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Three Essays on New Product Innovation and Innovation-Decision Process

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Abstract

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The development and management of a new product is considered the core engine of firm growth. The importance of this fact is even increasing, especially in high-tech industries, because of rapid technological developments, the shortening of product life cycle and intensified international competition. As the product life cycle becomes shorter and shorter, it becomes essential for firms to create and expand the market by developing new products.

Though many researchers have studied how to successfully develop and manage high-tech new products over the last few decades, new product development is still considered as an uncertain area with high risks to firms. This fact reflects that there are still a lot of problems remaining to be solved. By reviewing the previous literatures from innovation and high-tech marketing, three major research problems are found that have not been fully addressed so far. Thus, this dissertation deals with these three main research

problems by proposing three solutions respectively.

The first essay shows the impact of integration of R&D and marketing on new product development success without any parametric assumptions on model specification. In the innovation management context, it has generally been accepted that close integration between R&D and marketing successfully influences the development of an innovative product by stimulating a mutual understanding between people from different departments. However, a few researchers also pointed out that a too close a relationship between R&D personnel and marketing personnel can cause important information to be overlooked, thus reducing likelihood of new product development success. In the first essay, empirical results based on the application of the nonparametric regression method MARS (Multivariate Adaptive Regression Splines) show an even more diverse effect of integrating R&D and marketing if different performance criteria are considered. Marginal response functions with respect to R&D and marketing integration demonstrate that the effect of integration between R&D and marketing is non-constant and nonlinear, a finding that could not be captured with parametric assumptions. Therefore, the first essay provides an overarching explanation for the opposing observations reported in earlier work.

The second essay seeks to describe the dynamic effects of perceived innovation attributes, consumer innovativeness and message characteristics as conditioned by consumer decision-making in the high-tech product adoption. Unfortunately, innovation adoption studies have paid little attention to transition between each decision-making stage. In the second essay, with the proposed research framework based on the theories of

innovation adoption and consumer behavior, the Bayesian multivariate probit model successfully identifies the bottlenecks and drivers influencing consumers' transition between hierarchical decision-making stages. With our survey data set on E-book reader adoption, the empirical analysis shows that complexity is the main bottleneck blocking the adoption of dedicated E-book readers in every decision-making stage (cognitive-affective-behavioral response), whereas observability is the driver stimulating adoption in every stage. Moreover, the relative advantage of dedicated E-book readers is significant only in the affective stage, while compatibility is meaningful only in the behavioral stage. The main implication of the second essay is that this study provides a useful model and guidelines to help marketers implement effective marketing communication strategy depending upon consumers' decision making stage.

The third essay investigates the possible individual-specific transferal process in decision-making through cognitive, affective and conative stages. To this end, a general and flexible Bayesian multivariate regression model based on Gaussian mixture model is proposed and then fitted to a survey data set. As a result of application of the proposed model to survey data set on E-book reader, estimation results show that all paths are feasible transferal process except for the path "conation → cognition → affection". In terms of the market share, the potential market size of standard learning models, the path "cognition → affection → conation", is the biggest whereas the path "affection → conation → cognition" is the lowest. The third essay contributes to the innovation and hi-tech marketing literature along both academic and substantive dimension. Along the academic dimension, this

research developed an estimable model for capturing transferal process in decision-making path. Accordingly, the analysis empirically shows that there exist heterogeneity in individual decision-making path. In substantive domain, marketers are able to obtain insights into the marketing communication strategy for high-tech product by applying the proposed model. Finally, this study demonstrates that the impact of perceived innovation characteristics in high-tech product adoption occasion can be varying according to the one's decision-making path.

Overall, the dissertation has a couple of major contributions for academia and management. The academic contribution of the dissertation is that this proposes and empirically applies effective methodologies to solve major problems related to new product development and innovation adoption management. The managerial contribution of the dissertation is that this provides a strategic guideline for a successful new product development and market management including market segment and corresponding new product positioning strategy.

Keywords: New Product Development; R&D and Marketing Integration; Consumer Decision-Making Process; Multivariate Adaptive Regression Spline Model (MARS); Multivariate Probit Model; Gaussian Mixture Model.

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Chapter 1. Overall Introduction

1.1 Research background

The development and management of a new product is considered the core engine of firm growth. Importance of this matter is increasing, especially in high-tech industries, because of rapid technological developments, the shortening of product life cycle, and intensified international competition. As the product life cycle becomes shorter and shorter, it becomes essential for firms to create or expand the market by developing new products.

As can be experienced, successful new product development and product launch play a key role in achieving high profits in high-tech industries, and several firms are willing to do better. In this context, there have been many discussions regarding which factor has a bigger impact on successful development of new products: technology or market? Most previous studies argued that technology and market are both important factors in the high-tech industry. A new product without sufficient consideration of market demand will lead to failure, and, in the opposite case, it will be hard to implement and realize a product without technology. As a result, to understand both customers' needs and the technological possibility, firms need to have knowledge of both technology and the market.

One reason why strategic management of a new product is so emphasized in the high-tech industry is that the link between technology and marketing in this industry is stronger,

more complex, and more sensitive on performance than in other low-tech industries (Lu & Yang, 2004). As the implementation of marketing strategy needs the understanding of innovative technology, technology development also needs marketing information and knowledge. In the past, it was easier to identify customers' needs through market research and meet them by developing new products. However, recently, customers' needs have become more refined and subdivided. Therefore, the capability to develop new technology to meet customers' hidden needs has become the core competency, and it is now hard to succeed in the market. Because of this reason, strategic management of new product development and launch has become more sophisticated in the high-tech industry.

Another reason for the importance of successful new product development and management in the market in the high-tech industry is that each customer evaluates the value of high-tech products very differently (G. A. Moore, 1991; Reddy, 1997). This characteristic causes customers' response on new high-tech products to be heterogeneous. To restate, the attitude of the customers in the high-tech industry shows a huge variance. We can say that high-tech products are not essential goods, that is, not everyone needs them. For example, for early adaptors who want to increase productivity and differentiate themselves from others, high-tech products can be much more valuable than for others who believe that high-tech products are too complicated or a waste of time (Rogers, 2003). Thus, without an efficient marketing strategy on new product development, it is hard to satisfy the heterogeneous needs of customers and achieve success of the new product in the high-tech industry.

Customers in the high-tech industry show different values over new high-tech products; that is, a few might buy the product, some might not buy because they are not interested, and others may have a huge interest though they do not buy. In some cases, customers buy the product without knowing its functions. This heterogeneity of market response needs to be studied more carefully, and new product development must reflect the results of this study.

McGrath (2000) stated in his book, *Product Strategy for High Technology Companies,* that the role of product strategy in the high-tech industry is much more important and sophisticated than in other industries. However, product strategy on new product development and management is not about simply making a product with better performance; it includes the entire process from the stage in which ideas are gathered to the stage in which marketing message strategies are established. As we have seen, the main factor that differentiates success and failure in the high-tech industry, which has both high technological uncertainty and high market uncertainty, is the capability to fully understand the characteristics of high-tech customers and effectively deliver satisfying products. Therefore, this dissertation will discuss key problems related to successful new product development and management in the high-tech industry, which have not been dealt by others yet. Finally, developing a scientific decision-making model in the new product development and management field will be the focus of this dissertation.

1.2 Problem statement

Although many researchers have studied ways to successfully develop new products and manage them in the market (Ernst, 2002), new product development is still considered an uncertain area with high risks to firms. To restate, a few issues remain that need to be solved. By reviewing the previous studies on product development and management, three main issues are identified, which were not fully answered before and on which this dissertation will focus. These issues are as follows:

First, we must deal with understanding the marginal impact of each resource and capability for improving new product development performance. Previous studies that identified ways to ensure that new products succeed widened the scope of analysis by subdividing the type of industry, country, and culture of the industry and showed that the important resource and capability for product innovation can vary depending on the contingent (Eisend, Evanschitzky, & Calantone, 2016). In this trend, the important resources were identified well. However, in this phase, we need to pay attention to the fact that most of the previous studies used parametric methods to solve the problems empirically. However, such a parametric model cannot explain the change in the marginal impact of significant resource and capability, although this is a very imperative research question. In addition, the model specification based on the parametric model was largely determined by the researchers' prior beliefs, which inherently led to the model misspecification problem. Eventually, the previous studies did not deal properly with resource effectiveness and

included a possibility that suggests mixed or biased results by model misspecification. As an example, several studies interpreted the relation between R&D and marketing integration and new product success: Some studies showed that stronger integration between R&D and marketing leads to stronger performance, however, others argued that proper or optimal level of integration maximizes the performance of new product development. Although this question must be solved to understand and establish a proper level of R&D and marketing integration, it is difficult to suggest an answer using the parametric approach, and therefore the question remains unsolved.

Second, we must understand how to establish an effective marketing strategy to make the customers adopt innovative products by considering their decision-making process. Traditionally, the innovation adoption theory argues that customers follow the "knowledge-persuasion-adoption" flow when they adopt a new innovative product. Consumer psychology literature also explained that customers follow a similar hierarchical flow, and this has been accepted as an established theory. However, little research has been conducted to identify the factors affecting the transition of decision-making stages by statistically modeling the hierarchical decision-making process. Though some papers which studied main factors affecting each adoption stage mentioned that consumer experience sequential decision-making process, they did not successfully reflect the theoretical hierarchical decision-making process in the statistical and empirical model. Thus, statistically modeling consumers' hierarchical decision-making stages and finding the main factors affecting each stage's transition are the key problems.

Third, we must understand how we can position a new product in the market given that each consumer may experience a different decision-making path. Consumer psychologists have believed in the awareness-interest-intention flow for a long time as a process of new product adoption or attitude formation. However, although there is little disagreement among researchers regarding the importance of the three stages of the hierarchy, there has been significant disagreement regarding the order of the stages. Some researchers claimed that, depending on the characteristics of the new product, there can be other possible paths. This has been the area of most intense criticism and debate concerning the hierarchy of effect. Practically, it is important to identify heterogeneous decision-making paths because such information will help firms to establish different new product communication strategies based on the heterogeneity of the decision-making path. Despite the possibility of different decision-making paths within the same product category, little research has been conducted so far to validate the differences in the paths and the corresponding marketing strategies.

1.3 Research objective

Due to the rapid technological developments, the shortening of product life cycle, and intensified international competition, returns on new product development investments are often not satisfactory. In fact, the failure rate can be 50% or more, and this phenomenon becomes more serious in the high-tech industry. Under these circumstances, firms must

carefully establish new product development and diffusion strategies by effectively processing all the information they can gather about consumers, competitors, and market trends. Given this fact, this dissertation will deal with three problems related to strategic decision making on new product development and management.

The dissertation will address the research objective by presenting three essays, which address the three problems respectively.

The first essay aims to find the key success factors of new product development and, more importantly, to analyze the marginal impact of key resource and capabilities. By applying the nonparametric regression method, we will identify key resource variables not by model specification based on the researcher's prior belief but by the MARS model algorithm, which does not require any parametric assumption on model specification. Particularly, we will focus on the effect of R&D and marketing integration, which is one of the most important factors in new product development and yet has many conflicting research results. In addition, we will empirically analyze how R&D and marketing integration, which are under a trade-off relationship, influence the multi-dimensional success of new product development by applying the proposed research framework. Lastly, we will show that there is optimal configuration between the level of R&D and marketing integration and other strategic resources, which maximizes new product performance.

The second essay aims to provide a statistical model for capturing the relationship between factors affecting the innovation adoption and innovation decision processes. Three factors have been regarded conclusively as key components affecting innovation adoption:

product relevant factors, consumer relevant factors, and communication message factors that link the product and consumer. We will identify which factors are critical in the transition between the stages in the innovation adoption context. In summary, as the purchase decision-making process is hierarchical and sequential, the second essay aims to propose a model to detect key factors for a given decision-making stage. To this end, we will empirically apply the proposed model to survey data on a dedicated E-book reader and identify the resistance and driving factors affecting the transition of stages in the innovation adoption.

The third essay aims to provide a model for capturing market segments and product positioning by considering the heterogeneous decision-making paths of consumers. In consumer psychology, it has been widely suspected that consumers may experience heterogeneous decision-making paths rather than the traditional path when formulating attitudes toward a new product. Little empirical research has been conducted so far to identify such heterogeneity in decision-making paths. However, this is an essential research question in both the academic and management domains in order to understand how consumers formulate their positive attitude toward a totally new product and how the attitude can be stimulated by marketing communication messages. By reflecting on this importance, in the third essay, we aim to provide a statistical model that describes consumers' heterogeneous decision-making paths and applies the proposed model to the survey data set. To this end, we will identify possible decision-making paths and suggest which marketing communications are effective with respect to a given decision-making path.

1.4 Research question

Based on the research problem and research objective, three sets of research questions for this dissertation are defined as follows:

First set of research questions with respect to strategic management of R&D and marketing integration for multi-dimensional success of new product development

- Is the effect of integration between R&D and marketing constant and always positive, as stated in the literature?
- If a nonlinear effect is found, what does it look like?
- Is there any significant difference in the integration effect depending upon the criteria of new product development success?

Second set of research questions with respect to strategic management of new product planning considering the stage of the innovation adoption process

- How can we quantitatively identify drivers or bottlenecks affecting the transition of each stage in the innovation decision process?
- Which key factors affect the transition of each stage in innovation adoption?

Third set of research questions with respect to strategic management of new product positioning considering consumer heterogeneity on the decision-making path

- Is there individual heterogeneity in the decision-making path in the innovation

decision process?

- Which paths are reliable and unreliable in innovation adoption?
- In terms of proportion over total market, how many potential consumers follow each segment?
- Which key message strategies stimulate adoption for a given decision-making path in innovation adoption?

1.5 Research outline

This dissertation is composed of six chapters (Figure 1). The following chapter (Chapter 2) is a state-of-the-art review on the theory and practice of the new product development process. Its purpose is primarily to help in understanding new product development and new product adoption mechanisms by referring to key previous studies and their findings.

Chapter 3 (the first essay) is designed to examine the impact of R&D and marketing integration on multi-dimensional new product performance (i.e., the first set of research questions). To do so, this dissertation proposes a theoretical model reflecting the main resource and capability required for the new product development process, empirically estimates the proposed model with the project-level survey data set by using a nonparametric regression model, and graphically shows how R&D and marketing integration contribute to the new product's success through a Monte Carlo simulation.

Chapter 4 (the second essay) intends to provide a statistical model to reflect the

theoretical model about purchase decision making based on a hierarchical response framework and applies it into the survey data (i.e., to address the second set of research questions). Accordingly, this dissertation finds key drivers and bottlenecks depending on the stage. In other words, this essay identifies significant factors to stimulate transition between each decision-making stage.

Chapter 5 (the third essay) is designed to investigate consumers' heterogeneous decision-making paths at the individual level, which have been pointed out critically in previous literature (i.e., to answer the third set of research questions). When considering three different stages explicitly in the decision-making process, six possible paths are suggested without any presumption. This study identifies the reliable paths among them, estimates the market share of each path, and provides a marketing strategy for stimulating positive attitude formation for those who follow each decision-making path.

Finally, chapter 6 summarizes the analysis results by answering the research questions raised in the introduction, addresses the implications and contributions, and finally ends with the limitations and outlook. Besides providing a summary of the research presented in the different chapters of this dissertation, the following Figure 1 also indicates the relationships between the different chapters.

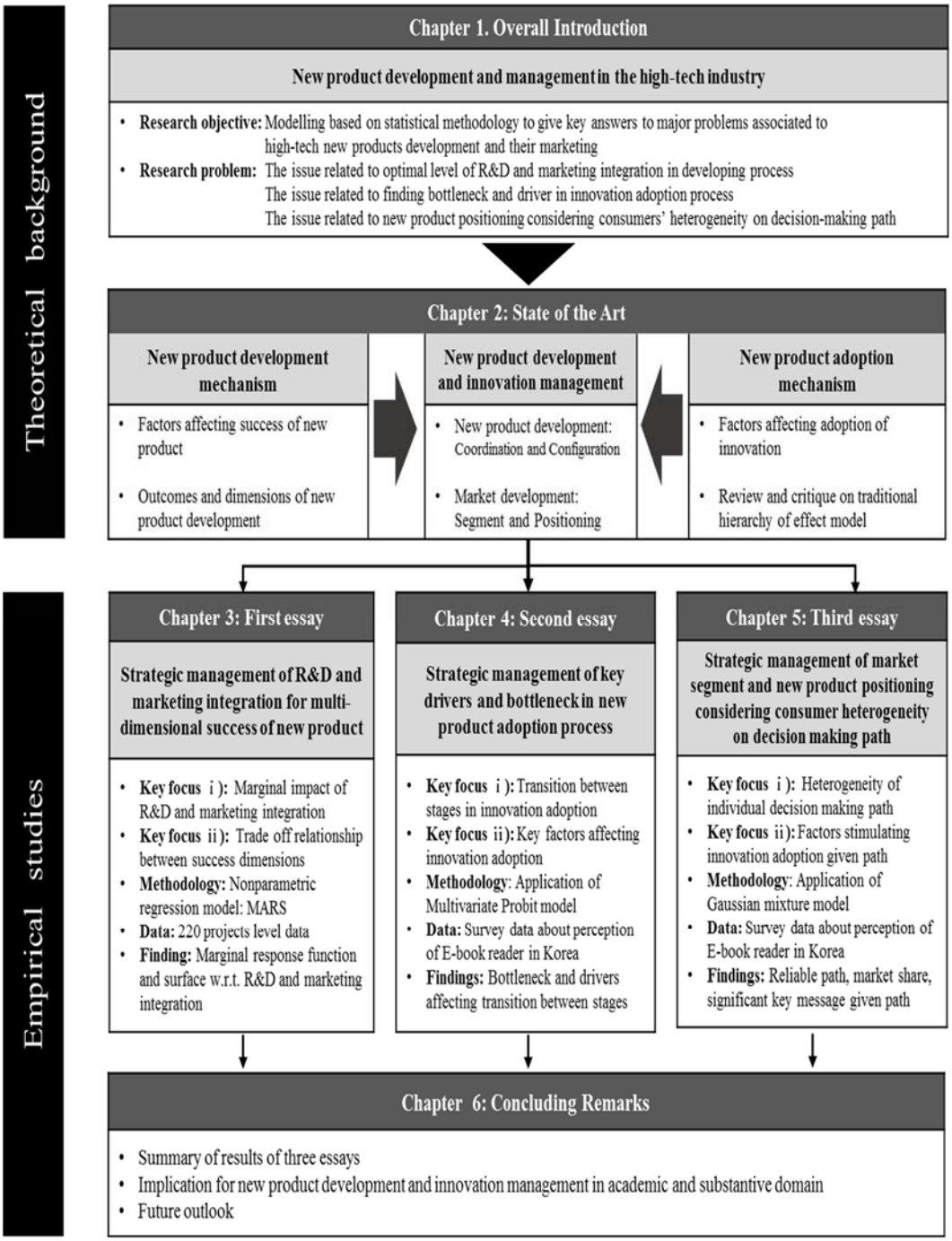


Figure 1. Research outline

Chapter 2. State-of-the-Art Review

2.1 New product development mechanism

2.1.1 Factors affecting success of new product development

Over the last few decades, there have been many studies that compared the success and failure of a newly developed product in order to find key success factors (Ernst, 2002).

