits as consumers are constrained in obtaining information, in accordance with previous research.

5.4.3 Simulation result 2: patterns of the emergence of the episodic change

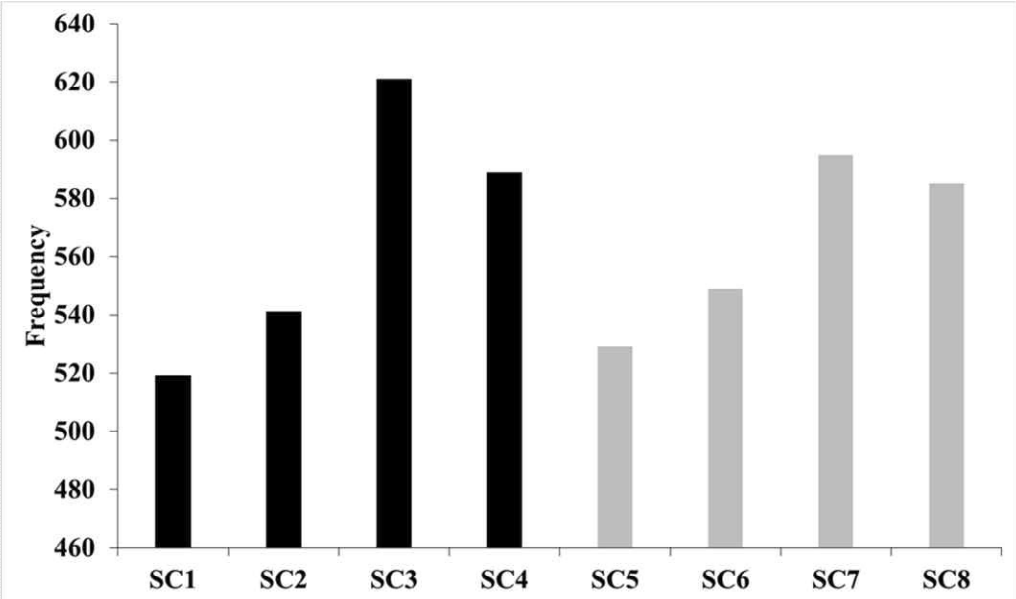
As the difference in performance between a start-up and a diversifying firm with high implementation experience is insignificant, the importance of implementation experience is likely to be underestimated. However, this does not indicate that implementation experience makes an insignificant contribution to the emergence of episodic change. The number of the episodic events fluctuates depending on the types of experiences of new entrants, resulting in changes in the timing of the emergence of the episodic change. In order to investigate the role of pre-entry experience, the frequency of the occurrence of episodic change was compared across the scenarios by calculating the emergence ratio of episodic change across the 1,000 replications. Converting the relative occurrence ratio $RelFreq_{SC_z}$ of the episodic change in each scenario SC_z to 100 by using the frequency $Freq_{SC_1}$ of the episodic change of SC_1, the equation for the conversion is as follows:

$$RelFreq_{SC_z} = \left\{1 + \frac{(Freq_{SC_z} - Freq_{SC_1})}{Freq_{SC_1}}\right\} \times 100 \quad \cdots\cdots \quad (31)$$

Next, for converting the relative occurrence timing $RelTEC_{SC_z}$ of the episodic change in each scenario SC_z to 100 by using the occurrence timing TEC_{SC_1} of the episodic change of SC_1, the equation for the conversion is as follows:

$$RelTEC_{SC_z} = \left\{1 + \frac{(TEC_{SC_z} - TEC_{SC_1})}{TEC_{SC_1}}\right\} \times 100 \quad \cdots\cdots \quad (32)$$

Figure 25 shows the relative frequency of episodic change across the scenarios. Pre-entry experience is considered as an important factor for the emergence of episodic change because it was associated with changes in the frequency. The probability of episodic change was highest when a firm with high design experience entered, leading to a 19.65 percent higher rate in the perfect information regime and a 14.64 percent higher rate in the imperfect information regime compared to SC1. The occurrence rate of episodic change was 4.24 percent and 5.78 percent higher, respectively, even when diversifying firms with high implementation experience entered. A firm with high levels of both types of experience had a positive impact on the occurrence of episodic change. However, when a firm with both types of experience entered, the frequency of the occurrence of episodic change was lower than in SC3 and SC7, which only addressed the impact of high design experience. This is because products with improvements in several technological characteristics, resulting from implementation experience, are more likely to be selected internally than products with new technological characteristics, leading to the launch of the new products with lower utility.

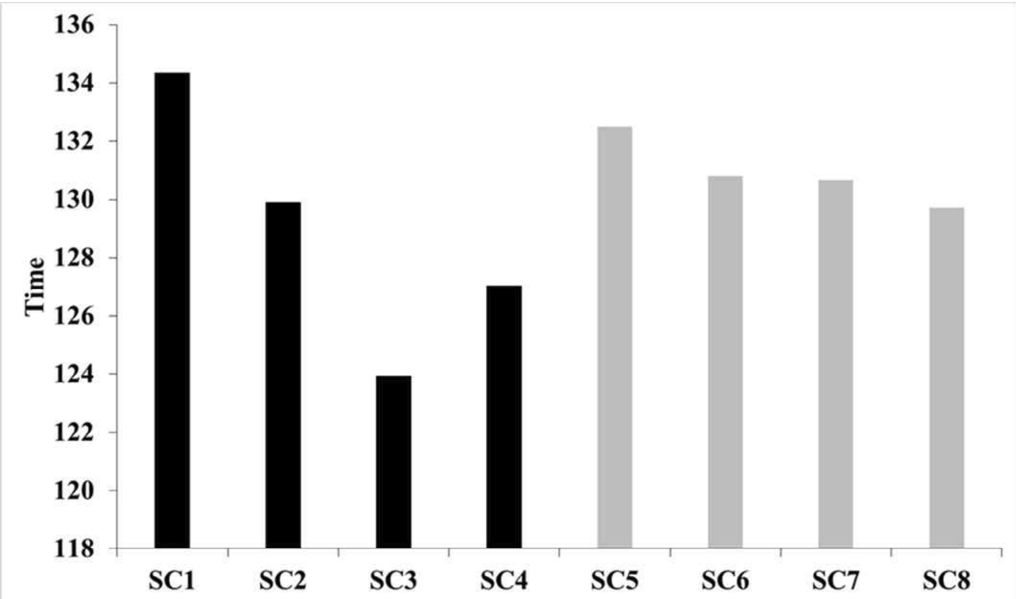


Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00%	104.24%	119.65%	113.49%	101.93%	105.78%	114.64%	112.72%

Figure 25 Frequency of the emergence of the episodic change

Figure 26 shows differences in the timing of episodic change across the scenarios. Similar to the results for frequency, episodic change was likely to occur faster when a firm with high levels of experience entered. Starting with the scenarios in the perfect information regime, episodic change occurred about 3.30 percent faster when a firm with high implementation experience entered. When a firm with high design experience became involved, the timing of the episodic change was hastened by 7.75 percent. A firm with high implementation experience tends to release products similar to those of the product categories that have already been introduced by the incumbents, and a firm with high design experiences is internally motivated to launch products belonging to new product categories. As a result, episodic change is caused by the initial entry, and the episodic change is hastened. Furthermore, a new entrant with both types of experience hastened the episodic change, but it happened more slowly than in the scenario where a new firm with high design experiences enters. $RelTEC_{SC_4}$ was about 5.43 percent lower than $RelTEC_{SC_1}$, but 2.5 percent higher than $RelTEC_{SC_3}$. This shows a different pattern from the conventional arguments made in previous research that the engagement of a more experienced firm hastens episodic change. Even if the level of design experience of such a firm is high, it tends to develop products belonging to existing product categories due to its high implementation experience. As a result, this new entrant is more likely to enter the market pursuing a risk-averse strategy by launching products belonging to existing product categories than by releasing new products in a new product category.

Next, in the environment where only a limited number of products were considered by consumers, episodic change occurred more rapidly as the experience of new entrants increased. The rate of episodic change was reduced by about 1.4 percent in SC5, especially for start-up entrants. This shows that episodic change can occur more quickly when consumers make purchases within a limited number of product models, meaning that they engage in local searches. Both implementation experience and design experience contributed to hastening the emergence of episodic change in this model, but the difference was insignificant. Since the products included in the consumers' consideration sets were randomly assigned, the demand for existing products tended to be higher when firms predicted the demand for newly released products based on their internal choice; therefore, there was little difference in the timing of the emergence of episodic change. For firms with high levels of both types of experience, there was no difference in the timing of the episodic change compared to SC2, which means that even if a firm is experienced in another industry before entering a new industry, it is not effective in hastening episodic change if consumers are given limited information on product models.



Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00%	96.69%	92.25%	94.57%	98.62%	97.36%	97.26%	96.56%

Figure 26 The timing of the emergence of the episodic change

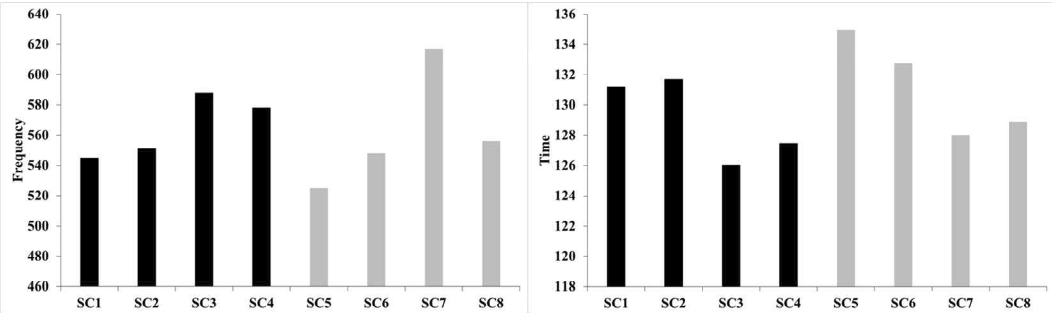
In summary, episodic change is more likely to occur when a diversifying firm with a high level of design experience enters, which also hastens the timing of episodic change. Therefore, in order to obtain a continuous competitive advantage in a new industry by accelerating the episodic change that triggers the transition to a new industry, firms with high design experience should be encouraged to participate. If a firm with high design experience finds it hard to enter, or is deterred from entering, then the information on the product models provided to consumers should be constrained in order to help new entrants trigger episodic change.

5.4.4 Sensitivity analysis

This research utilized the one-factor-at-a-time (OFAT) sensitivity analysis, as it was not necessary to reveal the relationship between all parameters and the output. OFAT sensitivity analysis varies one parameter at a time, while the other parameters remain fixed (ten Broeke, van Voorn, & Ligtenberg, 2016). It is useful for investigating the relationship between variation in a parameter and the output, and for this reason, it is referred to as a local method, in contrast to global sensitivity analysis which ascertains interaction effects by sampling the model output over a wide range of parameter values (ten Broeke et al., 2016).

In order to test the sensitivity of the model, changes in the imitation rate, the level of experience, and the number of products that consumers perceive were taken into consideration.

First, the sensitivity of the imitation rate depending on implementation experience was investigated by decreasing the probability to one-third of the baseline setting. **Figure 27** illustrates the result of the sensitivity analysis. Episodic change occurred more frequently when a diversifying firm with high design experience entered the market, even though the imperfect information regime was likely to encourage the emergence of episodic change, increasing the frequency by about 13 percent. A diversifying firm with high design experience hastened the emergence of the episodic change by about 4 percent under the perfect information regime and 2.5 percent under the imperfect information regime.

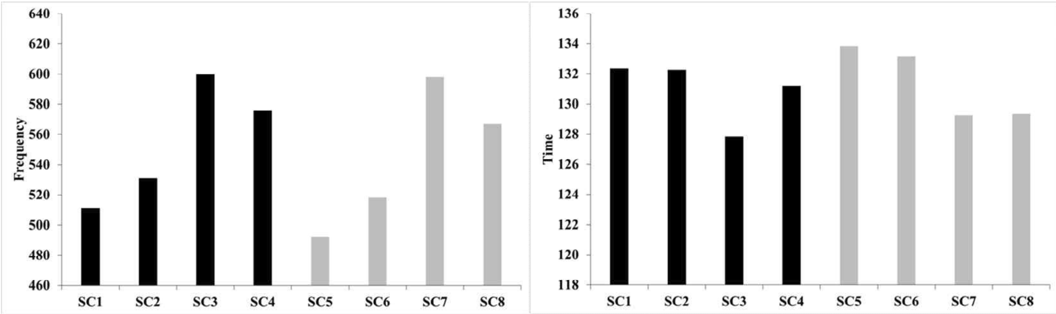


Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100	101.10	107.89	106.06	96.33	100.55	113.21	102.02

Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100	100.37	96.05	97.14	102.85	101.17	97.56	98.22

Figure 27 Frequency (left) and timing (right) of the emergence of the episodic change, decreasing the imitation probability to one-third

Figure 28 shows the result of the sensitivity analysis when the imitation rate was decreased by one-fifth of the baseline value. The impact of the design experience of the diversifying firm made episodic change more likely to occur, compared to other scenarios. The timing was also shortened when a diversifying firm with high design experience entered. Thus, although firms experience difficulty in imitating existing dominant products, the role of the diversifying firm with high design experience remains important for the emergence of episodic change.

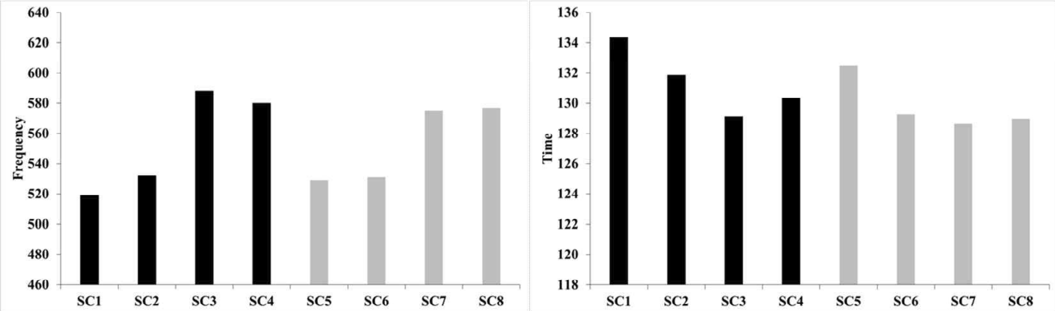


Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00	103.91	117.42	112.72	101.37	101.37	117.03	110.96

Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100	99.38	95.27	96.35	99.96	99.72	97.09	96.83

Figure 28 Frequency (left) and timing (right) of the emergence of the episodic change, decreasing the imitation probability to one-fifth

Figure 29 shows the result of the sensitivity analysis when the level of experience decreased by the half of the baseline setting. The frequency of episodic change decreased and the timing is lengthened, as diversifying firms are less likely to launch a new product belonging to the new product category.

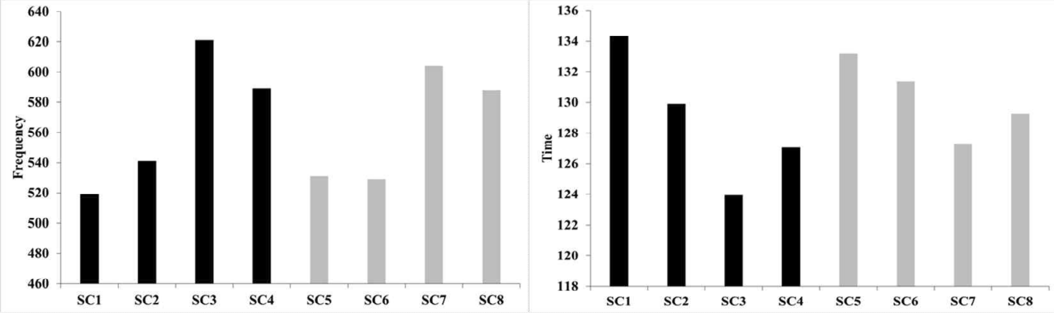


Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00	102.50	113.29	111.75	101.93	102.31	110.79	111.18

Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00	98.15	96.11	97.03	98.62	96.21	95.76	96.01

Figure 29 Frequency (left) and timing (right) of the emergence of the episodic change, decreasing the level of experience to the half

The results of the sensitivity analysis on the size of the consideration set are illustrated in **Figure 30**. As the size of the consideration set increased, consumers became more likely to acquire more information on the products, hastening the emergence of episodic change. In particular, in this case, a diversifying firm with high design experience hastened the episodic change by 5.23 percent, compared to 2.74 percent of the baseline in SC7.



Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00	104.24	119.65	113.49	102.31	101.93	116.38	113.29

Scenario	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8
Comparison	100.00	96.69	92.25	94.57	99.15	97.81	94.77	96.23

Figure 30 Frequency (left) and timing (right) of the emergence of the episodic change, increasing the size of the consideration set to double

Despite small differences in the frequency and the timing across the settings in the sensitivity analysis, the overall patterns of the emergence of episodic change remained unchanged. This indicates that the model proposed in this research is helpful for investigating the patterns of the emergence of episodic change.

5.5 Sub-conclusion

This chapter investigates the impact of the capabilities of firms and consumers on the emergence of episodic change by developing an ABSM for product evolution. New entrants are categorized based on their type of pre-entry experience. Implementation experience and design experience hasten the emergence of episodic change, as does the entry of new firms with both types of experience. The timing of the episodic change varied depending on the capability of consumers in the decision-making process, but the pattern changes according to the capabilities of the new entrant. When a start-up or a diversifying firm with high implementation experience enters the market, limitations in consumers' capability yield a pattern contributing to the emergence of episodic change. However, when a diversifying firm with high design experience enters the market, episodic change occurs more frequently and more rapidly in an environment where consumers' consideration set is not limited. These findings indicate that structural change in an industry is needed to trigger episodic change.

This study has three implications. First, it extends existing research on pre-entry experience by analyzing the impact of pre-entry experience on the emergence of a new industry. By dividing pre-entry experience into two types, implementation experience and design experience, the results suggest that the study of the role of pre-entry experience should be extended. Next, this study constructed a product evolution model considering the ecosystem of product evolution using an ABSM. By expanding previous models that focused on the performance of firms and market changes driven by changes in the consumer's behavior, the model proposed in this chapter considers the logic of product evolution based on interactions between agents in the environment. The model proposed herein contributes to the simulation of the industrial policy to manage changes in the industrial environment considering the factors that affect product change. Finally, this study supports policy-makers in proposing industrial and market policies that would be suitable for stimulating changes in the industry through a consideration of the effects of the capabilities of new entrants and consumers on the emergence of a new industry.

This study proposes a parsimonious product evolution model in ceteris paribus. For this reason, this model is limited in considering economic parameters such as production function, cost, profit and revenue, and investment. Therefore, although the model is suitable for investigating meso-level changes in response to micro-level dynamics, it is difficult to predict macro-level dynamics. Next, due to the limitations of this model as a theoretical construct, it does not consider the characteristics of products by industry. The complexity of products can vary from industry to industry, with implications for difficulties in imitation and innovation. Finally, this study does not take into account regulation and network externality effects because it is conducted within a framework that restricts the product evolution system to firms and consumers. Future research needs to be extended to empirical studies that take into consideration the characteristics of each industry by adding simulation modules not considered in this study.

Chapter 6. Conclusion

6.1 Summary of the study

This research investigates the evolutionary patterns that occur in the product market and identifies the driving forces for the emergence of industrial change.

Chapter 2 summarizes the underlying concepts and evolutionary patterns and analyzes the factors that affect the patterns of product evolution. First, it summarizes the concepts discussed in studies of biological evolution, and reviews existing studies to identify product evolution by applying evolutionary principles. Based on the results of the review, the concepts of a gene and the evolutionary process are defined by considering the product evolution system. Next, the environment of product evolution is defined from a system-based view. Furthermore, in order to construct a simulation model for investigating the components affecting evolutionary patterns, previous simulation models are reviewed in terms of the definitions of agents, simulation techniques, and the targeted evolutionary process. Finally, based on the outcomes of the review, possible research questions are suggested.