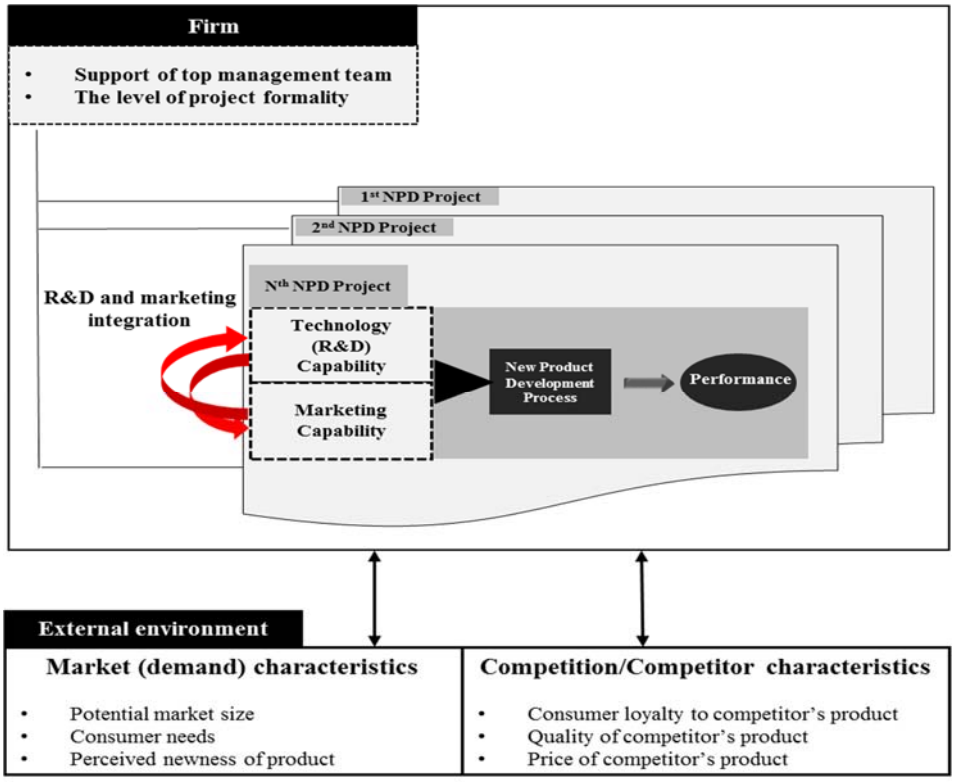


Figure 2. New product development mechanism of firm

Figure 2 describes main factors and the interaction between them, which influence the performance of new product development, based on findings of previous key literatures. The most important factor for the success of new product development is the strategic resource and capability owned by the new product development team. Of all the required resources and capabilities, marketing and technology capability are the most crucial element (Dutta, Narasimhan, & Rajiv, 1999).

Marketing capability is the key answer to following question: "What kind of new product will we make? (Weerawardena, 2003)" The first condition of new product success in the high-tech market is that the new product should meet the consumers' needs. To do this, the target consumer should be set carefully and their needs must be satisfied through the new product idea (Easingwood & Koustelos, 2000). These ideas must be first refined by gathering information of consumer needs. Then, the technology that solves the consumer needs must be found. After the new product is tested and launched in the market, new product team should continuously keep track of whether the benefit of the product is properly providing the requested needs of consumers, throughout the whole product lifecycle. Therefore, the marketing resource and capability inherently includes building up marketing strategy, market research analysis and demand forecasting. For the new product to succeed in the market, the product must not only meet the needs of the consumers but also provide higher utility than the price they pay. To achieve this goal, it is crucial to find what consumers value most, and the capability to understand these consumers' value is the heart of a new product marketing (Krasnikov & Jayachandran, 2008).

The fact that technological capability is the core factor of successful new product development is accepted widely both academically and practically. To restate, technological superiority is necessary to successfully develop a new product. The key components of technological resource and capability that influence new product development performance are R&D investment, R&D management, and all other capabilities that are needed to develop and manufacture prototype of products. The relation between the success of product and the technological capability gets stronger as the product is more innovative and technology-driven (Zhou & Li, 2012). However, the technological superiority does not simply mean possessing a matchless technology. It is true that, when a firm owns matchless technology, it is more likely that the firm might develop a successful new product. But it is more important to develop a product that provides the utility that the consumers want. Therefore, the main factor of successful new product development in technological perspective is whether the firm possesses market-driven technological superiority (Thomke & Von Hippel, 2002).

Though, the capability of the new product development team is very important, it is also known that the capability of the firm level or organization level is also a main factor of successful development. Especially, in the perspective of organization management, the importance of R&D and marketing integration cannot be overemphasized. Since the product development process is a work of collaboration between two departments, information sharing is important to improve the performance of this process. For example, it is possible to lower the uncertainty and stimulate the creativity by increasing the level of

R&D-marketing integration.

What we have to note, however, is that there are pros and cons regarding impact of R&D and marketing integration. William E Souder (1980) argued that if the level of integration is too high, the efficiency of each independent organization might be harmed. Too much integration might cause unnecessary managing cost, and the schedule of the new product development process can be delayed. Since there are both pros and cons of R&D and marketing integration impact, it is natural to question the proper level of integration.

Regarding organizational capabilities, successful new product development needs not only physical and tangible resource but also reasonable planning and execution of each step in the process (Robert G Cooper, 1992). Many studies pointed out that the process and flow of new product development tasks were critically important. In a same vein, it was widely accepted that the performance was higher as each step in the process was official and clear. In addition, there are also studies that highlight the support of top management team as one of the core organizational capabilities (Maidique & Zirger, 1984; Meng, Wei, Wong, & Singh, 1998). In these studies, researchers claimed that the most important factor of successful new product development was the support of top management team, which makes sure the product is launched in the market on time and the product gains technological innovativeness by providing full support of all kinds.

As an external environment, the market condition can also affect the success of new product. For the new product to be successful in the market, the market must have great potential of growth. Generally, a product with huge potential would mean a product that is

in the growth phase of the lifecycle, and the potential must be measured by the speed of obsolescence and the size of the potential market. However, fast growing market does not guarantee the success of the new product. Even though the market is growing fast, the number of competitors and their resource and capability must be considered. As an example, Xerox was the leading company in the printing industry by making big and fast printers for business clients, in 1970 United States. Surprisingly, Canon could achieve success by targeting SMEs and personal clients with CPC technology and Liquid toner applied to small printers, not competing Xerox in the same market (Markides, 1997).

In a nutshell, there have been various factors including technological capability, marketing capability and organizational capability determining successful new product development and sometimes there were conflicts between different studies about impact of such factors. The reason of these conflicts are mainly due to difference of industry, the scope of analysis, and the difference of research methodology. In particular, it should be noted that, when parametric model was applied as a research methodology, this cannot completely avoid model misspecification problem since an empirical model is partly specified by researcher's prior belief. Therefore, it is necessary to identify the relationship between factors affecting new product success and performance without any parametric assumption in order to capture unbiased and true impact of various factors.

2.1.2 Review on dimension and measurement of new product development results

There are several perspectives about the criteria and measurement of new product development success, but financial success is commonly used, regardless of industry (Craig & Hart, 1992). The reason why financial success is frequently used as an indicator is because profit is the eventual goal of a company, and it shows the productivity of each new product project. Financial success can also be measured objectively and it is easy to acquire the data and look through the change of accumulated data (Craig & Hart, 1992). But efficiency or effectiveness of the new product development are also recognized as an important criteria of new product success, alongside the financial success. In particular, the innovativeness of the technology and the time to market seem to be more important in the high-tech industry.

As seen, high-tech products' performance is composed of multiple dimension, and since there may be a trade-off between multiple dimensions, how we define and measure the performance of a new high-tech product is an important issue in deciding whether the product is successful or not.

The aim of new product development might differ between each firm so that the evaluation of success is subjective and relative. The performance of a new product has been defined in many ways because each study has a different perspective and the scope can be also different depending on whether it is either firm-level measurement or project-level

measurement (Benedetto, 1999). New product outcomes can be summarized and categorized by referring to previous studies, as follows.

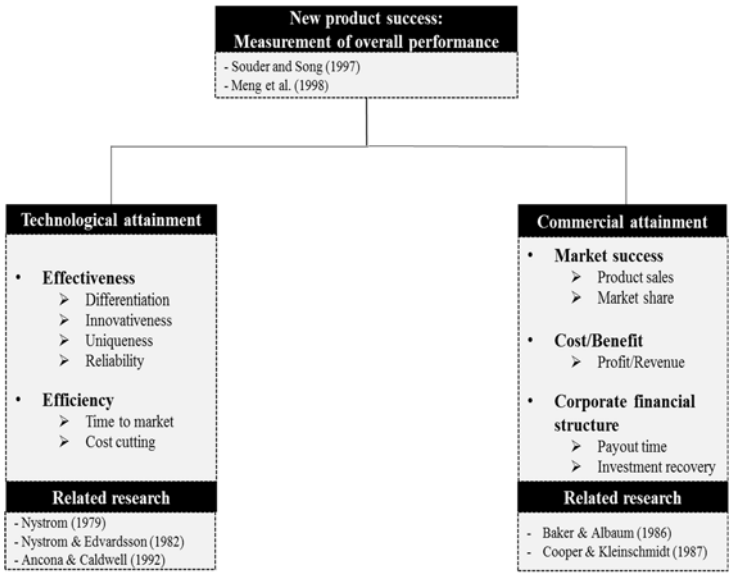


Figure 3. Multi-dimensional outcomes of new product development

Robert G Cooper (1984)'s study was an initiative study that suggested indicators of the performance of new product by choosing 3 factors out of 8 independent measurements. The three dimensions were 1) New product development program impact on firm, 2) New product success rate, 3) Relative performance. The achievement of this study was that this suggested three independent performance dimensions and revealed that each of the dimensions were irrelevant to each other, so sometimes increase in one dimension might lower the other dimension. After this study, Robert G Cooper and Kleinschmidt (1987) made progress to Robert G Cooper (1984) study by extracting three dimensions from ten

independent measurements, which are ‘Financial success’, ‘Window of opportunity’, and ‘Impact on market’.

Cordero (1990) classified the new product performance of high-tech R&D project by three dimensions; 1) overall performance, 2) technical performance and 3) commercial performance. This study claimed that there is no single performance dimension that can include all perspectives on the new product development performance and that the managers must utilize multiple performance dimension.

Hart (1993) thought that the previous studies were not consistent and challenged to suggest a systematic framework. They suggested four basic elements which new product performance dimensions satisfy; 1) measurement, 2) level of analysis 3) source of data and 4) way to collect the data.

Hultink and Robben (1995) did a research on 194 German firms and found that the importance of new product performance is related to the timer perspective of the firm. They analyzed the correlation between timer perspective and 16 performance dimensions suggested by Griffin and Page (1993). In the short period, time to market and launched on time was the most important factor and in the long period, financial performance such as met revenue goal and IRR/ROI were important factors. Also, they found that customer satisfaction, customer acceptance, met quality guidelines and product performance level were important in both short and long periods. Especially, customer satisfaction is the most important performance factor, regardless the timer perspective.

Montoya-Weiss and Calantone (1994), by carefully looking into previous studies,

claimed that performance of new product can be split into two categories; 1) commercial objective and 2) technical objective. The commercial objective can be subcategorized again into financial objective and market share objective. They also pointed out that there were not enough studies which dealt with technical objective.

Recently, launch-on-time has been discussed to be a very important objective, alongside the products' innovativeness. It is because the high-tech products' lifecycle is getting shorter and the rate of obsolescence is getting faster. In these circumstances, a great product idea can fail if the product is not launched on time in the market. For semiconductors, which is a technology-intensive product, there are many studies showing that the launched on time factor is the core barometer of the success of new product development. As a result, many semiconductor firms are trying to shorten the development time.

Taken together, firms creating unique, superior and novel products are able to experience success. New product 'success', however, can have many meaning. Some constructs were designed to capture either effectiveness or efficiency such as providing value-generating innovations, ensuring speed to market (Ancona & Caldwell, 1992b; Nyström, 1979; Nyström & Edvardsson, 1982) while others were suggested to measure commercial attainment such as obtaining profits (Baker & Albaum, 1986; Robert G Cooper & Kleinschmidt, 1987). And we can say that it is important to consider these success constructs together in a study because managers in general face limited resources in organization and are challenged to make trade-offs decision in emphasizing either efficiency or effectiveness.

2.2 New product adoption mechanism

2.2.1 Factors affecting new product adoption

Although a new product is novel enough in terms of functionality or design, it would be meaningless if the product is not adopted by potential consumers. Due to this fact, understanding factors affecting new product adoption in market is important topic in academic as well as substantive domain. Especially, a lot of research have been conducted to provide theoretical framework and empirical evidence for helping understanding high-tech product adoption mechanism which is easily distinguished from that of general consumer goods (Easingwood & Koustelos, 2000; Meldrum, 1995; Moriarty & Kosnik, 1989; Rogers, 2003). For example, high-tech product is generally consumer durables and difficult to learn usage. And this academic area which focuses on a new high-tech product adoption mechanism is called innovation adoption and, in this chapter, we will mainly discuss factors affecting new product adoption within innovation adoption theory.

Several theoretical models have been developed in the area of innovation adoption to describe individual or society's innovation adoption behavior. Among them, the Innovation Diffusion Theory (IDT) of Rogers (2003) has been frequently cited since the 1960s when it was initially suggested. Although not only IDT but also various similar concepts and frameworks have been developed and adopted in studies, the IDT is known as the most popular and powerful framework to explain factors affecting innovation adoption.

Therefore, we will review factors affecting new product adoption mechanism based on the Rogers' IDT theory.

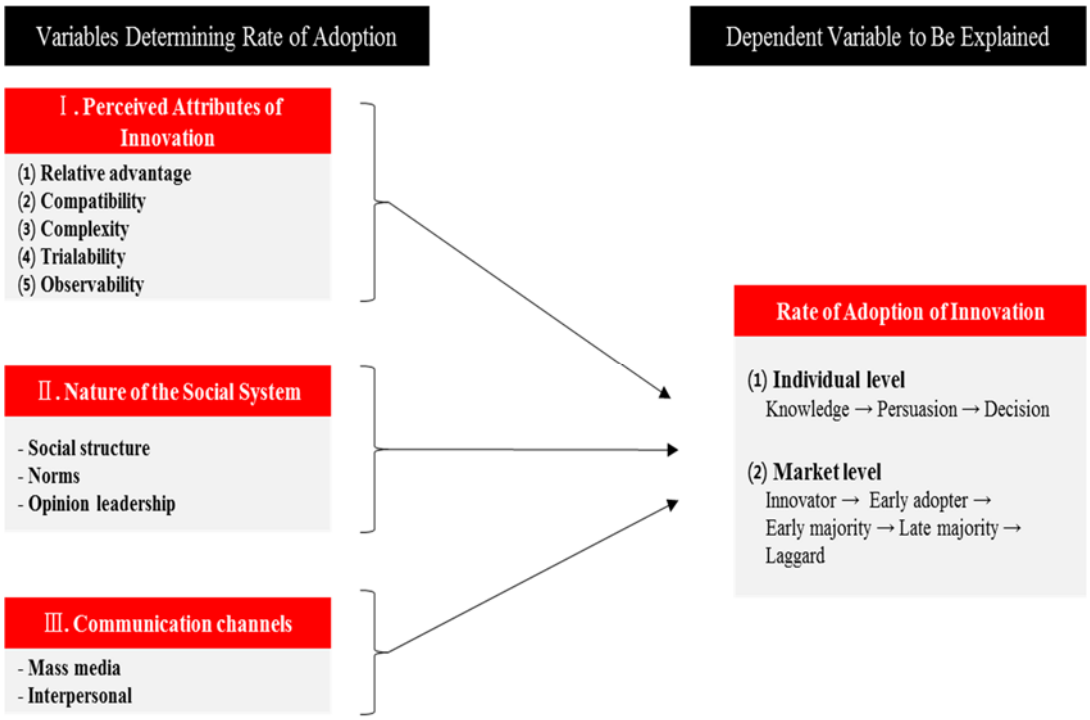


Figure 4. Factors affecting high-tech new product adoption cited from Rogers (2003)

Rogers (2003) defined diffusion as process by which an innovation is communicated through certain channels over time among the members of a social system in his masterpiece "Diffusion of innovation" and said that the four main element should be considered to understand adoption of innovation.