Chapter 3 proposes a quantitative index that can confirm each evolutionary principle and apply it to the case of the mobile phone industry to investigate whether the proposed evolutionary principle works to explain the evolution of mobile phones. The proposed evolutionary principles are expected to be used as a method to predict product evolution patterns in the system to which the product belongs.

Chapter 4 proposes a way to predict episodic change, one of the product evolutionary principles. Of the four episodic events addressed in biological evolution studies, three events before an episodic change are defined as precursors of an episodic change. The environment in which the product evolves includes firms, consumers, and other environmental variables. Therefore, the mechanism of an episodic event is defined as a change in technology, product differentiation, and a change in a company that produces a product. Episodic events are identified by applying the definition of an episodic event to the case study of how the feature phone evolved into the smartphone in the mobile phone industry. This suggests that episodic events, which are precursors of episodic change, can be used to predict changes in industry in the process of product evolution.

Chapter 5 explores the effect of consumers' imperfect information and firm's capabilities on the emergence of episodic change using an agent-based model. Firms are divided into those who have experience developing products and those who do not. Firms with product development experience are divided into incumbents that are active in the existing industry and diversifying firms that have entered a new industry while they operate in other industries. The interaction of these firms and consumers is likely to generate episodic events, and the simulation model confirms the impact of the capabilities of the two agents on the patterns of episodic event emergence. Consumers' imperfect information is operationalized by limiting the number of products among which they choose. Consumers determine the viability of the products that firms create. If consumers evaluate all products and choose them based on the results, then the product with the best functionality is likely to survive. In contrast, in environments where consumers cannot evaluate all products, the probability of survival for products with a lower level of functionality among the products included in the consideration set of consumers increases. In this environment, this study confirms that imperfect information of consumers plays a role in triggering episodic change. Finally, this research proposes industrial and market policies that governments should pursue to encourage episodic events in order to foster industries in a sustainable manner.

6.2 Implications

This research contributes to the field by addressing the evolutionary patterns of products and applying relevant indicators to the mobile phone industry to confirm the emergence of industry-level changes following the accumulation of evolutionary patterns.

First, this research yields insights into the black box of industrial change and proposes an operational definition of the evolutionary patterns caused by the accumulation of technology, product, and industrial changes. Previous research on forecasting has proposed changes in the technology field and sequential changes as characteristic of industrial change. However, previous studies have not discussed the dynamics that occur during the evolutionary process. Furthermore, even though previous research has proposed evolutionary patterns of products, it has merely presented qualitative case studies on the product market, rather than investigating the evolutionary patterns within a single product market through a quantitative approach. To overcome this limitation, this study operationalizes the definition of evolutionary patterns of the products using quantitative measures.

Second, this study contributes by extending the discussion on the role of firms' pre-entry experience. Previous research on pre-entry experience has focused on investigating whether a new entrant with pre-entry experience is likely to survive after the emergence of a new sector. Even though it has been discussed that new technological and product innovations, from which industrial shifts emerge, are caused by new entrants, previous research has not clarified how a new entrant with pre-entry experience contributes to the emergence of a new industry. Furthermore, pre-entry experience analyzed in this study is divided into implementation experience and design experience. Even though previous researchers have argued that pre-entry experience has a positive impact on industrial change and a firm's performance, the contribution of each type of experience has not been addressed. The findings of this study show that both types of experience are significant in the emergence of episodic change, but the synergy between the two experiences has a negative impact on hastening the occurrence of industrial change.

Third, this study also extends the discussion on the impact of the constrained consumer's capability on the emergence of a new industry. In particular, imperfect information on the product models in the market has been ignored. By applying the condition of imperfect information in the simulation study for the emergence of the episodic change, it is shown that imperfect information is more effective in promoting episodic change when a start-up enters the industry than in the perfect information regime.

Fourth, this study proposes a parsimonious ABSM for product evolution, by simplifying the decision-making process in the new product development and production stages. Existing models have only partially focused on the evolutionary process. Considering both the variation process by firms and the selection process by firms and consumers, the model suggested in this study accounts for the whole evolutionary process, which helps to investigate and predict industrial change. This model is also considered as a cornerstone that links micro-level phenomena, including changes in innovation routines and organizational routines, and meso- and macro-level changes such as economic growth by calculating the likelihood of the emergence of a new growth engine.

Last but not least, this study helps policy-makers analyze industries and predict industrial change, especially the emergence of new industries. This is vital because product evolution affects the decision-making of firms and consumers and the changes that occur through product evolution lead to the emergence of new industries. By analyzing the evolutionary patterns that occur in an industry, the current status of that industry can be identified and the agents in the ecosystem of product evolution, including the government, can predict the emergence of new technologies, product categories, and industries.

Technology development is fast and various products are being released to the market, but product innovation cannot lead to industry-level and further innovations if it does not take consumers' preferences into consideration. Analyzing the evolutionary patterns of products, which are the interface between companies and consumers, is important for policy-makers, as well as new product development managers. These evolutionary patterns can show policy-makers how the adoption of new technology leads to changes in firms' performance and the composition of the industry by providing historical evidence of such changes, which can be used as a predictor for encouraging the growth of industry and the economy. This study is expected to help establish the direction of industries nurtured by the government.

6.3 Limitations and future studies

This study has three main limitations. First, this research focused on analyzing the three evolutionary patterns that significantly affect the emergence of unexpected changes. Even though eleven evolutionary patterns are proposed in Chapter 2, some of them are seemed to be minor changes that are difficult to be figured out based on data, so the three major evolutionary patterns are operationally defined and investigated through an in-depth analysis, using both empirical research and a simulation model. To overcome the limitations of this research, future studies must consider and discover the applicability of other evolutionary patterns to industrial evolution.

Second, this research conducted an empirical case study on the Korean mobile phone market, analyzing the changes that occurred due to the actions of firms and consumers, and focusing on the episodic change from the feature phone category to the smartphone category. Even though the Korean mobile phone market is a representative example for investigating evolutionary patterns due to its fast-changing characteristics, evolutionary patterns can be differentiated across various product markets. In addition, despite the fact that the smartphone category generates a variety of new product categories, such as the smart watch category in recent years, this study concentrated on explaining micro-level (technological change) to meso-level changes (producer change), because these are the most representative examples in the mobile phone industry. Thus, future research should investigate the error bound of evolutionary patterns across industries and explore whether the emergence of the smart watch industry, as a bifurcation from the mobile phone industry, should be considered as an episodic change.

Furthermore, in the mobile phone industry, other agents such as telecommunication service providers and the government also may play important roles in the emergence of changes, but this research did not take other agents into consideration to simplify and sharpen the model. Future research will need to consider the behavioral changes of other agents that interact with firms and consumers.

Third, this research presents a parsimonious and simple simulation model to investigate unobserved logical patterns in the empirical case study. Even though the model helps to analyze the evolutionary patterns by considering the main factors of product evolution, the model has limitations in investigating macro-level changes caused by the accumulation of micro-level and meso-level changes. To extend the use of the model to investigate the macroscopic changes such as economic development in line with the TEVECON (Saviotti & Pyka, 2013) and SKIN models (Pyka et al., 2009), future research must model the logic of economic development based on economic interactions between agents, which will help to explain the economic development at the national level by considering episodic changes.

Bibliography

Abar, S., Theodoropoulos, G. K., Lemarinier, P., & O'Hare, G. M. P. (2017). Agent based modelling and simulation tools: a review of the state-of-art software. *Computer Science Review*, *24*, 13–33.

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of industrial innovation. *Technology Review*, *80*(7), 40–47.

Abrahamson, E., & Rosenkopf, L. (1997). Social network effects on the extent of innovation diffusion: a computer simulation. *Organization Science*, *8*(3), 289–309.

Achlioptas, D., D'Souza, R. M., & Spencer, J. (2009). Explosive percolation in random networks. *Science*, *323*(5920), 1453–1455.

Adner, R. (2002). When are technologies disruptive? a demand-based view of the emergence of competition. *Strategic Management Journal*, *23*(8), 667–688.

Adner, R., & Levinthal, D. A. (2001). Demand heterogeneity and technology evolution: implications for product and process innovation. *Management Science*, *47*(5), 611–628.

Adner, R., & Levinthal, D. A. (2002). The emergence of emerging technologies. *California Management Review*, *45*(1), 50–66.

Adomavicius, G., Bockstedt, J. C., Gupta, A., & Kauffman, R. J. (2007). Technology roles and paths of influence in an ecosystem model of technology evolution. *Information Technology and Management*, *8*(2), 185–202.

Agarwal, R., Echambadi, R., Franco, A. M., & Sarkar, M. (2004). Knowledge transfer through inheritance: spin-out generation, development, and survival. *Academy of Management Journal*, *47*(4), 501–522.

Aharonson, B. S., & Schilling, M. A. (2016). Mapping the technological landscape: measuring technology distance, technological footprints, and technology evolution. *Research Policy*, *45*(1), 81–96.

Albino, V., Carbonara, N., & Giannoccaro, I. (2006). Innovation in industrial districts: an agent-based simulation model. *International Journal of Production Economics*, *104*(1), 30–45.

Aldrich, H. E., Hodgson, G. M., Hull, D. L., Knudsen, T., Mokyr, J., & Vanberg, V. J. (2008). In defence of generalized Darwinism. *Journal of Evolutionary Economics*, *18*(5), 577–596.

Amábile-Cuevas, C. F., & Chicurel, M. E. (1993). Horizontal gene transfer. *American Scientist*, *81*(4), 332–341.

Andriani, P. (2017). Exaptation, serendipity and aging. *Mechanisms of Ageing and Development*, *163*, 30–35.

Andriani, P., Ali, A., & Mastrogiorgio, M. (2017). Measuring exaptation and its impact on innovation, search, and problem solving. *Organization Science*, *28*(2), 320–338.

Andriani, P., & Carignani, G. (2014). Modular exaptation: a missing link in the synthesis of artificial form. *Research Policy*, *43*(9), 1608–1620.

Andriani, P., & Cattani, G. (2016). Exaptation as source of creativity, innovation, and diversity: introduction to the Special Section. *Industrial and Corporate Change*, *25*(1), 115–131.

Andriani, P., & Cohen, J. (2013). From exaptation to radical niche construction in biological and technological complex systems. *Complexity*, *18*(5), 7–14.

Antonelli, C., & Ferraris, G. (2011). Innovation as an emerging system property: an Agent Based Simulation Model. *Journal of Artificial Societies and Social Simulation*, *14*(2).

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, *99*(394), 116–131.

Arthur, W. B. (2009). *The Nature of Technology: What It Is and How It Evolves*. New York: Free Press.

Avnimelech, G., & Teubal, M. (2006). Creating venture capital industries that co-evolve with high tech : insights from an extended industry life cycle perspective of the Israeli experience. *Research Policy*, *35*(10), 1477–1498.

Ayala, F. J. (2010). Darwin's explanation of design: from natural theology to natural selection. *Infection, Genetics and Evolution*, *10*(6), 839–842.

Baldwin, J. M. (1896a). A new factor in evolution. *American Naturalist*, *30*(354), 441–451.

Baldwin, J. M. (1896b). A new factor in evolution (Continued). *American Naturalist*, *30*(355), 536–553.

Barabási, A. L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., & Vicsek, T. (2002).

Evolution of the social network of scientific collaborations. *Physica A: Statistical Mechanics and Its Applications*, *311*(3–4), 590–614.

Bargigli, L., & Tedeschi, G. (2013). Major trends in agent-based economics. *Journal of Economic Interaction and Coordination*, *8*(2), 211–217.

Basalla, G. (1988). *The Evolution of Technology*. Cambridge, UK: Cambridge University Press.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, *15*(5), 215–227.

Bayus, B. (1994). Are product life cycles really getting shorter? *Journal of Product Innovation Management*, *11*(4), 300–308.

Bayus, B. L. (1998). An analysis of product lifetimes in a technologically dynamic industry. *Management Science*, *44*(6), 763–775.

Beckenbach, F., Daskalakis, M., & Hofmann, D. (2012). Agent-based modelling of novelty creating behavior and sectoral growth effects-linking the creative and the destructive side of innovation. *Journal of Evolutionary Economics*, *22*(3), 513–542.

Beinhocker, E. (2006). *The Origin of Wealth: Evolution, Complexity and the Radical Remaking of Economics*. Boston, MA: Harvard Business School Press.

Bessant, J. (2005). Enabling continuous and discontinuous innovation: learning from the private sector. *Public Money and Management*, *25*(1), 35–42.

Blackburn, D. G. (1998). Reconstructing the evolution of viviparity and placentation. *Journal of Theoretical Biology*, *192*(2), 183–190.

Boero, F. (1996). Episodic events: their relevance to ecology and evolution. *Marine Ecology*, *17*(1–3), 237–250.

Bohlmann, J. D., Calantone, R. J., & Zhao, M. (2010). The effects of market network heterogeneity on innovation diffusion: an agent-based modeling approach. *Journal of Product Innovation Management*, *27*(5), 741–760.

Brouillat, E. (2015). Live fast, die young? Investigating product life spans and obsolescence in an agent-based model. *Journal of Evolutionary Economics*, *25*(2), 447–473.

Brownlie, D. T. (1992). The role of technology forecasting and planning: formulating business strategy. *Industrial Management & Data Systems*, *92*(2), 3–16.

Butler, S. (1872). *Erewhon*. Harmondsworth, England: Penguin Books.

Calabrese, A., Costa, R., Levialdi, N., & Menichini, T. (2019). Integrating sustainability into strategic decision-making: a fuzzy AHP method for the selection of relevant sustainability issues. *Technological Forecasting & Social Change*, *139*, 155–168.

Campbell, D. (1960). Blind variation and selective retention in creative thought as in other knowledge processes. *Psychological Review*, *67*(6), 380–400.

Campbell, D. (1965). Variation and selective retention in socio-cultural evolution. In H. R. Barringer, G. I. Blanksten, & R. W. Mack (Eds.), *Social Change in Developing Areas: A Re-interpretation of Evolutionary Theory* (pp. 19–49). Cambridge, MA: Schenkman.

Campbell, R. S. (1983). Patent trends as a technological forecasting tool. *World Patent*

Information, *5*(3), 137–143.

Carignani, G., Cattani, G., & Zaina, G. (2019). Evolutionary chimeras: a Woesian perspective of radical innovation. *Industrial and Corporate Change*, *28*(3), 511–528.

Cartier, M. (2004). An agent-based model of innovation emergence in organizations: Renault and Ford through the lens of evolutionism. *Computational and Mathematical Organization Theory*, *10*(2), 147–153.

Castaldi, C., Fontana, R., & Nuvolari, A. (2009). "Chariots of fire": the evolution of tank technology, 1915-1945. *Journal of Evolutionary Economics*, *19*(4), 545–566.

Cefis, E., & Marsili, O. (2005). A matter of life and death: innovation and firm survival. *Industrial and Corporate Change*, *14*(6), 1167–1192.

Chandy, R. K., & Tellis, G. J. (1998). Organizing for radical product innovation: the overlooked role of willingness to cannibalize. *Journal of Marketing Research*, *35*(4), 474–487.

Chandy, R. K., & Tellis, G. J. (2000). The incumbent's curse? incumbency, size, and radical product innovation. *Journal of Marketing*, *64*(3), 1–17.

Chang, S. Bin. (2012). Using patent analysis to establish technological position: two different strategic approaches. *Technological Forecasting and Social Change*, *79*(1), 3–15.

Chen, P.-L., Williams, C., & Agarwal, R. (2012). Growing pains: pre-entry experience and the challenge of transition to incumbency. *Strategic Management Journal*, *33*, 252–276.

Chen, W., Liu, H., & Xu, D. (2018). Dynamic pricing strategies for perishable product in a competitive multi-agent retailers market. *Journal of Artificial Societies and Social Simulation*, *21*(2).

Cho, Y. Y., Jeong, G. H., & Kim, S. H. (1991). A Delphi technology forecasting approach using a semi-Markov concept. *Technological Forecasting and Social Change*, *40*(3), 273–287.

Cho, Y., Yoon, S. P., & Kim, K. S. (2016). An industrial technology roadmap for supporting public R&D planning. *Technological Forecasting and Social Change*, *107*, 1–12.

Choi, H., Kim, S.-H., & Lee, J. (2010). Role of network structure and network effects in diffusion of innovations. *Industrial Marketing Management*, *39*(1), 170–177.

Christensen, C. (1997a). Patterns in the evolution of product competition. *European Management Journal*, *15*(2), 117–127.

Christensen, C. (1997b). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Boston, MA: Harvard Business Review Press.

Christensen, C., Raynor, M. E., & McDonald, R. (2015). What is Disruptive Innovation? *Harvard Business Review*, *93*(12), 44–53.

Christensen, C., & Rosenbloom, R. (1995). Explaining the attacker's advantage: technological paradigms, organizational dynamics, and the value network. *Research Policy*, *24*(2), 233–257.

Chun, H., Lee, H., & Kim, D. (2012). The integrated model of smartphone adoption:

hedonic and utilitarian value perceptions of smartphones among Korean college students. *Cyberpsychology, Behavior and Social Networking*, *15*(9), 473–479.

Ciarli, T., Lorentz, A., Savona, M., & Valente, M. (2010). The effect of consumption and production structure on growth and distribution. A micro to macro model. *Metroeconomica*, *61*(1), 180–218.

Coccia, M. (2016). Radical innovations as drivers of breakthroughs: characteristics and properties of the management of technology leading to superior organisational performance in the discovery process of R&D labs. *Technology Analysis and Strategic Management*, *28*(4), 381–395.

Coccia, M. (2018). A theory of classification and evolution of technologies within a Generalised Darwinism. *Technology Analysis and Strategic Management*, *0*(0), 1–15.

Coccia, M., & Wang, L. (2015). Path-breaking directions of nanotechnology-based chemotherapy and molecular cancer therapy. *Technological Forecasting and Social Change*, *94*, 155–169.

Constant, E. (1980). *The Origins of the Turbojet Revolution*. Baltimore, MD: Johns Hopkins.

Cooper, R. G. (1994). Perspective third-generation new product processes. *The Journal of Product Innovation Management*, *11*(1), 3–14.

Cordes, C. (2006). Darwinism in economics: from analogy to continuity. *Journal of Evolutionary Economics*, *16*(5), 529–541.

Courville, L., & Hausman, W. (1979). Warranty scope and reliability under imperfect information and alternative market structures. *Journal of Business*, *52*(3), 361–378.

da Silveira Junior, L. A. B., Vasconcellos, E., Vasconcellos Guedes, L., Costa, R. M., & Guedes, L. F. A. (2018). Technology roadmapping: a methodological proposition to refine Delphi results. *Technological Forecasting and Social Change*, *126*, 194–206.

Daim, T. U., Rueda, G., Martin, H., & Gerdsri, P. (2006). Forecasting emerging technologies: use of bibliometrics and patent analysis. *Technological Forecasting and Social Change*, *73*(8), 981–1012.

Darvishi, M., & Ahmadi, G. (2014). Validation techniques of agent based modelling for geospatial simulations. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *40*(2W3), 91–95. Tehran, Iran.

Darwin, C. (1859). *The Origin of Species*. London: John Murray.

Davies, A. (1997). The life cycle of a complex product system. *International Journal of Innovation Management*, *1*(3), 229–256.

Davis, C., & Tomoda, Y. (2018). Competing incremental and breakthrough innovation in a model of product evolution. *Journal of Economics*, *123*(3), 225–247.