The first element is innovation itself. An innovation, simply put, is "an idea perceived as new by the individual". As restated, an innovation is an idea, practice, or object that is

perceived as new by an individual or other unit of adoption. The characteristics of an innovation as perceived by the members of a social system determines its rate of adoption. Perceived characteristics of an innovation includes relative advantage, compatibility, complexity, trialability and observability to those people within the social system whose perceived levels are evaluated by comparing on existing products or service.

The second main element in the diffusion of innovation is the social system. A social system is defined as a set of interrelated units that are engaged in joint problem-solving to accomplish a common goal. The members or units of a social system may be individuals, informal groups, organizations, or subsystems. The social system constitutes a boundary within which an innovation diffuses. In this context, how the system's social structure affects diffusion has been studied. And another research stream is how norms affect diffusion. Norms are the established behavior or patterns for the members of a social system. Lastly, research has been conducted about opinion leadership, the degree to which an individual is able to influence informally other individuals' attitudes or over behavior in a desired way with relative frequency. A change agent is an individual who attempts to influence clients' innovation-decisions in a direction that is deemed desirable by a change agency.

The third main element is communication. In innovation adoption context, communication is process by which members of society create and share information with one another in order to reach a mutual understanding. A communication channel is the means by which messages get from one individual to another. Mass media channels are

more effective in creating knowledge of innovations, whereas interpersonal channels are more effective in forming and changing attitudes toward a new idea, and thus in influencing the decision to adopt or reject a new idea. Most individuals evaluate an innovation, not on the basis of scientific research by experts, but through the subjective evaluations of near-peers who have adopted the innovation.

Lastly, the fourth is time. Time is involved in the innovation adoption process. In individual level, the innovation adoption process is the mental process through which an individual consumer (or other decision-making unit) passes from first knowledge of an innovation to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision. Thus, 5-step process of innovation adoption called innovation-decision process is *"Knowledge – Persuasion – Decision – Implementation – Confirmation"*. An individual seeks information at various stages in the innovation-decision process in order to decrease uncertainty about an innovation's expected consequences. In aggregate level, the diffusion of innovation over time typically exhibits an S-shape curve. This suggest that innovativeness of a new product is initially difficult and costly, but as the fundamental principles of the technology are worked out, it then begins to accelerate as the new product becomes better understood and finally diminishing returns set in as the new product approaches its inherent limits.

2.2.2 Review and critique on traditional new product adoption process model

In the real world, people do not immediately decide whether or not to adopt a product that is totally new to the market place when they encounter the new product or related information for the first time. Rather, they experience a series of hierarchical and sequential process to reach actual choice. In other words, consumers formulate their attitude toward a new product through a few steps and then decide whether to adopt it or not.

In this context, a lot of theoretical models have been developed in the innovation, psychology and marketing field to explain such a hierarchical decision-making process or attitude formulation process, and these models are very similar in a way that they explicitly provide three key constructs of attitude formation and suggest concept of sequential decision-making process.

In innovation literature, the innovation-decision process was developed and has been frequently cited. According to the Rogers, the innovation-decision process is 'the process through which individuals pass from gaining initial knowledge of an innovation, to forming an attitude toward the innovation, to making a decision to adopt or reject, to implementation of the new idea and to confirmation of this decision'. The first three steps were named as knowledge, persuasion and decision respectively by Rogers (2003). Each stage is related to awareness, interest and purchase intention. At the knowledge stage, the individual becomes aware of and acquires basic information of a new product. At the persuasion stage,

individuals form favorable or unfavorable attitude toward a new product. Finally, at the decision stage, people represent their intention to adopt or reject a new product.

In marketing literature, similar theoretical models on consumer purchase decision-making process have been developed to depict how people react to information delivered by advertising of a new product. The conceptual model applied to advertising is a simple causal 'Hierarchy of Effect' model, which is also known as AIDA model (Smith & Swinyard, 1982). The traditional hierarchy response models including 'Hierarchy of Effect' and 'AIDA' have been around in the literature of marketing for more than a century and little changed in its essentials from the AIDA model which has been around since 1898. The basic premise of the hierarchy of effect model is that advertising effects occur over a period of time and advertising communication may not lead to immediate behavioral response or purchase. Rather a series of effects must occur, with each step fulfilled before the consumer can move to the next stage in the hierarchy. Therefore, the traditional hierarchy framework asserts that consumers respond to advertising messages in a very ordered way. The best-known hierarchy response models are as follows.

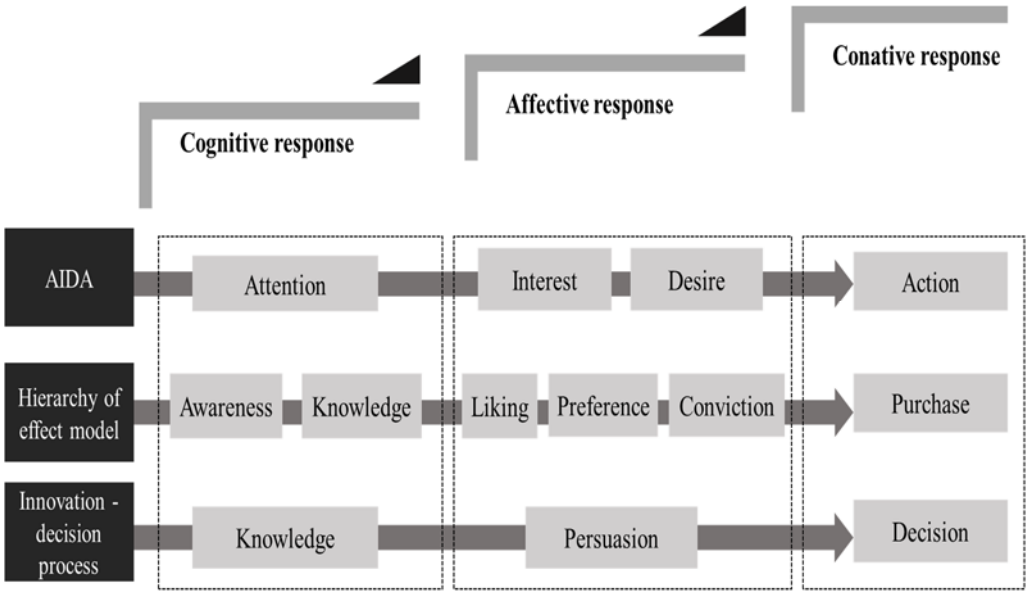


Figure 5. Concept of hierarchy response model

In two of the best-known hierarchy response models, while these response models may appear similar, they were developed for different reasons. The 'AIDA' model was developed to represent the stages a salesperson must take a customer through in the personal selling process (Belch & Belch, 2003). This model depicts the buyer as passing successively through attention, interest, desire, and action. The 'Hierarchy of Effect' model, meanwhile, was developed by Lavidge and Steiner (1961) showing the process by which advertising works. It assumes that 'a consumer passes through a series of steps in sequential order from initial awareness of a product or service to actual purchase'(Belch & Belch, 2003). In common, hierarchy response models work in a way that consumers change their minds about a product, then they change their attitude, and then they act. In other words,

the process begins with cognition, which translates to affect, which then translates to behavior.

From well-known AIDA model to recent alternative models, the hierarchy response models have had a lot of attention from researchers and managers as a managerial framework in marketing and advertising. As it was emphasized, it was strongly assumed that consumers become aware of and knowledgeable about a product, develop feelings toward it, form a desire or preference, and then make a decision whether or not to adopt it sequentially. This logical progression is often accurate, the response sequence of cognitive, affective and behavioral steps, however, does not always operate this way (Belch & Belch, 2003). The several alternatives to the original Lavidge and Steiner's model argued that heterogeneous paths can be reliable for various consumer decision-making situations.

For example, Vakratsas and Ambler (1999) suggested that the effects of advertising should be evaluated using three dimensions, with different sequence being more important than others, depending on factors such as the product category, stage of the product life-cycle, target audience, competition, and impact of other marketing mix components. Similarly, Hall (2002) argues that 'advertisers need to move away from explicit and implicit reliance on hierarchical models of advertising effects and develop models that place affect and experience at the center of the advertising process' (p. 23). The implication of these criticisms is that marketers should focus on cognition, affection, and conation as critical variables that advertising may affect, but at the same time they should not assume a particular sequence of responses. Extension of existing models to better understand how

advertising and other forms of communication may affect these intermediate variables in various product and market situations.

To sum it all up, hierarchy response model embraces effect of advertising and other marketing communication strategies as the communication process that attracts customer's attention. This is basically about there being different stages involved from a new product first coming into target customers' awareness to having a purchase intention or making the actual purchase. And the model accordingly includes explicit three main dimension; cognition ("*thinking*") dimension of person response, affection ("*feeling*") dimension of person response and conation ("*behavior*"). Essence of this conceptual model is that the model provides process to understand how people process information, form attitudes, and behave as a direct result of that information processed and those attitudes formed.

Despite their perceptive and rational interpretation on consumer decision-making process, the hierarchy response models have a weakness. One of the main limitations is about the order of three stages. (Barry & Howard, 1990) said that while there is little disagreement among researchers regarding the importance of the three stages of the hierarchy, there has been significant disagreement regarding the order of three stages. This has been the topic getting most intensive criticism in hierarchy of effect model. Additionally (Ray et al., 1973) also said that if we know nothing about hierarchy of effect then it would be reasonable to assume that they could be ordered in all six possible permutation of three things.

Whilst it is very likely that customers pass through all of these stages, the sequence in which they move through them is generally thought to depend on product category, consumer characteristics and marketing communication strategy. To restate, each consumer may show different response about communication strategy including advertising and there is high possibility that one experience different sequence of three dimensions toward the same marketing communication, even within relatively homogeneous segments. Thus, hierarchy models must move beyond just explaining the effects of advertising and consider how, and with what effects, consumers synthesize information from communication strategy by reflecting the weakness.

Chapter 3. Strategic Management of R&D and Marketing Integration for Multi-Dimensional Success of New Product Development

3.1 Introduction

New product development (NPD) teams often require not only physical and visible resources but also cooperation from different departments within the same organization. To facilitate coordination between different functional teams, many project leaders create a cross-functional NPD team to stimulate integration and cooperation. In this respect, the R&D and marketing integration has received truly substantial attention.

The term 'R&D and marketing integration' has been regarded as putting multiple people who have different backgrounds into a same team together as well as their collaborative activities during NPD project such as knowledge gathering or information sharing for mutual understanding. Bringing multiple people together into a team enables multiple bases of expertise to be collectively directed toward problem solving. However, if teams become too large, communication problems and administration cost can be significantly noticeable.

R&D and marketing integration is linked closely to diversity of team members, which ensures that the team can draw on different perspectives and bases of expertise (Damanpour, 1991; Kimberly & Evanisko, 1981). In particular, cross functional teams enable technology

and marketing objectives to be integrated in the NPD process. Diversity of team members ensures that the individuals in the team not only possess different knowledge but also have different sources of extra-team resources upon which to draw through boundary-spanning activities (Ancona & Caldwell, 1992a, 1992b). But diversity can also make it more difficult for teams to develop a common understanding of the NPD project and sometimes can result in lower group cohesion (Uzzi, 1997).

The impact of this interface on the new product success has been the focus of much more scientific scrutiny. However, despite the great amount of research in this area for understanding underlying impacts of R&D and marketing integration, findings are very mixed regarding how such R&D and marketing integration influences NPD performance. From this point, we deduced that these variations or mixed results were caused by several limitations of previous literatures.

First of all, prior works investigated the relationship between R&D and marketing integration and success typically by applying a parametric model in their empirical analyses In particular, most empirical studies have posited parametric linear models to describe the relationship between R&D and marketing integration and business performance (Roger J. Calantone & di Benedetto, 1988; Roger J Calantone, Schmidt, & Benedetto, 1997; Harmancioglu, Droge, & Calantone, 2009; Verona, 1999). These parametric assumptions were motivated largely by methodological convenience in terms of the model structure and estimation process (Ernst, 2002). However, the parametric model is inherently linked to a model misspecification problem, possibly leading to biased or mixed results. For example,

several studies have emphasized that close R&D and marketing integration positively influences the success of new products by stimulating a mutual understanding between people from different departments (Lu & Yang, 2004; Rudy K Moenaert & Souder, 1990; Rudy K. Moenaert, Souder, De Meyer, & Deschoolmeester, 1994; M. Song & Noh, 2006; X. M. Song & Parry, 1997). A few other studies, however, have found that too close a relationship between R&D personnel and marketing personnel can cause important information to be overlooked, resulting in a reduced possibility of NPD success (Kahn & Mentzer, 1998; William E Souder, 1980; Troy, Hirunyawipada, & Paswan, 2008).

Second, despite empirical evidence showing that there is considerable variation in the impact of R&D and marketing integration due to other strategic resources (Leenders & Wierenga, 2008), only a few prior works have investigated the joint effects of R&D and marketing integration and other strategic resources (e.g., marketing or R&D competency). The importance of examining joint effects is obvious, as any integration effort needs to be supported by additional R&D and marketing resources.

Lastly, most prior research has ignored the trade-off relationship between NPD performance criteria in the model structure. Bayus (1997) emphasized that there is a trade-off relationship between time-to-market and product novelty as expressed in a NPD outcome. Although there have been numerous studies which have defined new product success, especially since the work of Cooper and Kleinschmidt (1994) was published, few empirical effort has been made to capture the dynamic effects of R&D and marketing integration on multiple success criteria.

Consequently, it can be stated that the traditional parametric approaches are limited in terms of their model structure when attempting to show change of marginal impact of R&D and marketing integration, and are not capable of analyzing the marginal response surface between R&D and marketing integration and other strategic resources. Thus, the traditional methodology of explaining the relationship between R&D and marketing integration and performance has been unable comprehensively to describe the relationship found in the real world. The objective of the present study, therefore, is to address these shortcomings. In particular, our research questions are as follows:

- Is the effect of integration between R&D and marketing always positive as stated in the literature?
- If a nonlinear effect is found, what does it look like?
- Do other strategic resources moderate the effect of R&D and marketing integration on NPD success?
- Is there any significant difference in the integration effect depending upon the criteria of NPD success?

In order to answer these questions, we use one of the nonparametric regression methodologies to form the idea of a flexible functional relationship between R&D and marketing integration and NPD success. We apply the Multivariate Adaptive Regression Splines (MARS) regression model, which captures the functional form of the effect of

integrating R&D and marketing on NPD success without any parametric assumptions on model specification. Furthermore, the model can identify significant interaction effects between the integration of R&D and marketing and other strategic resources.

In order to conduct empirical research successfully, MARS is applied to survey data from the Korean ICT industry. The data was collected using survey questionnaires which targeted NPD project managers of NPD teams in Korean ICT companies. Additionally, we conduct Monte Carlo simulations to show what the marginal impact of R&D and marketing integration looks like and what the marginal response surface between R&D and marketing integration and other strategic resources is.

Consequently, this study can make a number of contributions to the NPD literature and to ongoing academic discussions regarding the effect of integrating R&D and marketing. From a theoretical perspective, this study provides an over-arching explanation of opposing observations in the literature. From a managerial perspective, NPD managers must carefully integrate R&D and marketing (i.e., identify strategies for information sharing between different functional teams) by considering their performance criteria and the strategic resources available.

3.2 Theoretical background

Numerous studies have explored the factors affecting NPD success. Of particular interest has been the inter-functional organization between R&D, production, marketing, and sales, as any lack of communication between these departments can be extremely detrimental to NPD outcomes. In an increasingly competitive environment, individual departments can no longer independently accomplish the task of NPD and increase business performance. In addition to this, due to the complexity of technological innovation, a department by itself can hardly implement the entire process of NPD (H. H. Chen, Lee, Wang, & Tong, 2008; Yao, Xu, Song, Jiang, & Zhang, 2014). In particular, the integration of and cooperation between R&D and marketing have been identified as important factors which contribute to NPD success (Troy et al., 2008). Robert G. Cooper (1983) found that R&D and marketing are interdependent in the process of new product innovation, as the R&D department cannot develop new products that meet consumer needs without market information provided by the marketing department.

In this context, the role of R&D and marketing integration and its effect on NPD success have been attracting attention from researchers across many disciplines over the past few decades. Academics and practitioners have identified commonly used measures of success in their efforts to find the underlying reasons behind NPD success and the effects of integrating R&D and marketing on project as well as company-level success (Griffin & Hauser, 1996).