Dawkins, R. (1976). *The Selfish Gene*. Oxford: Oxford University Press.

Dawkins, R. (1983). Universal Darwinism. In D. S. Bendall (Ed.), *Evolution from molecules to man* (pp. 403–425). Cambridge, MA: Cambridge University Press.

Dawkins, R. (2006). *The Selfish Gene* (30th anniv). Oxford: Oxford University Press.

Delre, S. A., Jager, W., Bijmolt, T. H. A., & Janssen, M. A. (2007). Targeting and timing promotional activities: an agent-based model for the takeoff of new products. *Journal of Business Research*, *60*(8), 826–835.

Delre, S. A., Jager, W., Bijmolt, T. H. A., & Janssen, M. A. (2010). Will it spread or not? The effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management*, *27*(2), 267–282.

Delre, S. A., Jager, W., & Janssen, M. A. (2007). Diffusion dynamics in small-world networks with heterogeneous consumers. *Computational and Mathematical Organization Theory*, *13*(2), 185–202.

Dennett, D. (1995). Darwin's dangerous idea. *The Sciences*, *35*(3), 34–40.

Desouza, K. C., Awazu, Y., & Ramaprasad, A. (2007). Modifications and innovations to technology artifacts. *Technovation*, *27*(4), 204–220.

Devezas, T. C. (2005). Evolutionary theory of technological change: state-of-the-art and new approaches. *Technological Forecasting and Social Change*, *72*(9), 1137–1152.

Dew, N., & Sarasvathy, S. D. (2016). Exaptation and niche construction: behavioral insights for an evolutionary theory. *Industrial & Corporate Change*, *25*(1), 167–179.

Dewenter, R., Haucap, J., Luther, R., & Rötzel, P. (2007). Hedonic prices in the German market for mobile phones. *Telecommunications Policy*, *31*(1), 4–13.

Dosi, G. (1982). Technological paradigms and technological trajectories. *Research Policy*, *11*(3), 147–162.

Dosi, G., & Nelson, R. R. (2010). Technical change and industrial dynamics as evolutionary processes. In *Handbook of the Economics of Innovation* (Vol 1., pp. 51–127). North-Holland, Amsterdam.

Duan, W., & Chen, Z. (2007). Key factor to drive success of new product with network effects: product quality or installed base? *Systems Engineering - Theory & Practice*, *27*(7), 144–148.

Dutrénit, G., & Teubal, M. (2011). Coevolution, emergence and economic development:some lessons from the Israeli and Mexican experience. In C. Antonelli (Ed.), *Handbook on the Economic Complexity of Technological Change* (pp. 451–491). Cheltenham, UK: Edward Elgar Publishing.

Eldredge, N., & Gould, S. J. (1972). Punctuated equilibria: an alternative to phyletic gradualism. In T. J. M. Schopf (Ed.), *Models in Paleobiology* (pp. 82–115). San Francisco: Freeman, Cooper and Co.

Erdos, P., & Renyi, A. (1960). On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Sciences*, *5*, 17–61.

Ettlie, J. E., & Rubenstein, A. H. (1987). Firm size and product innovation. *Journal of Product Innovation Management*, *4*(2), 89–108.

Fioretti, G. (2013). Agent-based simulation models in organization science. *Organizational Research Methods*, *16*(2), 227–242.

Fontana, R. (2011). Technological disequilibrium. Price indexes in hubs for Local Area Networks. *Telecommunications Policy*, *35*(1), 64–73.

Fontana, R., & Nesta, L. (2009). Product innovation and survival in a high-tech industry.

Review of Industrial Organization, *34*(4), 287–306.

Frenken, K. (2000). A complexity approach to innovation networks. The case of the aircraft industry (1909-1997). *Research Policy*, *29*(2), 257–272.

Frenken, K. (2006). *Innovation, Evolution and Complexity Theory*. Cheltenham, UK: Edward Elgar Publishing.

Frenken, K., Saviotti, P. P., & Trommetter, M. (1999). Variety and niche creation in aircraft, helicopters, motorcycles and microcomputers. *Research Policy*, *28*(5), 469–488.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5), 685–697.

Gal-Or, E. (1985). First mover and second mover advantages. *International Economic Review*, *26*(3), 649–653.

Ganco, M. (2017). NK model as a representation of innovative search. *Research Policy*, *46*(10), 1783–1800.

Garas, A., & Lapatinas, A. (2017). The role of consumer networks in firms' multi-characteristics competition and market share inequality. *Structural Change and Economic Dynamics*, *43*, 76–86.

Garcia-swartz, D. D., & Garcia-vicente, F. (2015). Network effects on the iPhone platform: an empirical examination. *Telecommunications Policy*, *39*(10), 877–895.

Garcia, R. (2005). Uses of agent‐ based modeling in innovation/new product development research. *Journal of Product Innovation Management*, *22*(5), 380–398.

Garud, R., Gehman, J., & Giuliani, A. P. (2016). Technological exaptation: a narrative approach. *Industrial and Corporate Change*, *25*(1), 149–166.

Gavetti, G., & Levinthal, D. A. (2000). Looking forward and looking backward: cognitive and experiential search. *Administrative Science Quaterly*, *45*(1), 113–137.

Gersick, C. T. G. (1991). Revolutionary change theories: a multilevel exploration of the punctuated equilibrium paradigm. *Academy of Management Review*, *16*(1), 10–36.

Gilfillan, S. C. (1935). *The Sociology of Invention*. Cambridge, MA: MIT Press.

Gilley, A., McMillan, H. S., & Gilley, J. W. (2009). Organizational change and characteristics of leadership effectiveness. *Journal of Leadership and Organizational Studies*, *16*(1), 38–47.

Glynn, P. W., & de Weerdt, W. H. (1991). Elimination of two reef-building hydrocorals following the 1982-83 El Niño warming event. *Science*, *253*(5015), 69–71.

Goldberg, V. (1974). The economics of product safety and imperfect information. *The Bell Journal of Economics and Management Science*, *5*(2), 683–688.

Goldenberg, J., & Efroni, S. (2001). Using cellular automata modeling of the emergence of innovations. *Technological Forecasting and Social Change*, *68*(3), 293–308.

Goldenberg, J., Libai, B., & Muller, E. (2010). The chilling effects of network externalities: perspectives and conclusions. *International Journal of Research in Marketing*, *27*(1), 22–24.

Gómez-Cruz, N. A., Loaiza Saa, I., & Ortega Hurtado, F. F. (2017). Agent-based simulation in management and organizational studies: a survey. *European Journal* *of Management and Business Economics*, *26*(3), 313–328.

Gould, S. J. (1991). Exaptation: a crucial tool for an evolutionary psychology. *Journal of Social Issues*, *47*(3), 43–65.

Gould, S. J. (2002). *The Structure of Evolutionary Theory*. Cambridge, MA: Harvard University Press.

Gould, S. J., & Eldredge, N. (1977). Punctuated equilibria: the tempo and mode of evolution reconsidered. *Paleobiology*, *3*(2), 115–151.

Gould, S. J., & Vrba, E. S. (1982). Exaptation-a missing term in the science of form. *Paleobiology*, *8*(1), 4–15.

Griffin, J. J., & Prakash, A. (2014). Corporate responsibility: initiatives and mechanisms. *Business and Society*, *53*(4), 465–482.

Grodal, S., & Suarez, F. F. (2015). The coevolution of technologies and categories during industry emergence. *Academy of Management Review*, *40*(3), 423–445.

Günther, M. (2016). Diffusion of multiple technology generations: an agent-based simulation approach. *2016 Portland International Conference on Management of Engineering and Technology (PICMET)*, 2931–2940. Honolulu, HI: IEEE.

Guseo, R., & Guidolin, M. (2009). Modelling a dynamic market potential: a class of automata networks for diffusion of innovations. *Technological Forecasting and Social Change*, *76*(6), 806–820.

Guseo, R., & Guidolin, M. (2010). Cellular Automata with network incubation in information technology diffusion. *Physica A: Statistical Mechanics and Its*

Applications, *389*(12), 2422–2433.

Hameri, A. P. (1996). Technology transfer between basic research and industry. *Technovation*, *16*(2), 51–57.

Heinrich, T. (2016). A discontinuity model of technological change: catastrophe theory and network structure. *Computational Economics*, *51*(3), 407–425.

Helfat, C. E., & Lieberman, M. B. (2002). The birth of capabilities: market entry and the importance of pre-history. *Industrial and Corporate Change*, *11*(4), 725–760.

Henderson, R. (1993). Underinvestment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry. *The RAND Journal of Economics*, *24*(2), 248–270.

Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, *35*(1), 9–30.

Heylighen, F. (2007). Accelerating socio-technological evolution: from ephemeralization and stigmergy to the global brain. *Globalization as Evolutionary Process: Modeling Global Change*, (1), 284–309.

Hirshleifer, J. (1973). Where are we in the theory of information? *American Economic Review*, *63*(2), 31–39.

Hodgson, G. M. (2002). Darwinism in economics: from analogy to ontology. *Journal of Evolutionary Economics*, *12*(3), 259–281.

Hodgson, G. M. (2005). Generalizing Darwinism to social evolution: some early attempts.

Journal of Economic Issues, *39*(4), 899–914.

Holme, P., & Newman, M. E. J. (2006). Nonequilibrium phase transition in the coevolution of networks and opinions. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, *74*(5), 1–5.

Hu, H., Lin, J., Qian, Y., & Sun, J. (2018). Strategies for new product diffusion: whom and how to target? *Journal of Business Research*, *83*(October 2017), 111–119.

Huenteler, J., Ossenbrink, J., Schmidt, T. S., & Hoffmann, V. H. (2016). How a product's design hierarchy shapes the evolution of technological knowledge—evidence from patent-citation networks in wind power. *Research Policy*, *45*(6), 1195–1217.

Hull, D. (1988). *Science as a Process: An Evolutionary Account of the Social and Conceptual Development of Science*. Chicago: University of Chicago Press.

Ioannidis, C., & Silver, M. (1999). Estimating exact hedonic indexes: an application to UK television sets. *Journal of Economics-Zeitschrift Fur Nationalokonomie*, *69*(1), 71–94.

Ioannidis, C., & Silver, M. (2003). Chained, exact and superlative hedonic price changes: estimates from microdata. *Applied Economics*, *35*(9), 1005–1014.

Jablonka, E. (2003). Lamarckian inheritance systems in biology: a source of metaphors and models in technological evolution. In J. Ziman (Ed.), *Technological Innovation as an Evolutionary Process* (pp. 27–40). Cambridge: Cambridge University Press.

Jablonka, E., & Ziman, J. (2003). Biological evolution: processes and phenomena. In J. Ziman (Ed.), *Technological Innovation as an Evolutionary Process* (pp. 13–26).

Cambridge: Cambridge University Press.

Jain, R., Rivera, M. C., & Lake, J. A. (1999). Horizontal gene transfer among genomes: the complexity hypothesis. *Proceedings of the National Academy of Sciences of the United States of America*, *96*(7), 3801–3806.

Jiang, G., Ma, F., Shang, J., & Chau, P. Y. K. (2014). Evolution of knowledge sharing behavior in social commerce: an agent-based computational approach. *Information Sciences*, *278*, 250–266.

Jin, G., Jeong, Y., & Yoon, B. (2014). Technology-driven roadmaps for identifying new product/market opportunities: use of text mining and quality function deployment. *Advanced Engineering Informatics*, *29*(1), 126–138.

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology*, *52*, 166–182.

Kauffman, S. A., & Macready, W. (1995). Technological evolution and adaptive organizations: ideas from biology may find applications in economics. *Complexity*, *1*(2), 26–43.

Kauffman, S., & Levin, S. (1987). Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology*, *128*(1), 11–45.

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, *20*(2), 183–230.

Kim, K., & Altmann, J. (2013). Evolution of the software-as-a-service innovation system through collective intelligence. *International Journal of Cooperative Information Systems*, *22*(3), 1340006 (25pages).

Kim, K., Lee, W.-R., & Altmann, J. (2015). SNA-based innovation trend analysis in software service networks. *Electron Markets*, *25*(1), 61–72.

Kim, S. T., Hong, S. R., & Kim, C. O. (2014). Product attribute design using an agent-based simulation of an artificial market. *International Journal of Simulation Modelling*, *13*(3), 288–299.

Kivi, A., Smura, T., & Töyli, J. (2012). Technology product evolution and the diffusion of new product features. *Technological Forecasting and Social Change*, *79*(1), 107–126.

Klingebiel, R., & Joseph, J. (2016). Entry timing and innovation strategy in feature phones. *Strategic Management Journal*, *37*(6), 1002–1020.

König, M. D., Battiston, S., Napoletano, M., & Schweitzer, F. (2011). Recombinant knowledge and the evolution of innovation networks. *Journal of Economic Behavior and Organization*, *79*(3), 145–164.

Korzinov, V., & Savin, I. (2017). General Purpose Technologies as an emergent property. *Technological Forecasting and Social Change*, *129*, 88–104.

Koski, H., & Kretschmer, T. (2007). Innovation and dominant design in mobile telephony. *Industry and Innovation*, *14*(3), 305–324.

Kuhn, T. (1962). *The Structure of Scientific Revolutions*. Chicago, IL: University of

Chicago Press.

Kwon, S., & Motohashi, K. (2017). How institutional arrangements in the National Innovation System affect industrial competitiveness: a study of Japan and the U.S. with multiagent simulation. *Technological Forecasting & Social Change*, *115*, 221–235.

Laciana, C. E., & Oteiza-Aguirre, N. (2014). An agent based multi-optional model for the diffusion of innovations. *Physica A: Statistical Mechanics and Its Applications*, *394*, 254–265.

Laciana, C. E., Rovere, S. L., & Podestá, G. P. (2013). Exploring associations between micro-level models of innovation diffusion and emerging macro-level adoption patterns. *Physica A: Statistical Mechanics and Its Applications*, *392*(8), 1873–1884.

Lancaster, K. (1979). *Variety, Equity, and Efficiency: Product Variety in an Industrial Society*. New York: Columbia University Press.

Lee, E., Lee, J., & Lee, J. (2006). Reconsideration of the winner-take-all hypothesis: complex networks and local bias. *Management Science*, *52*(12), 1838–1848.

Lee, H., Lim, J., Lee, K., & Kim, C. O. (2018). Agent simulation-based ordinal optimisation for new product design. *Journal of the Operational Research Society*, 1–14.

Lee, J., Baek, C., Maliphol, S., & Yeon, J. (2019). Middle innovation trap. *Foresight and STI Governance*, *13*(1), 6–18.

Lee, K., Lee, H., & Kim, C. O. (2014). Pricing and timing strategies for new product using agent-based simulation of behavioural consumers. *Journal of Artificial Societies and Social Simulation*, *17*(2), 1–19.

Leifer, R., O ’connor, G. C., & Rice, M. (2001). Implementing radical innovation in mature firms: the role of hubs. *Academy of Management Executive*, *15*(3), 102–113.

Levinthal, D. A. (1998). The slow pace of rapid technological change: gradualism and punctuation in technological change. *Industrial and Corporate Change*, *7*(1985), 217–248.

Lewontin, R. C. (1970). The units of selection. *Annual Review of Ecology and Systematics*, *1*, 1–18.

Lieberman, M. B., & Montgomery, D. B. (1988). First-mover advantages. *Strategic Management Journal*, *9*(S1), 41–58.

Lim, S. L., Bentley, P. J., & Ishikawa, F. (2016). The effects of developer dynamics on fitness in an evolutionary ecosystem model of the App Store. *IEEE Transactions on Evolutionary Computation*, *20*(4), 529–545.

Lin, M., & Li, N. (2010). Scale-free network provides an optimal pattern for knowledge transfer. *Physica A: Statistical Mechanics and Its Applications*, *389*(3), 473–480.

Lin, M., & Wei, J. (2018). The impact of innovation intermediary on knowledge transfer. *Physica A: Statistical Mechanics and Its Applications*, *502*, 21–28.

Lindsey-Mullikin, J., & Grewal, D. (2006). Imperfect information: the persistence of price dispersion on the web. *Journal of the Academy of Marketing Science*, *34*(2), 236–243.

Lyytinen, K., & Newman, M. (2008). Explaining information systems change: a punctuated socio-technical change model. *European Journal of Information Systems*, *17*(6), 589–613.

Ma, T., Grubler, A., & Nakamori, Y. (2009). Modeling technology adoptions for sustainable development under increasing returns, uncertainty, and heterogeneous agents. *European Journal of Operational Research*, *195*(1), 296–306.

Ma, T., & Nakamori, Y. (2005). Agent-based modeling on technological innovation as an evolutionary process. *European Journal of Operational Research*, *166*(3), 741–755.

Macal, C. M. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*, *10*(2), 144–156.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, *4*(3), 151–162.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, *2*(1), 71–87.

Marengo, L., & Valente, M. (2010). Industry dynamics in complex product spaces: an evolutionary model. *Structural Change and Economic Dynamics*, *21*(1), 5–16.

Martis, M. S. (2006). Validation of simulation based models: a theoretical outlook. *Electronic Journal of Business Research Methods*, *4*(1), 39–46.

Merker, B., Morley, I., & Zuidema, W. (2015). Five fundamental constraints on theories of the origins of music. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1664), 20140095–20140095.

Mitchell, W. (1991). Dual clocks: entry order influences on incumbent and newcomer market share and survival when specialized assets retain their value. *Strategic Management Journal*, *12*(2), 85–100.

Mitchell, W., & Singh, K. (1993). Death of the lethargic: effects of expansion into new technical subfields on performance in a firm's base business. *Organization Science*, *4*(2), 152–180.

Mokyr, J. (1990). Punctuated equilibria and technological progress. *American Economic Review*, *80*(2), 350–354.

Mokyr, J. (1991). Evolutionary biology, technological change and economic history. *Bulletin of Economic Research*, *43*(2), 127–149.

Mokyr, J. (1997). Innovation and selection in evolutionary models of technology: some definitional issues. *Conference on Evolutionary Models in Technology*. Wallingford, UK.

Mokyr, J. (2000). *Natural history and economic history: is technological change an evolutionary process?* Chicago.

Mokyr, J. (2003). Evolutionary phenomena in technological change. In J. Ziman (Ed.), *Technological Innovation as an Evolutionary Process* (pp. 52–65). Cambridge: Cambridge University Press.

Murmann, J. P., & Frenken, K. (2006). Toward a systematic framework for research on dominant designs, technological innovations, and industrial change. *Research Policy*, *35*(7), 925–952.

Negahban, A. (2017). Neural networks and agent-based diffusion models. In W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, & E. Page (Eds.), *Proceedings of the 2017 Winter Simulation Conference* (pp. 1407–1418). Las Vegas, NV.

Negahban, A., Yilmaz, L., & Nall, T. (2014). Managing production level in new product diffusion: an agent-based simulation approach. *International Journal of Production Research*, *52*(17), 4950–4966.

Nelson, R. R. (2007). Universal Darwinism and evolutionary social science. *Biology and Philosophy*, *22*, 73–94.

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change*. Cambridge, MA: Harvard University Press.

Nylén, D., & Holmström, J. (2015). Digital innovation strategy: a framework for diagnosing and improving digital product and service innovation. *Business Horizons*, *58*(1), 57–67.

O'Connell, J. (1992). The fine-tuning of a golden ear: high-end audio and the evolutionary model of technology. *Technology and Culture*, *33*(1), 1–37.

Obstfeld, D. (2005). Social networks, the tertius iungens orientation, and involvement in innovation. *Administrative Science Quarterly*, *50*(1), 100–130.

OECD/Eurostat. (2005). *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data, 3rd Edition*. Paris, France: OECD Publishing.

Ohori, K., & Takahashi, S. (2012). Market design for standardization problems with agent-based social simulation. *Journal of Evolutionary Economics*, *22*(1), 49–77.