The majority of previous studies have shown empirically that the intensive integration of R&D and marketing enhances project performance and the competitiveness of new products (Lu & Yang, 2004; Rudy K. Moenaert et al., 1994; M. Song & Noh, 2006; X. M. Song & Parry, 1997; William E. Souder, 1988). In earlier works, Robert G. Cooper (1994) investigated NPD success factors based on data conveyed from the international chemical industry, including 21 companies and 103 projects (68 successful projects and 35 failed projects), finding that a cross-functional approach had a positive impact on the profitability of new products. Another study Robert G Cooper and Kleinschmidt (1994) also discovered that the organization of project when it considers cross-functional integration and accountable teams positively influences the time efficiency of projects.

The underlying advantages of integrating R&D and marketing have also actively been discussed with regard to success factors of NPD. Inter-functional information transfer, uncertainty reduction, and knowledge creation have all been referred to as positive aspects of integration between different functional teams. Rudy K Moenaert and Souder (1990) has theoretically illustrated that R&D and marketing integration stimulates information transfers among different functional teams, thus playing a critical role within the process of technological innovation. It also reduces the uncertainty faced by each team. Rudy K. Moenaert et al. (1994) empirically found that communication flows between marketing and R&D were increased under the condition of a positive inter-functional climate, which was also positively correlated with the commercial success of new products. In addition, Takeuchi and Nonaka (1986) emphasized knowledge creation through high-level R&D and

marketing integration, stating that collaboration between different functional teams is a vehicle for introducing creative, market-driven ideas.

Aside from these merits of integration, a handful of studies have pointed out negative effects of the excessive integration of R&D and marketing. Based on the findings of these studies, the authors argued that more intensive integration may not always be a productive approach to enhance the performance of NPD, also arguing that there could be an optimal level of integration (Leenders & Wierenga, 2008; William E Souder, 1980). William E Souder (1980) found that if people from different functional teams have too much regard for each other or are too complacent in their relationships, important information and subtle observations may be overlooked. Therefore, the author argued that achieving an increased level of integration does not always guarantee increased performance. As a continuation of this line of thought, Gupta, Raj, and Wilemon (1986) proposed that a firm should strive for an appropriate level of integration depending on its strategy and its perceived uncertainty of the environment. The difference between the level of integration required and the level of integration achieved practically can influence new product innovation. However, they failed to show empirically such an optimal level of integration for successful new product development. In later works, Henard and Szymanski (2001) found, in their meta-analysis, that cross-functional integration issues and new product performance were not significantly correlated, although, on average, increased diversity in functional specialization may indeed be related to the rate of innovation. Kahn and Mentzer (1998) also contended that intensive interaction activities do not promote company performance, instead

overburdening personnel with too many meetings and stress.

The two abovementioned divergent observations regarding the effects of integrating R&D and marketing on NPD success triggered further studies that aimed to explain these divergent observations in one unified framework. For example, R. Calantone and Rubera (2012) reported that the effect of integration had only a negative impact on the performance of new product development if firms pursue an explorative innovation program. Leenders and Wierenga (2008) pointed out, based on survey data conveyed in the pharmaceutical industry, that integration of R&D and marketing need to be considered in conjunction with other NPD resources. Specifically, they found that if a firm has few NPD resources, the effort to pursue high level of integration may yield only modest returns. Brettel, Heinemann, Engelen, and Neubauer (2011), who used efficiency and effectiveness to measure the impact of the integration of R&D and marketing, pointed out that the integration effect depends on the type of innovation (i.e., incremental innovation versus radical innovation).

Summarizing these findings, we can state that the integration of R&D and marketing can have a positive impact on NPD performance under a few given conditions. However, existing studies have not answered the following two questions: (1) How does the impact of integration change as its intensity is enhances? (2) How does the impact of integration change depending on input of other NPD resources?

Most of all, existing studies could not investigate these issues due to the methodologies they applied. They assumed a parametric linear model between integration and NPD success largely motivated by methodological convenience in terms of its model structure

and estimation process. Thus, it was not possible to capture a flexible and unbiased relationship between R&D and marketing integration and NPD performance. In addition to the methodological limitations of previous studies and the fact that integration is embedded in a broad organizational context, the effects of any interaction between integration and other strategic resources devoted to the NPD process also remain to be tested in more detail. Traditional approaches do not describe the shape of the interaction effect. Furthermore, it is not clear how the impact of integration varies depending on the performance criteria (e.g., efficiency and effectiveness) considered. Generally, NPD managers must consider multiple performance objectives. For example, NPD managers not only have to implement new technologies (or technologies that already exist in competing products) into new products, but they also have to complete the project within a given period of time (as the on-time release of a new product heavily influences the competitiveness of the new product in the market). Therefore, with our research, we hope to shed some light on this trade-off relationship between success and the integration of R&D and marketing.

3.3 Research design

3.3.1 Research framework

Four steps were followed in order to design the theoretical research framework and to reach the research objectives (Figure 6). First, technological capability, marketing capability and organizational capability (with their corresponding resources) are included in the research framework as the main effect variables. The R&D and marketing integration variable was classified as one of the main effect variables belonging to organizational capability. The integration variable and the other explanatory variables are related to the theoretical model, which postulates that performance is affected by a firm's capabilities. Second, a questionnaire was used to measure retrospectively the intensity and specialty of resources invested in NPD processes. The questionnaire was also used to capture the degree of success of a new product with respect to different performance criteria. Third, based on the collected data, the nonparametric regression model, MARS, was applied to estimate the function of covariates and the response variable. Fourth, the estimated regression results were used as input into Monte Carlo simulations in order graphically to illustrate the marginal effect of R&D and marketing integration and to show the marginal response surface with other resources devoted to the NPD process.

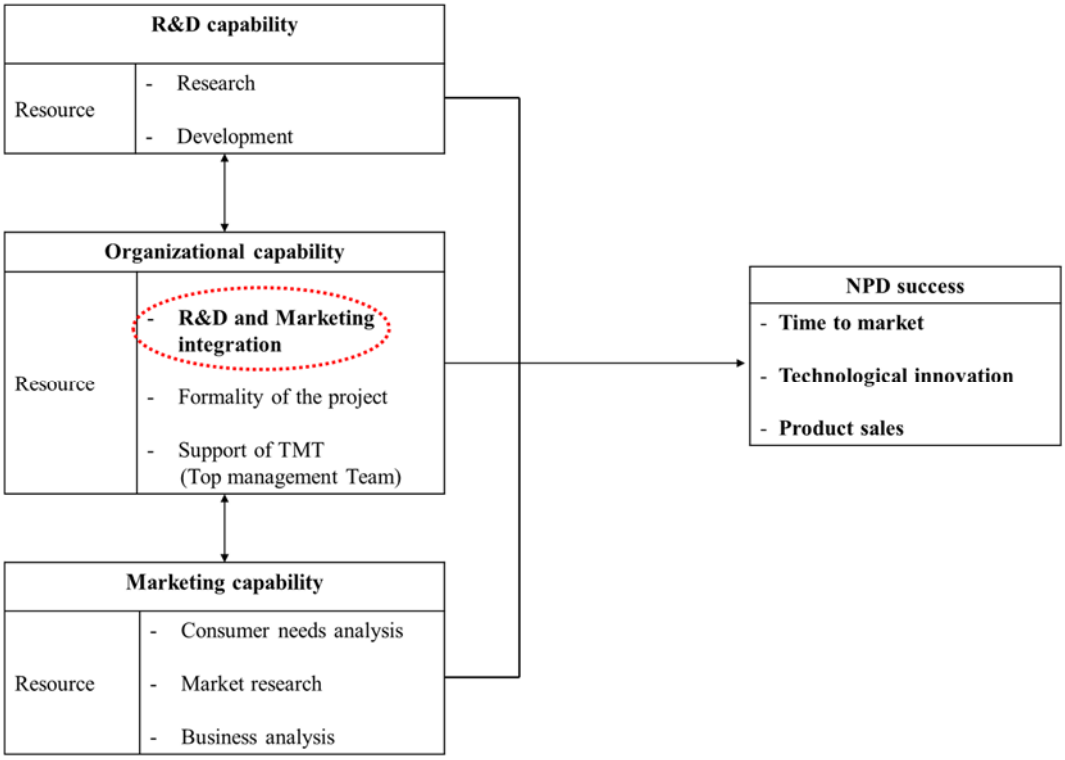


Figure 6. The proposed theoretical research framework

As indicated in Figure 6, the proposed research framework consists of three NPD capabilities (‘Technological capability’, ‘Marketing capability’, and ‘Organizational capability’) and three different success dimensions (‘Time to market’, ‘Technological innovation’, and ‘Product sales’). Without doubt, technological capability and marketing capability are the most important drivers of successful product development. This has been demonstrated in a number of theoretical and empirical studies (Harmancioglu et al., 2009; Keller, 2004; Verona, 1999).

Technological capability can be separated into research resources and development

resources (Figure 6). Research resources represent the ability to evaluate the technical specifications and preliminary technical assessments of new ideas. In other words, research resources are strongly linked to how much the firm's own technological assets are utilized in the early stage of the NPD process. Development resources represent the ability to develop prototypes and design final products. In other words, development resources refer to technological proficiency associated with specific technical activities to realize a final product. Developing and testing a prototype require one to concentrate on the functional attributes of the product and involve turning an idea into a high-quality product. Therefore, technological proficiency in the development stage increases the likelihood that the final product has few defects and meets consumer expectations. Ulrich and Eppinger (1995) reported that technological capability (e.g., knowledge about product architecture, aesthetics, and ergonomics) is the major source of competitiveness during the product development process.

Marketing capability consists of three different resources: a consumer needs analysis, in-depth market research, and an analysis of the competitive environment of new products (Figure 6). Marketing capability is not something that is applied after engineering has developed a new product. Rather, well-developed marketing capability includes a proactive consideration of the external environment (e.g., considering customers in the NPD process). This philosophy reflects the fact that customers and market-based information guide internal decision-making and resolve internal conflicts during the NPD process. For instance, they can help guide technical specifications by identifying consumers' hidden

needs and reflecting them in the product. They also help to determine an appropriate market segment based on well-implemented market research techniques. It is also possible to identify partners that could play a critical role in the product launch process and to capture a competitor's strategy. Probert et al. (2013) stated that during the new product development process, it is necessary to demonstrate a sufficient understanding of potential market opportunities rather than to rely on the current market. Hence, it can be suggested that technologists would benefit from insight into a two-way communication process with marketing in order to develop a 'pitch' for their technology. Considering these benefits, marketing capability can also be considered to be one of the major sources leading to NPD success (Kasprzak & Pelc, 1978).

Regarding the organization of NPD, organizational capability is also an important factor affecting a successful NPD outcome (Figure 6). As discussed above, the integration of R&D and marketing is an essential resource and part of what constitutes organizational capability. In addition, the formality of the NPD planning process (i.e., rigorous planning to adhere to the NPD process) and the support of the top management team (TMT) must also be considered as key components constituting organizational capability.

A formal planning process is an imperative resource related to organizational capability. Essentially, a formal planning process refers to a systemic approach for the evaluations of new ideas and the development and market launch of products during the NPD process (Robert G Cooper, 1994). Such a formal NPD process must be comprehensive and characterized by professionalism. Using a formal planning approach, leaders formulate

their intentions in a written plan and then elaborate on the plan with schedules to guide its implementation.

With respect to the support of TMT, Robert G Cooper, Edgett, and Kleinschmidt (2004) proposed that the support of top management through encouragement and risk-taking was one of the key factors of NPD success. Specifically, the commitment of top management is critical for the initiation of the NPD project, and it influences the quantity of the resources devoted to the NPD project, given that a firm's resources are only allocated through the decisions of its top managers (J. Lee, Lee, & Souder, 2000). Because the strategic orientation toward new product performance in the high-tech industry is influenced by the TMT and, in turn, the strategic orientation influences the success of a new product (Chou & Yang, 2011), TMT support is also included as a main component of organizational capability.

To measure the success of a new product, we include three success criteria: 'time to market' as a proxy for project efficiency, 'technological innovation' as a proxy for product effectiveness, and 'product sales' as a proxy for market performance of NPD (Figure 6). The purpose of utilizing three different performance criteria is to understand the trade-off effect between different competing NPD performance criteria. This information is needed by NPD managers, who must make strategic decisions about trade-offs while also emphasizing either efficiency or effectiveness in different situations (O'Cass, Heirati, & Ngo, 2014). For instance, the pressure quickly to develop a new product within a given time period has often led to few improvements and a failure to achieve planned

technological innovations within the new product. Therefore, in order to capture this trade-off relationship between NPD performance criteria, all equations will be estimated simultaneously. In particular, we will analyze all of these relationships in one unified framework, addressing the three different success criteria.

The proposed research framework is fundamentally guided by Rubera, Ordanini, and Calantone (2012), who found that the effect of integration depends strictly upon the type of competence that the firm uses to develop and launch a new product. However, the proposed framework is different from the extant body of studies in a way that this shows the unbiased effects of resources and capabilities on NPD success by decreasing the likelihood of model misspecifications while also providing an overarching explanation of the sometimes opposing R&D and marketing integration effects as identified in previous studies.

3.3.2 Application of the proposed research framework

We target Korean ICT industry for applying the proposed research framework into empirical research. One may counter that the use of a specific vertical industry (i.e., the South Korean ICT industry here) reduces the contributions of this research with respect to explaining the empirical anomalies in the literature. However, our study can be considered to be representative, as Korea is one of the leading countries in terms of ICT R&D investment and innovation performance. The Korean ICT industry is now not only the

driving force behind the economic growth of Korea but also a top-tier industry in terms of technological competence compared to other developed countries (J. Kim, Yoon, Yoon, & Lee, 2015). Therefore, considering the Korean ICT industry as representative of the high-tech industry in South Korea is suitable to address the research objectives of this study.

Additionally, among the high-tech industries, the ICT industry requires a higher balance between technology and market side information, since the new ICT industry goes through frequent technological innovation and severe competition. Over the last few years, ICT industry has led the evolution of digital convergence and made dramatic changes that have led to the growth of national economies around the world (Joung, Han, & Han, 2014). Ever since the term ‘smart’ were used for telephones, every media device has been manufactured as a smart device and, specifying the start of the smart media era. In particular, the popularization of smart devices, such as smartphone, smart TV, or smart tablet, has promoted innovation within the industry.

This study defines the new ICT industry as the "smart media industry" to distinguish it from outdated ICT trend. The smart media industry is facilitated by the emergence of smart media services (E. Kim, Lee, Bae, & Rim, 2015). As the walls between device and service have been removed, they converged very fast in the smart media industry. The smart media industry provokes technological convergence, and converging technologies have distinguishing features, such as high rate of growth, high value of concentration of patent activities, and high technological influences.

These changes in the smart media industry made technological uncertainty and market

uncertainty extremely high, while developing new products. Technological uncertainty is whether the customers are satisfied with the new technology and market uncertainty is how the market would respond to the new technology or product (P. R. Kim, 2013). Accordingly, the firm's strategic decision-making on new product development and management in the smart media industry are now highlighted more than ever.

3.3.3 Data

We used a questionnaire consisting of two parts to collect data. The first part of the questionnaire includes general questions about the organization. This includes the type of firm, the kind of product or service developed, the number of employees participating in the project, and the development period.

The second part of the questionnaire focuses on collecting data about the constructs that have been described in relation to the research framework. This includes data about the resources (measured in person-months) and capabilities devoted to the NPD process, in which the respondents were actively involved. To measure the intensity of R&D and marketing integration, M. Song and Noh (2006) employed a three-item semantic differential scale. Similarly, we measured data about the conceptual constructs corresponding to each resource by three or four questions in the questionnaire. Furthermore, all questions were designed to be answered on a seven-point Likert scale. The questionnaire is described in Appendix A of the dissertation.

Questions designed by Atuahene-Gima (1996) and Robert G. Cooper (1983) were used in the ‘consumer needs analysis’, ‘market research’, and ‘business analysis’ part of the questionnaire to assess those aspects as they pertain to the marketing capability of the firm. The items on the questionnaire by Tatikonda and Rosenthal (2000) were used to measure the formality of the project, and the item used to measure the support of the TMT was based on work by Swink (2000) and R. Calantone, Garcia, and Dröge (2003).

The sample was collected through a web-based survey system of the Korean panel survey company ‘Do-It-Survey’ and the Korean job market information company ‘Incruit’. Do-It-Survey is a firm specializing in web-based surveys, and Incruit manages a database on the human resources of Korean ICT firms. Both companies worked together to conduct this survey. A sample of Incruit’s survey panel was asked to participate in this survey. As compensation, the respondents were offered a small amount of money, delivered electronically. The survey was conducted from March of 2013 to April of 2013. It targeted managers or directors who actively participated in and supervised the development of a new and recently introduced product in the ICT industry. Out of the entire sample collected, 21 respondents were removed due to incompleteness of the questionnaire, leaving a final sample of 220 respondents. This sample was used in the empirical analysis.

The characteristics of the firms of the respondents are as follows: 59.1% of the firms are independent companies, whereas 40.9% correspond to companies affiliated with a corporate group; 29.5% of firms are listed on the Korean stock exchange, KOSPI, and 10% are listed on the Korean stock exchange for small and medium sized enterprises, KOSDAQ.

The industry type includes hardware and devices (20.9%), mobile contents (35.5%), and package software (27.3%). In terms of the number of employees, 28.2% of the firms have fewer than 50 employees, while 45.9% have more than 300 employees.