Oi, W. (1973). The economics of product safety. *The Bell Journal of Economics and Management Science*, *4*(1), 3–28.

Orihata, M., & Watanabe, C. (2000a). Evolutional dynamics of product innovation: the case of consumer electronics. *Technovation*, *20*(8), 437–449.

Orihata, M., & Watanabe, C. (2000b). Interaction between product concept and institutional inducement: a new driver of product innovation. *Technovation*, *20*(1), 11–23.

Otto, K. N., & Wood, K. L. (1998). Product evolution: a reverse engineering and redesign methodology. *Research in Engineering Design*, *10*(4), 226–243.

Oyama, K., Learmonth, G., & Chao, R. (2015). Applying complexity science to new product development: modeling considerations, extensions, and implications. *Journal of Engineering and Technology Management*, *35*, 1–24.

Payson, S. (1995). Product evolution: what it is and how it can be measured. *Eastern Economic Journal*, *21*(2), 247–262.

Payson, S. (1997). Product evolution and the classification of business interest in scientific advances. *Knowledge, Technology & Policy*, *9*(4), 3–26.

Pegoretti, G., Rentocchini, F., & Vittucci Marzetti, G. (2012). An agent-based model of innovation diffusion: network structure and coexistence under different information regimes. *Journal of Economic Interaction and Coordination*, *7*(2), 145–165.

Petroski, H. (1992). *The Evolution of Useful Things: How Everyday Artifacts-From Forks* *and Pins to Paper Clips and Zippers-Came to be as They are*. New York: Vintage Books.

Petruzzelli, A. M., & Savino, T. (2014). Search, recombination, and innovation: lessons from haute cuisine. *Long Range Planning*, *47*(4), 224–238.

Phaal, R. (2004). Technology roadmapping—a planning framework for evolution and revolution. *Technological Forecasting and Social Change*, *71*(1–2), 5–26.

Phillips, F., & Linstone, H. (2016). Key ideas from a 25-year collaboration at technological forecasting & social change. *Technological Forecasting and Social Change*, *105*, 158–166.

Phillips, F., & Su, Y. S. (2009). Advances in evolution and genetics: implications for technology strategy. *Technological Forecasting and Social Change*, *76*(5), 597–607.

Przybyła, P., Sznajd-Weron, K., & Weron, R. (2014). Diffusion of innovation within an agent-based model: spinsons, independence and advertising. *Advances in Complex Systems*, *17*(1), 1450004 (22 pages).

Pyka, A., Gilbert, N., & Ahrweiler, P. (2009). Agent-based modelling of innovation networks—the fairytale of spillover. In A. Pyka & A. Scharnhorst (Eds.), *Innovation Networks* (pp. 101–126). Berlin, Heidelberg: Springer Berlin Heidelberg.

Querbes, A., & Frenken, K. (2017). Evolving user needs and late-mover advantage. *Strategic Organization*, *15*(1), 67–90.

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: guidelines for rigor. *International Journal of Research in Marketing*, *28*(3), 181–193.

Riikonen, A., Smura, T., Kivi, A., & Töyli, J. (2013). Diffusion of mobile handset features: analysis of turning points and stages. *Telecommunications Policy*, *37*(6–7), 563–572.

Rivkin, J. W. (2000). Imitation of complex strategies. *Management Science*, *46*(6), 824–844.

Roozmand, O., Ghasem-Aghaee, N., Hofstede, G. J., Nematbakhsh, M. A., Baraani, A., & Verwaart, T. (2011). Agent-based modeling of consumer decision making process based on power distance and personality. *Knowledge-Based Systems*, *24*(7), 1075–1095.

Rothschild, M. (1973). Models of market organization with imperfect information: a survey. *Journal of Political Economy*, *81*(6), 1283–1308.

Rowe, G., & Wright, G. (1999). The delphi technique as a forecasting tool. *International Journal of Forecasting*, *15*(4), 353–375.

Roy, R., & Cohen, S. K. (2015). Disruption in the US machine tool industry: the role of inhouse users and pre-disruption component experience in firm response. *Research Policy*, *44*(8), 1555–1565.

Salop, S. (1976). Information and monopolistic competition. *American Economic Review*, *66*(2), 240–245.

Saviotti, P. P., & Metcalfe, J. (1984). A theoretical approach to the construction of technological output indicators. *Research Policy*, *13*(3), 141–151.

Saviotti, P. P., & Pyka, A. (2013). From necessities to imaginary worlds: structural change, product quality and economic development. *Technological Forecasting and Social Change*, *80*(8), 1499–1512.

Saviotti, P. P., & Trickett, A. (1992). The evolution of helicopter technology, 1940–1986. *Economics of Innovation and New Technology*, *2*(2), 111–130.

Scaringella, L. (2016). Knowledge, knowledge dynamics, and innovation: exploration of the internationalization of a multinational corporation. *European Journal of Innovation Management*, *19*(3), 337–361.

Schluter, D. (2009). Evidence for ecological speciation and its alternative. *Science*, *323*(5915), 737–741.

Schramm, M. E., Trainor, K. J., Shanker, M., & Hu, M. Y. (2010). An agent-based diffusion model with consumer and brand agents. *Decision Support Systems*, *50*(1), 234–242.

Schubert, C. (2014). “Generalized Darwinism” and the quest for an evolutionary theory of policy-making. *Journal of Evolutionary Economics*, *24*(3), 479–513.

Schumpeter, J. A. (1934). *The Theory of Economic Development*. New Brunswick: NP Transaction Publishers.

Schwartz, A., & Wilde, L. (1985). Product quality and imperfect information. *Review of Economic Studies*, *52*(2), 251–262.

Shibata, T., Yano, M., & Kodama, F. (2005). Empirical analysis of evolution of product architecture. *Research Policy*, *34*(1), 13–31.

Shinde, A., Haghnevis, M., Janssen, M. A., Runger, G. C., & Janakiram, M. (2013).

Scenario analysis of technology products with an agent-based simulation and data mining framework. *International Journal of Innovation and Technology Management*, *10*(5), 1340019.

Silver, M. (2000). Hedonic regressions: an application to VCRs using scanner data. *Omega*, *28*(4), 399–408.

Smaldino, P. E., Janssen, M. A., Hillis, V., & Bednar, J. (2017). Adoption as a social marker: innovation diffusion with outgroup aversion. *Journal of Mathematical Sociology*, *41*(1), 26–45.

Smallwood, D. J., & Conlisk, J. (1979). Product quality in markets where consumers are imperfectly informed. *Quarterly Journal of Economics*, *93*(1), 1–23.

Solé, R., Valverde, S., Casals, M. R., Kauffman, S. A., Farmer, D., & Eldredge, N. (2013). The evolutionary ecology of technological innovations. *Complexity*, *18*(4), 15–27.

Sommer, S. C., & Loch, C. H. (2004). Selectionism and learning in projects with complexity and unforeseeable uncertainty. *Management Science*, *50*(10), 1334–1347.

Sood, A., & Tellis, G. J. (2005). Evolution and radical technological innovation. *Journal of Marketing*, *69*(3), 152–168.

Stiglitz, J. (1979). Equilibrium in product markets with imperfect information. *American Economic Review*, *69*(2), 339–345.

Stummer, C., Kiesling, E., Günther, M., & Vetschera, R. (2015). Innovation diffusion of repeat purchase products in a competitive market: an agent-based simulation approach. *European Journal of Operational Research*, *245*(1), 157–167.

Swann, G. M. P. (2001). The demand for distinction and the evolution of the prestige car. *Journal of Evolutionary Economics*, *11*(1), 59–75.

Szymczyk, M., & Kaminski, B. (2014). Dynamics of innovation diffusion with two step decision process. *Foundations of Computing and Decision Sciences*, *39*(1), 39–53.

Teece, D. J. (1986). Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. *Research Policy*, *15*(6), 285–305.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

ten Broeke, G., van Voorn, G., & Ligtenberg, A. (2016). Which sensitivity analysis method should I use for my agent-based model? *Journal of Artificial Societies and Social Simulation*, *19*(1), 1–35.

Thiele, S., & Weiss, C. (2003). Consumer demand for food diversity: evidence for Germany. *Food Policy*, *28*(2), 99–115.

Usher, A. P. (1954). *A History of Mechanical Inventions*. Cambridge, MA: Harvard University Press.

Utterback, J. M., & Abernathy, W. J. (1975). A dynamic model of process and product innovation. *Omega*, *3*(6), 639–656.

Utterback, J., & Suarez, F. (1993). Innovation, competition, and industry structure. *Research Policy*, *22*(1), 1–21.

Vaghely, I. P., & Julien, P. A. (2010). Are opportunities recognized or constructed? An information perspective on entrepreneurial opportunity identification. *Journal of Business Venturing*, *25*(1), 73–86.

Valverde, S., & Solé, R. (2015). Punctuated equilibrium in the large scale evolution of programming languages. *Journal of Royal Society Interface*, *12*(107), 20150249.

van Eck, P. S., Jager, W., & Leeflang, P. S. H. (2011). Opinion leaders' role in innovation diffusion: a simulation study. *Journal of Product Innovation Management*, *28*(2), 187–203.

Varian, H. R. (1980). A model of sales. *American Economic Review*, *70*(4), 651–659.

Verganti, R. (2008). Design, meanings, and radical innovation: a metamodel and a research agenda. *Journal of Product Innovation Management*, *25*(5), 436–456.

Villani, M., Bonacini, S., Ferrari, D., Serra, R., & Lane, D. (2007). An agent-based model of exaptive processes. *European Management Review*, *4*, 141–151.

Volkenstein, M. V., & Livshits, M. A. (1989). Speciation and bifurcations. *Biosystems*, *23*(1), 1–5.

Wagner, A., & Rosen, W. (2014). Spaces of the possible: universal Darwinism and the wall between technological and biological innovation. *Journal of the Royal Society, Interface*, *11*(97), 1–11.

Wagner, G. P. (2015). Evolutionary innovations and novelties: let us get down to business! *Zoologischer Anzeiger*, *256*, 75–81.