The characteristics of the respondents are as follows. Regarding the background related to their department, most of the respondents belonged to R&D (64.5%) and only 35.5% worked in a business department. In detail, 25.5% belong to the marketing department and 10% belong to the sales department or the communication department. The majority of those respondents are senior managers (83.7%), followed by directors (10.5%) and CEOs (5.8%). During the data collection process, we excluded general staff or research staff. Doing this increased the reliability of the responses to the survey.

Table 1 shows the descriptive statistics of the variables of our research framework. Each variable is represented as the mean of the responses. The means of all variables, except for the variable 'Research Resource', are between 4 and 5 (i.e., between "good" and "relatively good" on the Likert scale). The variable 'Research Resource' has the highest value (greater than 5), while its variance is the lowest. It is also interesting that the mean of the variable 'Time to Market' is the lowest, while the variance of 'Product Sales' is the highest. These findings indicate that the NPD teams show relatively low performance in their efforts to deliver the final product on time, whereas they show high performance in sales.

Table 1. Descriptive statistics of variables

Capability Dimensions	Resource	Variable	Cronbach Alpha	Mean	Standard Deviation
Organizational capability	R&D and Marketing Integration	RMI	0.838	4.808	1.064
	Formality of Project	FOR	0.861	4.752	1.136
	Support of TMT	TMT	0.873	4.794	1.186
R&D Capability	Research Resource	RES	0.831	5.068	0.967
	Development Resource	DEV	0.834	4.974	1.064
Marketing Capability	Consumer Needs Analysis	CON	0.858	4.625	1.193
	Market Research	MRS	0.896	4.560	1.216
	Business Analysis	COM	0.893	4.921	1.161
Success Dimension	Time to Market	TIME	0.843	4.203	1.101
	Technological Innovation	FADV	0.889	4.675	1.052
	Product Sales	SALE	0.932	4.329	1.222

Table 1 also shows Cronbach's alpha values for each variable in the research model. The alpha values were used to check the reliability of multiple survey questions, which were chosen to measure the same construct. As these values are high (i.e., the inter-correlations among the multiple survey questions are high), we can conclude that the collected answers have high internal consistency.

3.4 Methodology

Previous studies on success factors of NPD have typically assumed that the functional forms are parametric, especially linear, even though there is no theoretical evidence on the linear relationship. This assumption is motivated largely by methodological convenience in terms of model structure and estimation. However, a parametric model cannot show how the marginal impact of integration impact changes as the intensity of integration increases. Therefore, in order to achieve main purpose of this study, we explore the unvarnished relationships between intensity of integration between R&D and marketing and the success of a new product by not imposing any parametric assumption on the model specification. Thus, we adopted MARS (Multivariate Adaptive Regression Spline), one of the nonparametric regression methods. Using MARS, we are able to explore non constant marginal effects of covariates, especially the effect of integration on new product success.

MARS has been developed by Friedman (1991). It finds a nonlinear flexible function without any functional assumptions, using smoothing splines to fit the relationships between a set of independent variables and a response variable. It allows obtaining a very smooth line that can capture shifts in the relationships between variables. It only requires curve segments, in which these shifts occur, to be continuous. The locations are designated as 'knots'.

Following the MARS algorithm, in the first step, MARS builds a collection of basis functions. Basis functions are transformations of independent variables taking into account

nonlinearities and interactions between independent variables in the model. This means basis functions $h_m(X)$ can be highly nonlinear transformations of independent variables. The response variable Y, however, is a linear function of the basis functions. In the second step, MARS estimates a least-square model with its basis functions as independent variables (Deichmann, Eshghi, Haughton, Sayek, & Teebagy, 2002). Once MARS determines the optimal number of basis functions and knot configurations, then the model is fitted on the selected basis functions to find regression coefficients through a least square regression.

For detailing the methodological framework, we consider here the following MARS model form:

$$f(\mathrm{X}) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(\mathrm{X}) \tag{3.1}$$

where M is the number of basis functions, and X represents a set of candidate explanatory variables. With respect to our research framework, X is the set of independent variables (e.g., 'R&D and Marketing Integration'). $h_m(\mathrm{X})$ denotes the m-th basis (spline) function. It is a hinge function that makes it possible to model separate effects on the dependent variable through a piecewise domain of independent variables. In other words, $h_m(\mathrm{X})$ is represented by either $\max(0, \mathrm{x}-\mathrm{t})$ or $\max(0, \mathrm{t}-\mathrm{x})$, in which t is the location of the knot. It should be noted that Y is a piecewise linear function with respect to the basis functions. Basis functions themselves are highly nonlinear transformations of

X , so that the model can express any functional relationships. In addition to this, significant interaction effects among explanatory variables can be captured as a form of hyper-planes and represented by multiplication of basis functions of a single variable. Lastly, β_m are the estimated spline coefficients, corresponding to the basis functions $h_m(\mathrm{X})$, which are chosen by minimizing the sum of squared residuals for a given model.

By specifying the basis functions in more detail, our MARS model can be represented in more detail as follows:

$$f(x) = \beta_0 + \sum_{m=1}^{M} \beta_m \prod_{k=1}^{K_m} [s_{km}(x_{v(k,m)} - t_{km})]_+ \tag{3.2}$$

where K_m is the number of knots, s_{km} takes on values of either 1 or -1, indicating the right or left sense of the associated step function, $v(k,m)$ is the label of the independent variable, and t_{km} indicates the knot location. The product over all knots Km represents the basis function $h_m(\mathrm{X})$ in equation (3.1).

Following the MARS estimation suggested by Friedman (1991), MARS model is basically estimated in a two-stage procedure. Figure 7 shows pseudo-code of MARS forward step

$B_1(\mathbf{x}) \leftarrow 1; M \leftarrow 2$

Loop until $M > M_{\max}$: lof* $\leftarrow \infty$

  For $m = 1$ to $M - 1$ do :

    For $v \notin \{v(k,m) \mid 1 \le k \le K_m\}$

      For $t \in \{x_{vj} \mid B_m(\mathbf{x}_j) > 0\}$

        $g \leftarrow \sum_{i=1}^{M-1} a_i B_i(\mathbf{x}) + a_M B_m(\mathbf{x})[+(x_v - t)]_+ + a_{M+1} B_m(\mathbf{x})[-(x_v - t)]_+$

        lof $\leftarrow \min_{a_1, a_2, \ldots, a_{M+1}} \mathrm{LOF}(g)$

        if lof < lof*, then lof* $\leftarrow$ lof; $m^* \leftarrow m$; $v^* \leftarrow v$; $t^* \leftarrow t$ end if

      end For

    end For

  end For

  $B_M(\mathbf{x}) \leftarrow B_{M^*}(\mathbf{x})[+(x_{v^*} - t^*)]$

  $B_{M+1}(\mathbf{x}) \leftarrow B_{M^*}(\mathbf{x})[-(x_{v^*} - t^*)]$

  $M \leftarrow M + 2$

end loop

end algorithm

* The MARS forward stepwise algorithm is based on Friedman (1991)

Figure 7. MARS: Forward stepwise

In the forward step, MARS constructs a very large number of basis functions to over fit the data initially, where variables are allowed to enter as continuous, categorical, or ordinal. After the forward step (i.e., after an iteration of $M_{\max}$ times, the model $f_M(\mathrm{X})$ is a sequence of $M_{\max} - 1$ models, each one having one less basis function than the previous one.

At the end of forward step, a large model typically overfitting the data is obtained. Then, a backward elimination is implemented to refine the model. Figure 8 shows pseudo-code of MARS backward step

$J^* = \{1, 2, ..., M_{\max}\}; K^* \leftarrow J^*$

$\text{lof}^* \leftarrow \min_{\{a_j | j \in J^*\}} \text{LOF}(\sum_{j \in J^*} a_j B_j(\mathbf{x}))$

For $M = M_{\max}$ *to* 2 *do* : $b \leftarrow \infty$; $L \leftarrow K^*$

  For $m = 2$ *to* M *do* : $K \leftarrow L - \{m\}$

    $\text{lof} \leftarrow \min_{\{a_k | k \in K\}} \text{LOF}(\sum_{k \in K} a_k B_k(\mathbf{x}))$

    if $\text{lof} < b$, then $b \leftarrow \text{lof}$; $K^* \leftarrow K$ end if

    if $\text{lof} < \text{lof}^*$, then $\text{lof}^* \leftarrow \text{lof}$; $\text{J}^* \leftarrow K$ end if

  end for

end for

end algorithm

* The MARS backward stepwise algorithm is based on Friedman (1991)

Figure 8. MARS: Backward stepwise

In this pruning step, basis functions are deleted in the order of least contributions using the generalized cross-validation (GCV) criterion. The importance of a variable can be assessed by observing the decrease in the calculated GCV value due to the removal of a variable from the model. The GCV can be expressed as follows:

$$\text{GCV}(M) = \frac{1}{N} \sum_{i}^{N} [\text{y}_i - f_M(x_i)]^2 \Big/ \left[1 - \frac{C(M)}{N}\right]^2 \tag{3.3}$$

where N represents the number of observations, and $C(M)$ is the cost penalty measure of a model containing M basis functions. The numerator $[\text{y}_i - f_M(x_i)]^2$ measures the lack of fit on the M basis function model $f_M(x_i)$, and the denominator denotes the penalty for the model complexity $C(M)$.

In summary, MARS uses piecewise linear functions for local fit and apply an adaptive procedure to select the number and location of breaking points called knots. The function estimation is basically generated via a two stepwise procedure: forward selection and backward elimination. In the first forward step, a large number of local fits is obtained by selecting large number of knots via a lack-of-fit criteria; and in the latter backward one, the least contributing local fits or knots are removed.

Concluding, the advantage of the MARS approach lies in its ability to implement the basis functions so that both the additive and the interactive effects of independent variables can impact the response variable. Consequently, the MARS method generates a continuous regression model with continuous derivatives and has the capability and flexibility to model relationships that are additive or have interactions (Deichmann et al., 2002; Steinberg & Colla, 1999). By allowing any arbitrary shape for the functions and any interactions, and by using the above-mentioned two-stage model testing procedure, MARS can reveal very complex data structure that often hide in high-dimensional data. Therefore, the MARS model highly suits our research objectives of observing change of marginal impact of R&D and marketing integration, as well as finding marginal response function with respect to R&D and marketing integration (T.-S. Lee & Chen, 2005).

3.5 Empirical analysis

3.5.1 Model selection and validity

Three different MARS models were estimated with our data set by allowing the different number of interaction between basis functions. In order to choose the best fitting model, the Likelihood-Ratio (LR) test was adopted to statistically compare goodness of fit between estimated models having a different number of interactions of splines and to find the best model in accord with the given data.

Essentially, LR test is a statistical test used to compare the goodness of fit of two models, one of which (the null model) is a special case of the other (the alternative model). The test is based on the likelihood ratio, which expresses how many times more likely the data are under one model than the other. And the test statistics is given by follows.

$$R = L(\hat{\beta}^H) / L(\hat{\beta}) \tag{3.4}$$

Where $L(\hat{\beta}^H)$ is the constrained maximum value of the likelihood function under the null hypothesis and $L(\hat{\beta})$ is the unconstrained maximum value of the likelihood function. As a result, the test statistics is given by follows

$$\begin{aligned} &LR = 2\ln R = -2(\mathrm{LL}(\hat{\beta}^H) - \mathrm{LL}(\hat{\beta})) \sim \chi^2(q) \\ &where\ \ q : the\ number\ \ of\ \ restiction \end{aligned} \tag{3.5}$$

As a lower interaction model is nested into a higher one, we applied the LR-test (Table 2), in which the lower interaction model is represented through the null hypothesis and the higher interaction model is represented as the alternative hypothesis. The LR-test does not reject the null hypothesis, if the value of test statistics is too small.

Table 2. LR test of estimated MARS models

Model	DF	Log Likelihood	DF	Chi sq.	Sig.
Main effect model	31	-752.43			
Main effect with two-way interaction model	37	-732.94	6	38.979	***
Main effect with two-way interaction model	37	-732.94			
Main effect with three-way interaction model	43	-712.90	6	40.089	***

We estimated three different models, ranging from the main effect model to the main effect with three-way interaction model. Using these estimates, we assessed which model is most suited to our data-set using the LR-test. We found that the two LR-tests statistics reject the null hypotheses, which demonstrates that the high interaction model is superior to explain our empirical data. In detail, Table 2 shows that the main effect with three-way interaction model is preferred compared to the other two models. It is preferred, as it is superior to the main effect model with two-way interaction model, and as the main effect model with two-way interaction model is superior to the main effect model.

The Akaika Information Criterion (AIC) and Bayesian Information Criterion (BIC) were also used to compare the model fit (Table 3).

Table 3. Comparison of AIC and BIC between estimated MARS models

Model	AIC	BIC
Main effect model	1566.864	1706.124
Main effect with two-way interaction model	1539.885	1706.098
Main effect with three-way interaction model	1511.796	1704.963

Table 3 depicts that the AIC and BIC values of the main effect with three-way interaction model is lowest among the three different models. This additionally confirms the superiority of the main effect with three-way interaction model over the other two models. Note, we also tested the main effect with four-way interaction model. The results of the main effect with four-way interaction model are identical to the main effect with three-way interaction model, meaning that there is no significant four-way interaction term. Consequently, the results decisively show that the main effect with three-way interaction model is best-fitted to our data. Therefore, we adopted the main effect with three-way interaction model and discuss the estimation results with that model hereafter.

One may appeal validity of nonparametric regression model over parametric regression model. To check the validity of the nonparametric regression model over the corresponding parametric linear regression models, we applied the model fit test (i.e., LR-test) between the MARS regression model and the parametric regression models (Table 4). To do this, the same covariates (i.e., the basis function as given in Table 6) are selected for both models. The only difference between the models is that the MARS model includes the knot configurations that reflect the discontinuous effects of the selected covariates.

Therefore, the parametric linear regression model is estimated with those covariates but without knot configurations.

Table 4. LR test of nonparametric model and parametric model

Model	DF	Log likelihood	DF	Chi sq.	Sig.
Parametric model	37	-756.38			
Nonparametric model: MARS	43	-712.90	6	86.961	***

Table 4 shows that the LR-test rejects the null hypothesis (i.e., the parametric linear regression model), statistically supporting that the MARS model result better explains the collected data.

We also compared the adjusted R-square values of both models. Table 5 illustrates that the adjusted R-squares of MARS are higher than the adjusted R-squares of the parametric model for each response variable. Therefore, we can conclude that the MARS model is decisively preferred to a parametric linear regression model.

Table 5. Comparison of adjusted R-square between nonparametric MARS model and parametric linear regression model

Model	Time to Market	Technological Innovation	Product Sales
Parametric model	0.4182	0.4702	0.3664
Nonparametric model: MARS	0.5402	0.5121	0.4831

3.5.2 Estimation result

Before discussing the estimation result of the MARS regression model with three-way interaction (Table 6), it should be noted that we tried to achieve homogeneity of our data. First, we restricted our analysis to product level or project level activities in the Korean ICT industry, and did not consider firm level activities or the firm level performance. Consequently, we expected only a little possibility of heterogeneity. Nonetheless, as a few prior works in NPD research utilized control variables to detect heterogeneity, we also included three control variables, to guarantee homogeneity of the sample data and to ensure the reliability of analysis result. As product-level control variables, the number of NPD team members (*NPD_Size*) and the product type (*NPD_Type*) were selected. As a firm level control variable, the number of employees of the corresponding firm (*Firm_Size*) was selected. *NPD_Size* is a continuous variable representing the number of people, who officially participated in the NPD team. *NPD_Type* is a binary variable, in which 1 represents a hardware-and-device-related product and 0 represents a software-and-contents-related product. Finally, *Firm_Size* is a categorical variable, where 1 indicates firms with less than 50 employees, 2 indicates firms with 50 to 300 employees, and 3 indicates firms with more than 300 employees. The estimation result of the control variables showed that only the *NPD_Type* variable is significant and the other variables are insignificant.

Table 6. Estimation results: Main effects with three-way interaction model

Basis functions \ Response Variables	Time to Market	Technological Innovation	Product Sales
Intercept	3.935 (0.220)***	4.527 (0.217)***	3.809 (0.259)***
Max(0, 6-DEV)	0.268 (0.088)**	-0.018 (0.087)	0.362 (0.105)***
Max(0, MRS-2.5)	0.187 (0.057)**	0.154 (0.056)**	0.249 (0.067)***
Max(0, RMI-4.75)	0.254 (0.122)*	0.424 (0.120)***	0.332 (0.143)*
Max(0, DEV-6) *Max(0, CON-6)	4.199 (1.040)***	2.399 (1.024)*	2.746 (1.225)*
Max(0, 6-DEV) *Max(0, RMI-6)	-1.013 (0.269)***	0.147 (0.264)	-1.110 (0.316)***
Max(0, 4.67-FOR) *Max(0, TMT-5.25)	-1.471 (0.290)***	0.028 (0.285)	-1.329 (0.341)***
Max(0, FOR-5.67) *Max(0, 5.25-TMT)	1.146 (0.448)**	1.326 (0.441)**	1.833 (0.527)***
Max(0, 5.67-FOR) *Max(0, 5.25-TMT)	-0.262 (0.036)***	-0.174 (0.034)***	-0.282 (0.042)***
Max(0, 6-DEV) *Max(0, FOR-3)* Max(0, 6-RMI)	-0.148 (0.028)***	-0.061 (0.028)*	-0.156 (0.033)***
Max(0, 3.25-COM) *Max(0, FOR-5.67)* Max(0, 5.25-TMT)	0.645 (1.361)	-4.377 (1.339)**	-4.208 (1.601)**
NPD_Size	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)
NDP_Type	0.505 (0.133)***	0.168 (0.131)	0.246 (0.157)
Firm_Size	-0.002 (0.065)	-0.041 (0.063)	0.019 (0.076)
sample	220	220	220
Adjusted R-s square	0.5402	0.5121	0.4831

* P<0.10** P <0.05, ***P<0.01

The regression results, as shown in Table 6, shows some interesting results. First, we found a nonlinear effect of R&D and marketing integration on NPD success. The fact that the knot of the integration variable was found to be significant implies that the relationship between the integration of R&D and marketing and the NPD success is not linear but non-linear. The effect of R&D and marketing integration on all performance criteria is positive, only if the integration is larger than 4.75 (basis function Max(0, RMI-4.75) of Table 6). It opens up the possibility that an optimal configuration between resources and integration might exist. Therefore, we can state that the answer to the first research question is positive.

Second, the amount of development resources devoted to the NPD process impacts the interaction effect between the R&D and marketing integration and the NPD success (basis function Max(0, 6-DEV) * Max(0, RMI-6) of Table 6). The fact that the interaction effect between the R&D and marketing integration and the amount of development resources was captured is noteworthy, as it validates that the level of integration is influenced by the amount of available R&D resources allocated to the NPD project. In particular, among multiple technological and marketing resources that we explicitly considered in the model framework, development resources were found to have a significant interaction effect with R&D and marketing integration. This supports our second research question about whether the impact of integration is affected by the amount of R&D resources.

Furthermore, with respect to the second research question, the estimation result also shows that there is a significant interaction effect between project formality and R&D and

marketing integration (basis function Max(0, 6-DEV) * Max(0, FOR-3) * Max(0, 6-RMI) of Table 6). If both the level of integration and the development resources are lower than 6, an increase in the level of formality delays the time to market and hampers the technological innovation of new products, consequently leading to a deterioration of profitability. This shows that an excessive pursuit of project formality without collaboration of R&D and marketing and sufficient R&D resources results in a poor NPD outcome. Therefore, we can also state that the second research question has a positive answer.

In conclusion, the MARS algorithm found 3 main effects and 7 interactions (Table 6), using statistical optimization on a recursive partitioning tree, which did not require an a priori parametric model structure. Therefore, our estimation result gives a more comprehensive interpretation about the interaction effects as well as about the unbiased effect of R&D and marketing integration.

3.6 Monte Carlo simulation

By considering the spline coefficients of the regression results only, we face a limitation in understanding the marginal effect of R&D and marketing integration and the marginal effect of the resource variables. In order to address this limitation and to able to answer the third research question, we run simulations. The aim of the simulation is to visualize how the integration effect varies based on the estimated regression results.

The simulation (Monte Carlo simulation) helps controlling variables that are not the

focus of the analysis. In detail, for the simulation, three steps were executed. First, the range of the main variable RMI, which is between 1 and 7, has been divided into 61 intervals. Second, in order to understand the relationship between RMI and NPD success in detail, we control the effects of all other independent variables (i.e., all independent variables except for RMI). For controlling the effect of the other independent variables, 10,000 data sets were generated by drawing values for all the independent variables from a uniform distribution in the range between 1 and 7 (i.e., the potential values of the independent variables). Third, the marginal effects of the variable RMI on the three NPD success variables for each of the 70 intervals is calculated by averaging the spline function value for the 10,000 data sets. The simulation results for each of the NPD success factors are illustrated in Figure 9.

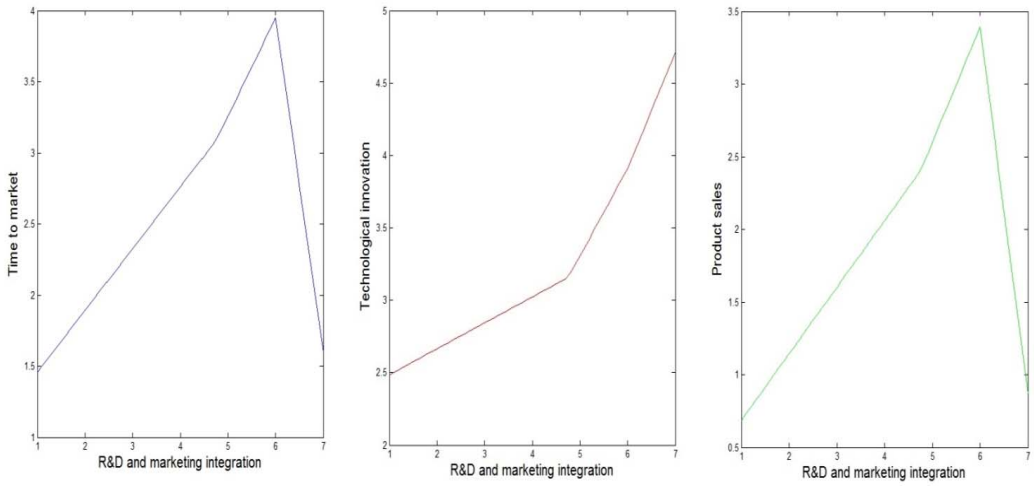


Figure 9. Marginal response functions of Time To Market, Technological Innovation, and Product Sales with respect to R&D and marketing integration.

Figure 9 shows a few interesting simulation results that need to be pointed out. First, meeting our expectation, the intensity of R&D and marketing integration has a nonlinear impact on Time To Market, Technological Innovation, and Product Sales. Particularly, the effect of integration on Technological Innovation dramatically grows after it exceeds the middle point of the integration level. It indicates that the strategy "more is better" holds for the Technological Innovation dimension. For the dimensions Time To Market and Product Sales, however, the impact becomes saturated and eventually drops at the intensive integration area (i.e., a value of 7).

Concluding, we found that the R&D and marketing integration effect depends on the performance criteria considered. An interpretation of these results is that an intensive integration of R&D and marketing may seem to be successful from the perspective of an organization if managers do not know consumer responses to new products in the market yet. However, an excessive integration leads to a decrease in product sales. Although an intensive integration also contributes to technological innovation if the new product is launched, it deteriorates market performance by delaying time to market of the new product. This may be an answer to the important managerial question about what the best R&D and marketing integration strategy for NPD success is.

In addition to this, it might be necessary for NPD team managers to pay attention to the effect of R&D and marketing integration together with the amount and the variety of strategic resources devoted to the NPD process. Figure 10 illustrates the marginal effect of R&D and marking integration together with the amount of development resources.

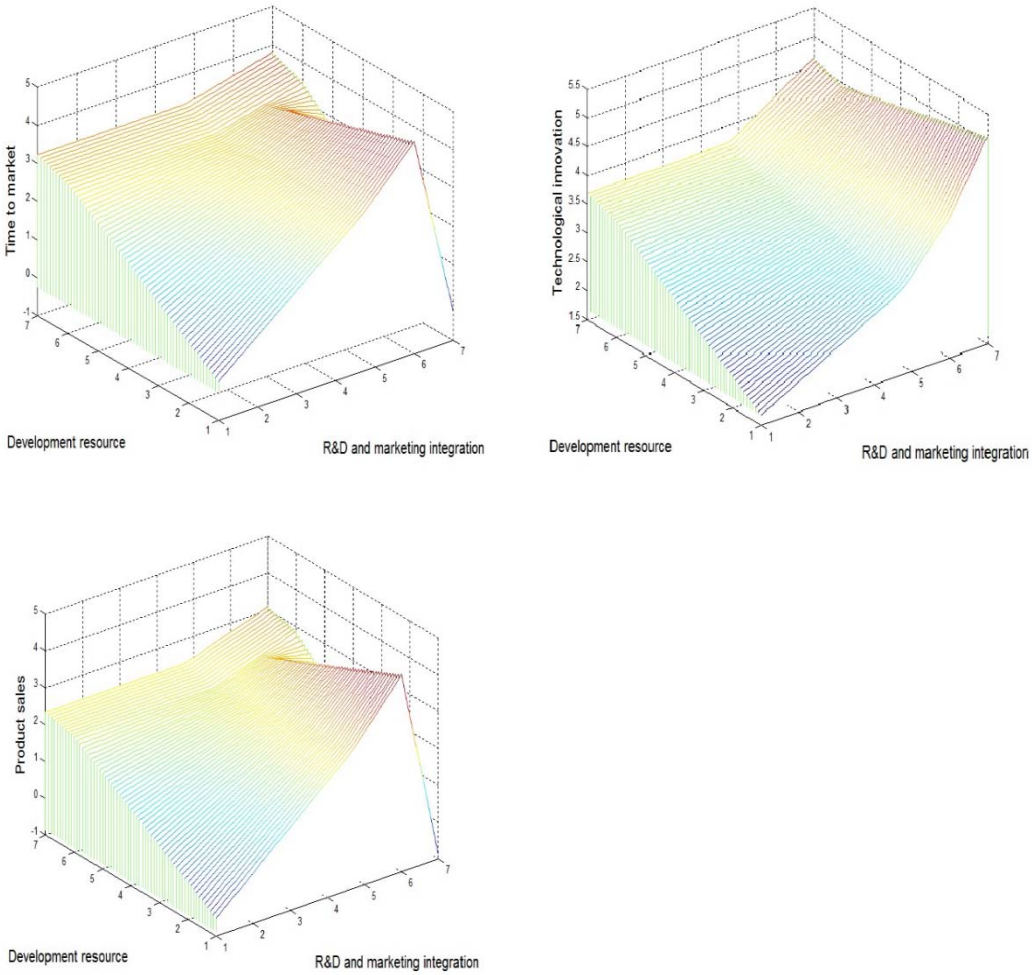


Figure 10. Marginal response surface of Time To Market, Technological Innovation, and Product Sales with respect to R&D and marketing integration and development resource

Figure 10 shows how development resources moderate the relationship between integration and NPD success. If the development resources are sufficient, the impact of R&D and marketing integration on 'Time To Market', 'Technological Innovation', and 'Product Sales' show a peak (i.e., at a value of 7). While the impact of technological innovation is at 5.4, the impact of the other two NPD success criteria is below 3.9. Even if the development resources are less, the impact of integration on 'Time To Market', 'Technological Innovation', and 'Product Sales' shows only a slightly lower level of impact. The results show that R&D-marketing integration has a positive impact on NPD success, if the NPD team has even little R&D resources available.

To suggest the rational reasons for that, we need to remember the practical role of R&D and marketing integration in NPD process. R&D and marketing integration reduces uncertainty for the NPD team and generates innovative ideas in principle by information sharing. In this mechanism, R&D and marketing integration is more conducive to the use of the information. In other words, R&D and marketing updated their market and technological information through integration. The R&D team can take information about consumer needs into consideration during the development process. The marketing team can utilize the technological information to establish marketing plans. This way, information sharing is an important factor for successful implementation of marketing plans and profit improvements. This results coincides previous finding (Leenders & Wierenga, 2008). Leenders and Wierenga (2008) argued that integration of R&D with marketing need to be considered in conjunction with variety and intensity of NPD resources

devoted to the NPD process. And our finding goes way beyond the model of Leenders and Wierenga as proposed model is able to explicitly identify the optimal level of integration that maximizes the NPD performance.

To go through the main points again, if a firm does not have enough skillful technicians or scientists and knowledge, which is required to turn ideas into feasible products, then technical information cannot be conveyed to the marketing people through the process of R&D-marketing integration. For example, without enough technological capability, a marketing department cannot educate consumers about a new product and, finally, cannot increase revenue. Accordingly, the efforts to attain intensive R&D and marketing integration lead to poor performance in the market. However, if a firm has enough technological experience in dealing with similar products then activities related to R&D and marketing integration stimulates the performance of new products.

3.7 Conclusion

3.7.1 Implication

The integration of R&D and marketing is a highly complex phenomenon, especially considering the performance criteria, the variety of resources, and the intensity of resources devoted to the NPD process. In this point, this study is the first empirical examination to address the marginal impact of integration between R&D and marketing. Hence, the study

provides an overarching explanation of the findings of earlier studies which appear to be contradictory with regard to our findings. Most of those studies showed either only positive effects of integration or negative effects of excessive integration. The findings of our study empirically support not only a positive or negative impact of integration but also show that both outcomes can occur within the same context. In particular, our results show that integration has a different impact depending on the NPD performance criteria applied. In terms of the time to market and product sales variables, it was found that an optimal level of integration between R&D and marketing exists. Moreover, in terms of technological innovation, we found that stronger integration leads to more success. It even increases success at a high level of integration. The results also reveal that the effect of R&D and marketing integration can be moderated by the intensity and expertise of the resources committed to the NPD team. Consequently, the results of this study have three important implications.

First, using a nonparametric analysis method, it is possible to conceptualize and investigate empirically the unbiased impact of the integration of R&D and marketing with a fairly large sample at the project level. Given that the integration effect becomes saturated and ultimately decreases, we conclude that prior empirical studies of cross-functional integration ignored an important aspect of NPD by assuming a linear relationship between integration and NPD success. In particular, the findings of this study indicate that the effects of integration are diverse and diminishing. Therefore, the realized level of integration should receive distinctive attention in further NPD research.

Second, our analysis produced mixed findings with respect to performance criteria which are connected to vital managerial questions, such as which aspects of NPD outcomes should be emphasized. Particularly, when technological innovation is a performance criterion, the impact of R&D and marketing integration continues to increase without reaching a peak point. This result supports the findings of William E Souder and Chakrabarti (1978), who found that the interface between R&D and marketing stimulates technological innovation. However, when time to market and product sales are the performance criteria, the impact of integration is diminished. In consequence, managers must not only support the integration of different functional teams but also must limit the much interaction between R&D and marketing. Only then can managers achieve the multiple objectives of delivering new products on time and encouraging technological innovation. Furthermore, the graphical findings illustrate that completing projects on time is more closely linked to product sales than technological innovation. To understand this in more detail, further research is required to uncover the underlying reasons. It will be interesting to determine why the time-to-market performance shows a pattern more similar to that of product sales than technological innovation in terms of R&D and marketing integration.

Third, we showed that the amount of development resources devoted to the NPD team moderates the effect of integration on NPD success. Different intensity levels of development resources lead to different levels of integration. The main managerial implication of this finding is that managers should not automatically determine the level of

integration of R&D and marketing. Instead, the decision regarding integration should consider the available technological resources. For example, if managers consider a firm with sufficient development resources that is willing to develop a new product, then they should strive to attain a high level of integration of R&D and marketing to increase the possibility of NPD success. In contrast, a firm with moderate development resources can be successful only if managers manipulate the optimal level of integration during a project. Too much integration slows the process, mainly because R&D must consider marketing's opinions and insights and cannot focus solely on product development. Hence, we can conclude that the amount of resources available to the NPD team determines the optimal level of integration between R&D and marketing.

3.7.2 Limitation and outlook

The main limitation of this research stems from the definition of the R&D and marketing integration variable. Similar to other NPD studies, the manner in which the variables are measured depends on the definitions of the variables. Although we defined the concept of R&D and marketing integration based on the literature, no study could be found which developed objective indicators which could be used to measure the integration level. Future research should address this limitation.

Following the approaches that were applied in previous studies, the present study also depended on a survey to collect data, though this method is somewhat affected by the

subjective beliefs of the respondents. If it would be possible to determine, for instance, the number of meetings or the meeting hours per week between R&D and marketing personnel, the validity of the findings could be increased.

Another limitation of this research is its generalizability, given that the sample was only drawn from those involved in ICT products. Although the ICT industry is a fairly typical example of a high-tech industry, there is the likelihood that a large part of variation takes place across industries. Specifically, in low-tech industries, the causes and effects pertaining to the integration of R&D and marketing may take on new aspects. Therefore, further research is needed to examine the impact of integration in other industries. In this regard, a direction of future research could be to compare the marginal effect of R&D and marketing integration across industries or across nations.

We expect that examining the mechanism that influences this type of integration activity can be an important next step. In other words, what makes managers integrate R&D and marketing people during NPD processes or what problems do they face when the realized integration does not reach the optimal level. These questions suggest that more can be learned about R&D and marketing integration in the NPD context.

Finally, our study finds that the significant interaction between development resources and the consumer needs analysis has stronger effects on the three NPD performance criteria. This finding implies that observing not only the impact of the integration of R&D and marketing at the organizational level but also determining the impact of the interaction of physical R&D and marketing resources may be a potential stream of further research. That

is, research to examine how the combination of R&D resources and marketing resources influences the outcomes of NPD results and finding the optimal configuration between R&D resources and marketing resources to maximize NPD performance will be a highly meaningful future research area in relation to NPD.

Chapter 4. Strategic Management of Key Drivers and Bottleneck in Innovation-Decision Process

4.1 Introduction

Implementation of effective marketing strategy to make potential buyers adopt innovation has long been one of the essential research topics in marketing and innovation area. Traditionally, innovation adoption theory pointed out that the customers follow the 'knowledge-persuasion-adoption' flow sequentially when they adopt a new innovation. Consumer psychology literature also explains that customers follow the similar hierarchical decision-making flow so called 'Hierarchy of Effect Model' and this is accepted as an established theory.