Wall, F. (2016). Agent-based modeling in managerial science: an illustrative survey and study. *Review of Managerial Science*, *10*(1), 135–193.

Wallace, R. (2014). A new formal perspective on "Cambrian explosions." *Comptes Rendus Biologies*, *337*(1), 1–5.

Watanabe, N., Nakajima, R., & Ida, T. (2010). Quality-adjusted prices of Japanese mobile phone handsets and carriers' strategies. *Review of Industrial Organization*, *36*(4), 391–412.

Weick, K. E., & Quinn, R. E. (1999). Organizational change and development. *Annual Review of Psycholgy*, *50*, 361–386.

Wersching, K. (2010). Schumpeterian competition, technological regimes and learning through knowledge spillover. *Journal of Economic Behavior and Organization*, *75*(3), 482–493.

Whyte, L. L. (1964). Internal factors in evolution. *Acta Biotheoretica*, *17*(1), 33–48.

Wi, J. (2006). Organizational behavior of established firms to a disruptive innovation: the case of NEC's behavior in the Japanese laptop computer industry. *Asian Journal of Technology Innovation*, *14*(2), 29–48.

Windrum, P., & Birchenhall, C. (2005). Structural change in the presence of network externalities: a co-evolutionary model of technological successions. *Journal of Evolutionary Economics*, *15*(2), 123–148.

Windrum, P., Diaz, C., & Filiou, D. (2009). Exploring the relationship between technical and service characteristics. *Journal of Evolutionary Economics*, *19*(4), 567–588.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical validation of agent-based models: alternatives and prospects. *Journal of Artificial Societies and Social*

Simulation, *10*(2).

Wirtz, B. W., Mathieu, A., & Schilke, O. (2007). Strategy in high-velocity environments. *Long Range Planning*, *40*(3), 295–313.

Wolf, I., Schröder, T., Neumann, J., & de Haan, G. (2015). Changing minds about electric cars: an empirically grounded agent-based modeling approach. *Technological Forecasting and Social Change*, *94*, 269–285.

Wolinsky, A. (1984). Product differentiation with imperfect information. *The Review of Economic Studies*, *51*(1), 53–61.

Wu, Y. R., Huatuco, L. H., Frizelle, G., & Smart, J. (2013). A method for analysing operational complexity in supply chains. *Journal of the Operational Research Society*, *64*(5), 654–667.

Xiao, Y., & Han, J. (2016). Forecasting new product diffusion with agent-based models. *Technological Forecasting and Social Change*, *105*, 167–178.

Yilmaz, L. (2006). Validation and verification of social processes within agent-based computational organization models. *Computational and Mathematical Organization Theory*, *12*(4), 283–312.

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, *23*(5), 1398–1408.

Zhang, H., & Vorobeychik, Y. (2017). Empirically grounded agent-based models of innovation diffusion: a critical review. *Artificial Intelligence Review*, 1–35.

Zhang, Tao, & Zhang, D. (2007). Agent-based simulation of consumer purchase decision-making and the decoy effect. *Journal of Business Research*, *60*(8), 912–922.

Zhang, Ting, Gensler, S., & Garcia, R. (2011). A study of the diffusion of alternative fuel vehicles: an agent-based modeling approach. *Journal of Product Innovation Management*, *28*(2), 152–168.

Zhong, X., & Ozdemir, S. Z. (2010). Structure, learning, and the speed of innovating: A two-phase model of collective innovation using agent based modeling. *Industrial and Corporate Change*, *19*(5), 1459–1492.

Ziman, J. (2003). *Technological Innovation as an Evolutionary Process*. New York: Cambridge University Press.

Zollo, M., & Winter, S. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, *13*(May 2016), 339–351.

Abstract (Korean)

기술혁신의 발생 주기가 짧아지면서 기술변화와 그에 따른 산업의 변화를 예측하는 것은 점차 어려워지고 있다. 많은 예측 연구들이 기술의 변화를 분석하고, 그로 인한 산업의 탄생과 같은 변화를 파악하였다. 이들은 산업이 변하는 과정에서 기업이 산업에서 성공적으로 생존하기 위한 전략을 제시하려는 시도도 하였다. 그러나 점차 산업을 구성하는 요소들의 복잡성이 증가하면서 산업의 변화를 예측하는 것은 어려워졌다. 이에 기존 연구들에서 제안한 방법 중 하나는 복잡계 시스템의 성질을 보이는 산업에서 나타나는 변화를 생물진화와 유비하여 설명하는 것이다.

생물진화논리 중 하나인 다윈주의는 모든 복잡계의 진화를 설명하는데 도움이 된다. 기존 연구들은 다윈주의의 핵심인 점진적인 변이, 선택, 그리고 전승 프로세스를 제품의 진화프로세스에 적용하기 위한 합의점을 찾으려 노력하였으며, 그 결과, 제품의 진화에 영향을 미치는 행위자로 기업과 소비자를 정의하였다. 기존 연구의 연장선상에서, 본 연구는 제품의 진화과정에서 기업과 소비자의 의사결정루틴이 제품의 발현을 결정하는 유전형이며, 발현된 제품은 표현형으로 정의한다. 유전형과 표현형 간의 상호작용에 의해 나타나는 진화적 패턴을 정의하고, 이를 통해 산업의 변화를 예측할 수 있는 새로운 접근법을 제안하고자 한다.

본 연구의 목적은 제품진화시스템을 정의하고 이를 분석하여 산업의 변화의 동인을 규명하는 것이다. 이와 관련된 연구질문은 다음과 같다. 1) 제품진화시스템으로 제품의 진화 패턴을 도출하여 제품이 속한 산업의 변화 과정을 설명할 수 있는가? 2) 산업의 변화 과정 중, episodic change로 정의되는 새로운 산업으로의 전환의 동인을 어떻게 정의할 수 있는가? 3) 어떠한 역량을 행위자가 새로운 산업으로의 전환을 촉발하는가?

실증 데이터를 기반으로 하는 제품진화 연구는 현상 규명에 집중하기 때문에, 현상이 발생하는 원인을 파악하는데 한계를 보인다. 실증 연구의 한계점을 보완하기 위해, 본 연구는 제품의 진화과정을 행위자기반모형으로 모사하여 제품의 진화 패턴을 확인하고, 시나리오에 따라 산업의 변화가 달라지는 양상을 도출하고자 한다. 행위자기반모형은 기업과 소비자 등과 같은 행위자들의 의사결정과 이들 간 상호작용에 의해 환경이 변하는 과정을 보이는데 적합한 모형이다. 본 연구에서 제안하는 행위자기반모형은 기업과 소비자의 의사결정 루틴과 그들의 역량에 의해 제품이 발현되고, 그 결과가 산업의 변화에 미치는 영향을 규명하고자 한다.

본 연구의 세부 구성은 다음과 같다. 2장에서 제품의 진화 생태계를 정의하고, 진화 생태계 내에서 발생하는 제품의 진화 패턴을 정리한다. 또한 제품진화 프로세스를 모사하는 행위자기반모형을 제시하기 위해 기존의 행위자기반모형에서 다룬 의사결정프로세스를 확인한다. 다음으로 3장에서는 제품진화패턴 중 제품혁신의 우연성을 설명하기 위한 굴절적응, 행위자들 간 공진화를 설명하기 위한 유전 정보 전이, 새로운 산업으로의 전환을 설명하기 위한

episodic change의 조작적 정의를 제시하고, 이를 한국의 휴대폰 사례에 적용하여 규명한다. 4장에서는 episodic change를 추동하는 요인인 episodic event를 기술적변화, 제품의 종분화, 그리고 생산자의 변화로 정의하고, 한국의 휴대폰 산업에서 나타난 episodic event들을 확인한다. 4장의 결과는 휴대폰 산업이 피처폰 산업에서 스마트폰 산업으로 전환될 때 발생한 급격한 변화를 보여주며, 이러한 변화는 누적적인 사건들의 합에 의한 것임을 규명한다. 5장에서는 제품 진화환경의 행위자인 기업과 소비자의 역량이 episodic change의 발생에 미치는 영향을 분석한다. Episodic change에서 신규진입기업의 역할이 중요하기 때문에 기업의 역량은 신규진입자의 사전 경험을 통해 정의되며, 소비자의 역량은 제품 종류에 대한 정보 획득 양으로 정의된다.

본 연구는 제품의 진화 패턴의 조작적 정의를 제시하고, 변화 속도가 가장 빠른 제품 중 하나인 휴대폰의 진화 패턴을 규명하였다. 본 연구에서 생물진화에서 나타나는 일부 패턴들이 제품 진화에 적용가능하다는 것을 도출하였기 때문에, 향후 제품진화과정에서 나타나는 산업의 변화를 분석하는데 진화적 논의가 기여할 수 있음을 시사한다. 특히, 휴대폰 산업에서 피처폰이 스마트폰으로 전환되는 현상을 episodic change임을 확인하고, 전환과정에서 나타난 기술적 변화, 제품의 카테고리의 변화, 그리고 신규진입기업의 출현이 episodic change를 발생시키는 episodic event임을 확인하였다. 또한 제품진화프로세스를 기반으로 한 행위자기반모형을 통해 기업의 사전 경험의 유형과 소비자의 구매 의사결정 역량이 episodic event의 발생에 미치는 영향을 파악하여 산업의 변화를 촉발하기 위한 기업 전략과 산업 정책을 제시하였다. 이는 향후 신산

업육성 및 신산업 창출을 위한 정책을 수립할 때 의사결정을 지원하기 위한 도구로 활용될 수 있을 것으로 기대한다. 또한 제시된 행위자기반 모형은 향후 경제 발전 연구를 위한 시뮬레이션 모형으로도 확장될 수 있으므로, 미시 수준의 복잡계 시뮬레이션을 통해 경제 성장을 설명하는데 기여할 것으로 기대된다.

주요어 : 제품진화, 진화패턴, episodic change, 행위자기반모형, 사전 경험, 정보불완전성
학 번 : 2014-30282