In this context, it is natural to assume that one may perceive different benefits or different drawbacks toward innovation as he or she passes through certain stage. For instance, a consumer may be aware of innovative product (e.g., their functionalities or usage) but may not be interested in it. Other consumers may be interested in it but unwilling to buy one. In this situation, high relative advantage of innovation may influence consumers to have interest on it while low complexity may affect consumers to have purchasing intention. To restate, there is high possibility that different innovation attributes affect

transition in decision-making path depending on consumers' current stage. This theoretical background strongly implies that different marketing communication strategy must be implemented by considering consumers' current stage in innovation adoption process.

However, little research has been conducted to find the factors (e.g. consumer relevant factors, and the communication message factors which link the product and consumer) affecting transition of each stage in new product adoption based on the hierarchical decision-making process. Though there were some studies that mentioned the consumer hierarchical decision-making while they were investigating main factors affecting consumer response such as awareness, interest and intention to purchase, they did not successfully reflect this theoretical hierarchical decision-making process to the empirical model. In other words, they estimated independent regression models by adopting different response variables such as awareness or interest by neglecting theory on hierarchical decision-making process about new product purchase or innovation adoption. Thus, it is very meaningful to statistically model consumers' hierarchical decision-making stage and find main factors affecting each stage transition.

Therefore, the objective of second essay is to propose a statistical model that evaluate different impacts of factors affecting innovation adoption, depending upon consumers' decision-making stage. The aim of this study, in methodology perspective, also can be regarded as identifying state-dependent utility function. To this end, we will construct statistical model for capturing relationship between factors affecting innovation adoption and hierarchical innovation decision process.

In a nutshell, we will propose a theoretical framework and a statistical model for capturing the relationship between the factors (e.g., innovation characteristics, consumer innovativeness, and message characteristics) affecting innovation adoption and consumers' decision-making stage through cognitive, affective, and behavioral reactions. And the model will be fitted to a survey data set on dedicated E-book reader and identify the resistance factors and the driving factors in each stage in the innovation adoption process. To the best of our knowledge, this appears to be the first study to identify factors affecting consumers' transferal process from unawareness to having purchase intention.

4.2 Theoretical background

4.2.1 Hierarchy of decision-making process

Consumers in the real world do not immediately decide whether to purchase a new product after obtaining information about it. Rather, they experience a series of hierarchical and sequential stages before reaching a decision (e.g., to purchase). The Hierarchy of effects model was developed to explain these sequential stages. This theoretical model, proposed by Lavidge and Steiner (1961), is used to describe the accumulated effect of advertising on consumer purchase decision-making. The model involves sequential stages, beginning with the product's arrival in the target customers' awareness, passing through purchase intention, and terminating in the actual purchase. The term "hierarchy" denotes the sequence of steps a consumer follows from the initial exposure to a product (or

advertisements) to the purchase decision.

Innovation researchers have developed a similar model—the innovation decision process model—to explain the relative impact of the knowledge–persuasion–decision components (Rogers, 2003). The validity of the hierarchical decision-making model for the innovation decision process was first proved by an Iowa study (Beal & Rogers, 1960), in which most respondents recognized that they had passed through a series of stages, from awareness and knowledge to an adoption decision. Figure 11 describes the hierarchy of effect model.

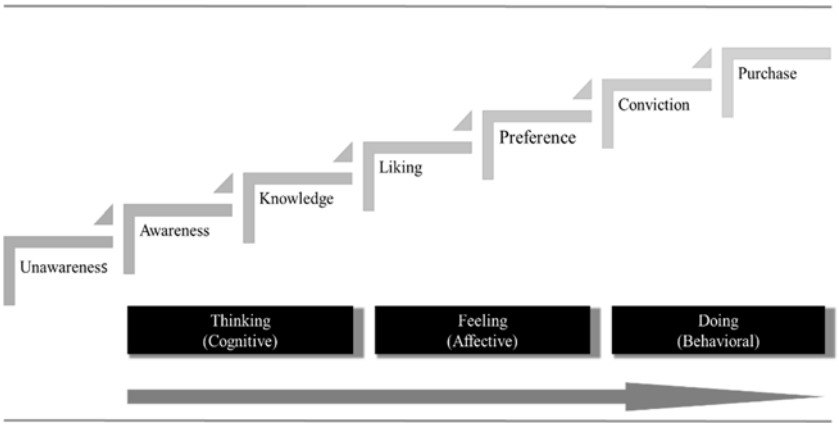


Figure 11. Hierarchy of effect model based on Lavidge and Steiner (1961)

According to the hierarchy of effect model and innovation decision process model (see Figure 11), consumers at the cognitive stage form beliefs about a product by accumulating knowledge about its attributes (i.e., knowledge stage). Next, in the affective stage, consumers evaluate these beliefs and form a feeling about the new product (i.e., persuasion

stage). Later, in the behavioral stage, consumers engage in behavior such as product adoption or rejection based on their evaluation (i.e., decision stage). This theoretical background on the hierarchical stages of innovation adoption shows that the drivers or bottlenecks affecting the intention to adopt an innovation differ across the stages.

Despite the theoretical and empirical evidence that consumer decision-making occurs in stages and that consumers' reactions to innovation adoption can change at any stage due to drivers or hurdles, most studies ignore this hierarchical and sequential process while identifying the factors affecting adoption. For example, Chan-Olmsted and Chang (2006) studied digital television adoption, comparing the factors affecting awareness with those affecting the intention to adopt digital television. They found significant differences between the factors' influences on adoption and intention to use. Jung, Chan-Olmsted, Park, and Kim (2012) attempted to identify the predictors of E-book reader diffusion in terms of consumer awareness, interest, and intention to use. Although they evaluated the impact of the meaningful predictors of E-book reader adoption depending on different consumer reactions, they failed to capture the hierarchical process of consumer decision-making as described by Lavidge and Steiner (1961) in their empirical model structure and estimation.

In innovation adoption studies, then, capturing the hierarchical decision-making process and empirically estimating the model are essential; otherwise, a model will produce biased empirical results. However, the overwhelming majority of studies have neglected this process in their analyses. Therefore, we develop a theoretical and empirical framework that explicitly describes consumers' sequential decision-making for innovation adoption.

4.2.2 Factors affecting innovation adoption

Several theoretical models have been suggested in the area of innovation adoption including technology acceptance model: TAM (Davis, 1989), its intension model: TAM2 (Venkatesh & Davis, 2000) and unified theory of acceptance and use of technology: UTAUT (Venkatesh, Morris, Davis, & Davis, 2003). Among them, Innovation Diffusion Theory (IDT) of Rogers has been frequently citied since the 1960s in the research of a variety of innovation adoption contexts (Rogers, 2003). Various factors inherent to IDT have been applied in empirical studies, and they have proven to provide reliable frameworks for examining innovation adoption. These factors affecting individual's innovation adoption behavior comprise perceived attributes of innovation, adopter's characteristics, and message characteristics. Hereafter, we will review these factors and will examine how such factors influence adoption behavior in detail by focusing on the theoretical concept and existing empirical findings.

4.2.2.1 Perceived attributes of innovation

One of the most influential models describing the perceived attributes of innovation to illustrate customers' adoption of innovation is based on Rogers' framework (Rogers, 2003), according to which five characteristics influence a customer's potential adoption of a new innovation: relative advantage, compatibility, complexity, observability, and trialability. Relative advantage refers to the degree to which potential customers perceive a

new product as superior to existing substitutes. Compatibility refers to the degree to which potential consumers feel that a new product is consistent with their needs, values, and practices. Complexity refers to the degree to which a new product is difficult to understand or use. Observability refers to the ease with which a product's benefits or attributes can be observed, imaged, or described to potential customers. Finally, trialability refers to the degree to which a new product has been tried on a limited basis by potential consumers. The greater the opportunity to try a new product, the easier it is for consumers to evaluate it and ultimately adopt it. It is widely accepted among researchers that these five product characteristics account for much of the rate and speed of adoption. Table 7 summarizes these five innovation characteristics and provides the related attributes.

Table 7. Overview of the conceptual basis for the five perceived innovation characteristics

Innovation Characteristics	Definition	Example
Relative advantage	The perceived benefit of adopting innovation.	Speed; Reliability
Compatibility	The extent to which using the innovation is based on existing ways of doing things	Complementary goods e.g.)EV car and station
Complexity	The difficulty involved in using innovative products.	Quality of a user interface
Observability	The extent to which the benefits of the new product are observable to everyone.	Noticeable design; Availability of information center
Trialability	The extent to which a new product can be tried at a limited basis by consumers.	Rental of product; Beta test of software

Numerous studies have adopted Rogers' framework to explain consumer innovation adoption (Tornatzky & Klein, 1982). But they have not captured the dynamic effects of the innovation attributes on the decision-making process despite the empirical evidence that the impacts of innovation characteristics differ across stages. For example, consumers employ different evaluation criteria at each stage of their decision-making, and these characteristics have different impacts at each stage (Gardial, Clemons, Woodruff, Schumann, & Burns, 1994; Karahanna, Straub, & Chervany, 1999; Mittal, Kumar, & Tsiros, 1999; Wilton & Pessemier, 1981). Therefore, we propose a framework to capture the dynamic effects of the perceived innovation characteristics on the cognitive, affective, and behavioral stages of the innovation-decision process.

Moreover, it is important to note that the perceived innovation characteristics influencing innovation adoption may differ across countries. For instance, Craig Van, Bélanger, and Varadharajan (2005) compared the perception of electronic commerce among U.S. and Indian consumers and found that relative advantage, complexity, and compatibility differed between the two countries. This result suggests that the perceived innovation characteristics of other innovative products might also hold an importance for Korean consumers different from that held by consumers in other countries where those products are very popular. Our research framework therefore estimates the dynamic effects of perceived innovation characteristics on cognitive, affective, and behavioral reactions in the innovation-decision process

4.2.2.2 Consumer innovativeness

Consumer innovativeness has been used in innovation adoption studies as an explanatory variable predicting the diffusion of innovation. Consumers' innate innovativeness refers to the "predisposition to buy new and different products and brands rather than remain with previous choices and consumer patterns (Steenkamp, Hofstede, & Wedel, 1999)" . Based on this definition, consumer innovativeness, as a force that leads to innovative behavior, has often been adopted in research on the adoption of innovation (Roehrich, 2004). For example, Im, Bayus, and Mason (2003) empirically proved that a high level of consumer innovativeness increases the intention to use and accelerates the adoption process for new products. These researchers argued that the measurement of the "innate innovativeness" construct could be applied to any domain and used in surveys on innovation.

Nonetheless, researchers have also reported that this way of measuring innovativeness cannot statistically explain consumers' adoption behaviors. For example, researchers demonstrated that no significant correlation existed between consumer innovativeness and new product adoption behavior (Gordon R. Foxall, 1988; Varma Citrin, Sprott, Silverman, & Stem Jr, 2000). Other researchers found a significantly positive relationship with an explanatory power that accounted for less than 10% of the variance in behavior (Cotte & Wood, 2004). Due to this concern, different theoretical conceptualizations of innovativeness have been developed. For example, Goldsmith and Hofacker (1991) argued that domain-specific innovativeness along with Internet usage directly influenced

consumers' adoption behavior in Internet shopping. Gordon R Foxall (1995) showed that the relationship between consumer innovativeness and new product adoption behavior was contingent on the level of involvement in the product category. Vandecasteele and Geuens (2010) acknowledged the importance of different motivations for innovativeness. They found that a multi-dimensional scale concerning motivation had better predictive power than other models and that multi-dimensional motivation played a key role in new product development and marketing communication. This approach incorporates various motivations into a multi-dimensional innovativeness scale to better account for consumer and product relationships.

Following the seminal paper, Vandecasteele and Geuens (2010), on motivated innovativeness, our research framework includes the conceptual basis for the four dimensions of motivated innovativeness: hedonic innovativeness, functional innovativeness, social innovativeness, and cognitive innovativeness. Hedonic innovativeness is defined as the "drive to adopt innovations for hedonic reasons, such as to enjoy the newness of the product" (Chesson, 2002; Steenkamp et al., 1999). Functional innovativeness emphasizes the "utilitarian reasons for buying products" as opposed to the hedonic or affective reasons (Hirschman, 1980, 1984; Venkatraman, 1991). Social innovativeness refers to the "degree to which consumers build certain identity such as social reward or social differentiation through the possession of innovative products" (Tian, Bearden, & Hunter, 2001; Tian & McKenzie, 2001). Finally, cognitive innovativeness is defined as the "desire for new experiences with the objective of stimulating the mind"

(Venkatraman & Price, 1990). Table 8 lists the definitions and related academic concepts concerning the four dimensions of motivated consumer innovativeness as proposed by Vandecasteele and Geuens (2010).

Table 8. Overview of the conceptual basis for the four motivated consumer innovativeness dimensions

Dimension	Definition	Related Concepts	Examples of Motivation
Functional innovativeness	Self-reported consumer innovativeness motivated by the functional performance of innovation and focus on task management and accomplishment improvement	- Utilitarian - Attraction to useful products	- Usefulness - Handiness - Quality - Reliability
Hedonic innovativeness	Self-reported consumer innovativeness motivated by affective or sensory stimulation and gratification	- Sensory innovativeness	- Pleasure - Fun - Excitement
Social innovativeness	Self-reported consumer innovativeness motivated by the self-assertive social need for differentiation	- Identity building - Social reward	- Being unique - Status - Prestige
Cognitive innovativeness	Self-reported consumer innovativeness motivated by the need for mental stimulation	- Mental stimulation	- Knowledge - Information - Logical thinking

* This is the shortened version of (Vandecasteele & Geuens, 2010) Table 1.

Therefore, our research framework takes into account the four different motivational dimensions proposed by Vandecasteele and Geuens (2010) and identifies the types of motivational innovativeness that stimulate consumers' cognitive, affective, and behavioral

reactions in innovation adoption.

4.2.2.3 Communication and message characteristics

Research has shown that communication channels for new products play a critical role in determining the rate of innovation adoption (Rogers, 2003). The marketing literature has also suggested that a marketing communication strategy in support of product launch is an essential factor and can explain new product adoption behavior. From this perspective, all information on and efforts towards product attribute exposure and strong persuasion influence the decision to adopt a new product (Crawford & Di Benedetto, 2003). However, most innovation studies have focused on the types of communication channels (e.g., whether a consumer gains information from mess media or word of mouth) and how they affect adoption behavior. Little attention has been paid to specific message characteristics, even though the features and credibility of the messages are also important.

We consider four determinants of the message characteristics influencing decision-making. In principle, any message disseminated to consumers possesses a dual nature through rational and emotional elements (Johar & Sirgy, 1991; Liebermann & Flint-Goor, 1996). The rational element comprises the informational message, which includes factual and meaningful descriptions of the product. The emotional element comprises the transformational message, which conveys affect-based content such as about the experience of using a new product with psychological characteristics. C.-W. Chen, Shen, and Chiu (2007) found that an informational message was positively linked to effective

communication and sales of new products in the high-tech industry.

Source credibility is also an important characteristic influencing decision-making (Buda & Zhang, 2000; Ratneshwar & Chaiken, 1991). A highly credible source is perceived to be useful and reliable and thereby facilitates the transfer between decision-making stages. If a message delivered by a sender is considered credible, it is likely to influence the receiver's perception of the new product. When the source is respected by the intended audience, the message is likely to be believed and is much more likely to influence the adoption of new products. Conversely, a message from an untrustworthy or unreliable source is likely to be received with skepticism and probably rejected. Theoretically, source credibility is defined as the extent to which an information source is perceived to be believable and trustworthy by information recipients (Buda & Zhang, 2000). Ratneshwar and Chaiken (1991) showed that a credible source could be particularly persuasive if the consumer had not yet learned much about a product or formed an opinion about it.

Other researchers found that expertise (basically, the knowledge and competence of the sender) and trustworthiness were the two most significant components of credibility (Cheung, Lee, & Rabjohn, 2008). McGinnies and Ward (1980) found that communicators frequently conveyed a mixed impression between expertise and trustworthiness. The source of a message may lack trustworthiness but be reputed for expertise; it may also be viewed as trustworthy but not particularly competent. McGinnies and Ward (1980) demonstrated that expertise and trustworthiness were exclusive factors explaining source credibility.

Therefore, our research framework explicitly considers not only the nature of a

message but also its source credibility, consisting of expertise and trustworthiness. Table 9 describes the two dimensions of messages and their characteristics in the innovation adoption context.

Table 9. Overview of the conceptual basis for marketing communication message

Dimension	Characteristics	Operational definition
Nature of message (C.-W. Chen et al., 2007)	Informational message	Message conveys information about the identity of a new product logically.
	Transformational message	Message conveys experimental and sentimental information about using a new product.
Credibility of message (Buda & Zhang, 2000) (Cheung et al., 2008)	Expertise	Source, which conveys messages, has knowledge for evaluating a new product.
	Trustworthiness	Source, which conveys message, is reliable.

4.3 Research design

4.3.1 Research framework

This study identifies the factors affecting innovation adoption by considering the hierarchical stages of the innovation decision-making process. We suggest a statistical model for capturing how perceived innovation characteristics, consumer innovativeness, and message characteristics sequentially drive consumers' cognitive, affective and behavioral reactions. In this end, the proposed model is fitted to survey data set on

dedicated E-book reader and we discuss implications for E-book industry

The innovation adoption process is described in Figure 12. The essence of the process is that consumers pass through three sequential stages, starting with a product's attracting the target customers' awareness, through the creation of purchase intention, to making the purchase. The consumer's adoption process consists of cognitive, affective, and behavioral reactions. After the initial exposure to an innovative product, where people are unaware of them, consumers experience several stages. Their reactions in each stage are influenced by various factors affecting innovation adoption.

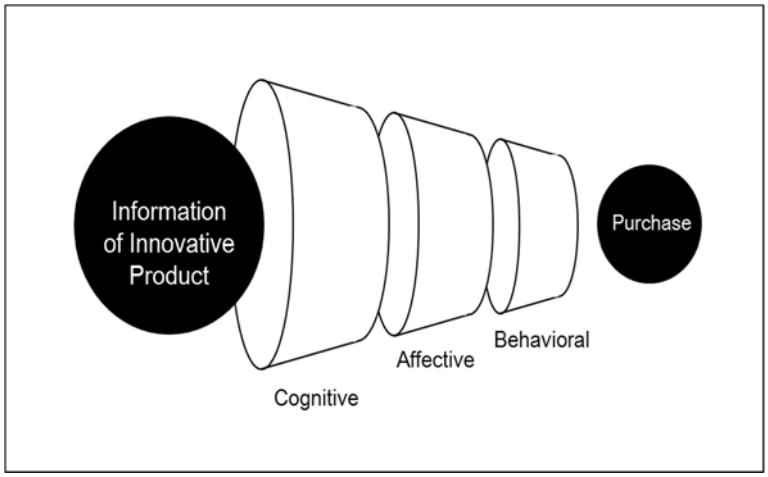


Figure 12. Innovation adoption process

Figure 13 describes the research framework, which examines the impact of various factors affecting innovation adoption. More importantly, it sheds light on the relationships between the key constructs used in innovation adoption studies and the hierarchical

decision-making stages. Our proposed framework has advantages over previous frameworks in that it addresses the dynamic nature of innovation adoption by explicitly considering the stages during which people are aware of the readers and show affective and behavioral reactions to them rather than considering only the simple dichotomous alternatives of adoption or non-adoption.

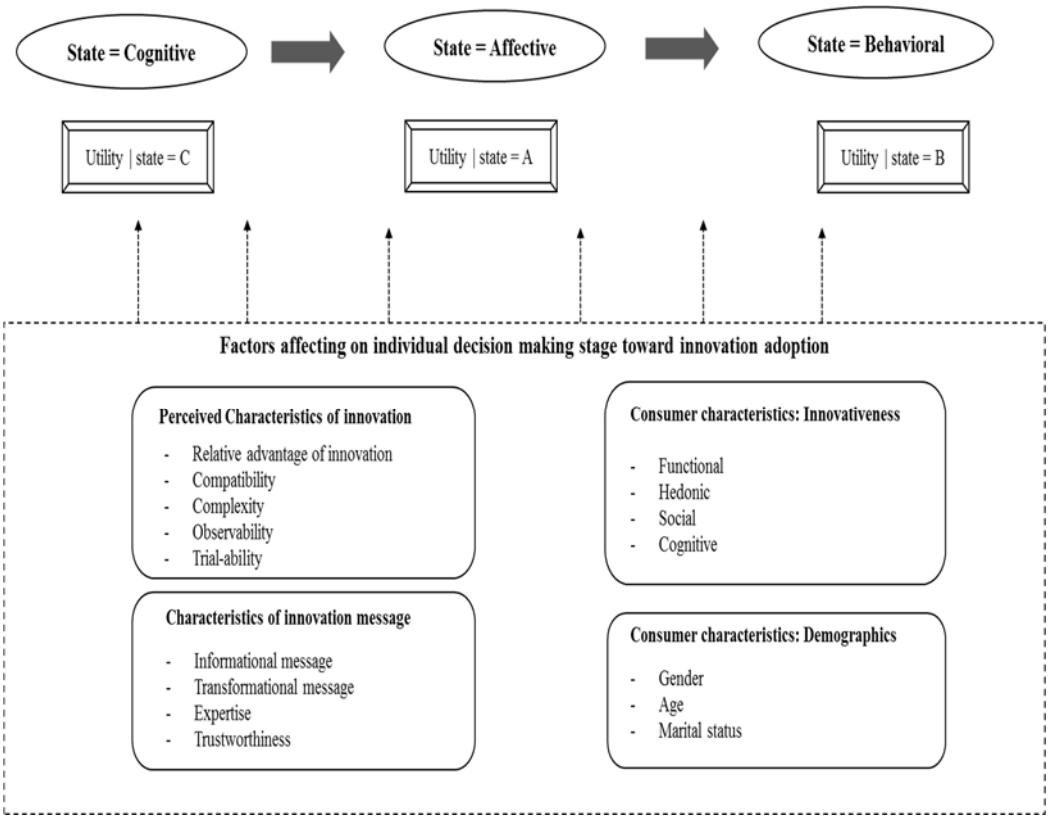


Figure 13. The proposed theoretical research framework

4.3.2 Application of the proposed research framework

We targeted the dedicated E-book reader for application of the proposed research framework in empirical analysis. And we conducted survey about consumers' perception and adoption toward dedicated E-book reader. This section explains why we targeted dedicated E-book reader for empirical analysis.

As Internet-capable mobile and smart devices continue to be diffused throughout the market, the number of advanced devices equipped with multiple functionalities quickly increases (Reeves, Lang, Kim, & Tatar, 1999). This breakthrough technology allows users to read text across a variety of devices, such as tablet PCs, smartphones, and dedicated electronic book readers. An E-book reader (often also called an "E-book device" or "'E-reader") is a dedicated electronic device designed primarily for reading digital books and periodicals. It uses e-ink technology to display content (Burk, 2001). This E-book technology emerged in the early 1990s with the expectation that it would pose a serious threat to the traditional print publishing industry (Catenazzi, 1997; Shin, 2011).

In the wake of the successful introduction of Kindle (the Amazon E-book reader and E-book reader application for multi-purpose devices), the PWC (2013) reported an increase in global sales of E-book content of almost 33.6% in 2013 over the previous year. Reflecting this trend, the proportion of E-books available in U.S. libraries increased almost twofold, from 38.3% in 2007 to 67.2% in 2011, according to the American Library Association's public Library Funding and Technology Access Study (American Library

Association, 2012). This increase in the demand for E-book content paralleled the skyrocketing sales of new reading devices in the U.S.

However, the market for E-book readers in Korea has not yet taken off. In fact, E-book readers such as SAM, Paper, Crema, and Papyrus (released by Kyobo/iRiver, Ridibooks, Yes24, and Samsung, respectively) have failed to gain popularity in Korea. Samsung Electronics even withdrew from the E-book reader market completely. Experts have argued that Korea, where growth in smart devices has been high, is entering an era in which users read E-books on non-dedicated devices directly without having passed through an era, as in the U.S., in which users read from dedicated E-book readers (Sim, 2011). Korean E-book readers have received little research attention, as consumers' interest in E-book readers has not been as high as was expected. Experts in the Korean publishing industry speculate that the E-book reader market is small due to a complex function of the difficulty-of-use and a low familiarity with the readers. Given the low adoption of E-book readers in Korea relative to that in the U.S., we pose the following research question: What makes Korean consumers hesitate to adopt E-book readers?

The purchase of an E-book reader can be described in terms of the sequential stages of the decision-making process, but only a few attempts have been made to identify the bottlenecks or drivers in the stages of the adoption process. For instance, a consumer may be aware of E-book readers (e.g., their functionalities) but may not be interested in them. Other consumers may be interested in them but unwilling to buy one. Thus, consumers may get stuck with any of the decision-making stages. Following a similar line of research, Jung

et al. (2012) empirically tried to identify the factors affecting E-book reader awareness, interest, and intention to use, but they overlooked the fact that innovation adoption is a sequential decision-making process suggested by Lavidge and Steiner (1961) and were thus unable to reliably describe the impact of the independent variables in their empirical model. Little is known about what factors lead to the use of E-book readers or make users hesitate to adopt them during the decision-making process. To fill this gap, we have chosen dedicated E-book reader for empirical analysis and collected the survey data.

4.3.3 Data

Data were collected through a structured survey questionnaire with a set of single-item and multi-attribute scales in order to populate the constructs of the proposed research framework. All innovativeness variables in the research framework were measured through multi-attribute scales. This composite scale approach allowed us to gauge psychological variables that otherwise could not be directly quantified. A 7-point Likert scale was used to measure the constructs. A value of 1 indicated that the respondent completely disagreed with the statement, and a value of 7 indicated that the respondent strongly agreed.

The survey was conducted using the Web-based EZ Survey, a professional survey company that maintains millions of potential participants. A sample from the EZ survey panel was asked to participate. Respondents were offered a small amount of electronic cash as payment for participating. The survey was completed by 536 respondents aged 20 years

or older in September and October 2014.

The distribution of respondents according to their decision-making stage is shown in Table 10. Of the 536 respondents, 257 (47.94%) were unaware of the E-book reader; 110 (20.52%) knew of the use and functionality of E-book readers, and 62 (11.56%) were interested in E-book readers; 107 (19.96%) were willing to purchase an E-book reader.

Table 10. Distribution of respondents with respect to their decision-making stage

Unawareness	Cognitive	Affective	Behavioral	Total
257	110	62	107	536

We measured Cronbach's alpha to check the internal consistency of the variables measured in multiple-item scales. All Cronbach's alpha values were greater than 0.7, and the lowest value was 0.713, for trialability (see Table 11). The alpha values for the four different types of innovativeness were over 0.9. Thus, we can conclude that all multi-scale items satisfied internal consistency.

Table 11. Variable measurement items and scale reliability

Variable (# of items)	Mean (S.D.)	Question / Item	Alpha	Source
Perceived Innovation				
Relative advantage (1)	3.84 (1.10)	(1) Using E-BR makes reading books easier than paper-based books.	n.a.	G. C. Moore and Benbasat (1991)
Compatibility (2)	4.02 (1.21)	(1) Using E-BR is compatible with my lifestyle. (2) Using E-BR gives me the same pleasure as reading paper-based books.	0.769	
Complexity (2)	3.52 (0.99)	(1) Operation of E-BR is complex. (2) The process of purchasing E-BR content is not convenient. (3) It is too difficult for me to use an E-BR.	0.812	
Observability (2)	3.43 (1.27)	(1) I have seen what others can do using E-BR. (2) I have seen E-BR demonstrations at stores.	0.759	
Trialability (2)	3.78 (1.19)	(1) I had an opportunity to try E-BR. (2) I was able to try it out at E-BR stores.	0.713	
Consumer innovativeness				
Functional (4)	3.82 (1.17)	(1) If a new time-saving product is launched, I will buy it right away. (2) If a new product gives me more comfort than my current product, I would not hesitate to buy it. (3) If an innovation is more functional, then I usually buy it. (4) If I discover a new product in a more convenient size, I am very inclined to buy it.	0.917	Vandecasteele and Geuens (2010)
Hedonic (4)	4.84 (1.10)	(1) Using novelties gives me a sense of personal enjoyment. (2) It gives me a good feeling to acquire new products. (3) Innovations make my life exciting and stimulating. (4) Acquiring an innovation makes me happier.	0.933	
Social (4)	4.23 (1.21)	(1) I like to own a new product that distinguishes me from others, who do not own this new product. (2) I prefer to try new products, with which I can present myself to my friends and neighbors. (3) I like to outperform others, and I prefer to do this by buying new products that my friends do not have. (4) I deliberately buy novelties that are visible to others and command respect from others.	0.915	
Cognitive (4)	3.90 (1.17)	(1) I mostly buy those innovations that satisfy my analytical mind.	0.919	

		(2) I find innovations that need a lot of thinking intellectually challenging and, therefore, I buy them instantly. (3) I often buy new products that make me think logically. (4) I often buy innovative products that challenge the strengths and weaknesses of my intellectual skills.		
Message Characteristics				
Informational (1)	4.44 (1.06)	(1) Communicated message emphasized the specification of the focused E-BR.	n.a.	C.-W. Chen et al. (2007)
Transformational (1)	4.30 (1.10)	(1) Communicated message emphasized experiences in using E-BR.	n.a.	
Expertise (1)	4.24 (1.09)	(1) People, who left messages about E-BR, are knowledgeable in evaluating the quality of E-BR.	n.a.	McGinnies and Ward (1980)
Trustworthy (2)	4.45 (0.93)	(1) People, who left messages about E-BR, are trustworthy. (2) People, who left messages about E-BR, are reliable.	0.854	

* n.a: the alpha value of a single item cannot be measured.

4.4 Methodology

Because the response variable of individual is multivariate vector form and its element is binary variable, we estimate the proposed theoretical model using the multivariate probit method (Albert & Chib, 1993; Chib & Greenberg, 1998; Edwards & Allenby, 2003), based on McFadden's random utility model (McFadden, 1980). The multivariate probit method allows the construction of sequential multiple stages as dependent variables, enabling us to describe the consumer's current stage at each decision-making point and to estimate the impact of innovation characteristics, innovativeness, and message characteristics at each stage. In analyzing the consumer's cognitive, affective and behavioral reaction, it is assumed that reactions at each stage can be expressed by the latent utility and that the utilities are composed of two parts: a deterministic part and a random part. The latent utility V_{ij} can be represented by assuming that consumers may remain in any one of the three stages:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \sum_k \beta'_{jk} X_{ki} + \varepsilon_{ij} \tag{4.1}$$

$$y_{ij} = \begin{cases} 1 \ if \ U_{ij} > 0 \\ 0 \ if \ U_{ij} < 0 \end{cases} \quad for \ j = 1,2,3 \tag{4.2}$$

where i stands for the ith individual, and j stands for the decision-making stage j, which can be either 1, 2, or 3. Finally, k stands for k^{th} independent variable affecting the decision-making stage. Therefore, X_{ki} denotes individual i's k^{th} independent

variable that affect the utility, and β_{jk} denotes their parameter vector (regression coefficients) in the decision-making stage j. The distribution of random disturbance ε_{ij} captures the factors affecting the utility but are not included in the utility V_{ij}. Consumer i chooses alternative j (i.e., stays in stage j in our study) if and only if the utility obtained by choosing j is greater than the utility of not choosing it (i.e., $y_{ij} = 1$).

$$
\begin{aligned}
y_{i1} &= \begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{cases} 1 & \textit{if a respondent } i \textit{ went through cognitive stage} \\ 0 & \textit{otherwise} \end{cases} \\
y_{i2} &= \begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{cases} 1 & \textit{if a respondent } i \textit{ went through affective stage} \\ 0 & \textit{otherwise} \end{cases} \\
y_{i3} &= \begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{cases} 1 & \textit{if a respondent } i \textit{ went through behavioral stage} \\ 0 & \textit{otherwise} \end{cases}
\end{aligned}
\tag{4.3}
$$

It is assumed that the random disturbance vector ε_i ($\varepsilon_i = \{\varepsilon_{i1,}\varepsilon_{i2},...,\varepsilon_{iJ}\}$) has a multivariate normal distribution with zero mean and variance covariance matrix Σ:

$$\varepsilon_i \sim MVN[0,\Sigma], \quad \Sigma : \mathrm{J} \times \mathrm{J}\ \text{variance} - \text{covariance matrix} \tag{4.4}$$

$$\phi(\varepsilon_i) = \frac{1}{(2\pi)^{J/2} |\Sigma|^{1/2}} e^{-\frac{1}{2}\varepsilon_j' \varepsilon_i} \tag{4.5}$$

For identification, the multivariate probit model is needed to normalize all diagonal elements in the variance-covariance matrix (Σ) to1. Chib and Greenberg (1998) and Edwards and Allenby (2003) each suggested an identification method for the multivariate

probit model in the Bayesian estimation perspective wherein the variance-covariance matrix is estimated first in the unidentified model; then the estimated covariance matrix is normalized as correlation matrix by transposing all diagonal elements in the estimated variance-covariance matrix to 1 by using matrix C, which is a transpose matrix. Thus, the identified variance covariance matrix ($\tilde{\Sigma}$) is analyzed by using Eq. (4.6).

$$\tilde{\Sigma} = C^{-1}\Sigma C^{-1},\ where\ C = \begin{bmatrix} \sigma_{11} & 0 & 0 & 0 \\ & \ddots & \vdots & \vdots \\ & & \sigma_{J-1,J-1} & 0 \\ & & & \sigma_{J,J} \end{bmatrix} \tag{4.6}$$

The estimation procedure for Bayesian multivariate probit estimation in (Edwards & Allenby, 2003) was chosen for this study. Their methodology uses the Markov Chain Monte Carlo (MCMC) Gibbs sampling instead of the classical MLE approximation. The Gibbs sampling is the workhorse of the MCMC method (Jackman, 2000). The Bayesian multivariate probit with Gibbs sampling was used in our analysis rather than the classical approach for several reasons. Above all, it avoided the complicated integration of the multivariate density function and overcame the initial point problem, as it does not require the maximization of any function. Furthermore, the result of a Bayesian estimation can be converted into a classical estimation result.

Basically, the Gibbs sampling method was adopted to estimate parameters, since a direct estimation of the full posterior density is not analytically tractable. Gibbs sampling

is based on the idea that successive sampling from the posterior conditional distributions produces a Markov chain that converges in its distribution to a marginal posterior distribution (McCulloch & Rossi, 1994). Thus, it is possible to consider successive sampling from the posterior conditional distribution.

We discuss the specific model structure and procedure of Bayesian estimation with Gibbs sampling of multivariate probit model. Suppose the multivariate probit model with J choice (J stages in this study). In this case, a J -dimensional multivariate regression model can be describes as follows:

$$U_i = X_i\beta + \varepsilon_i, \qquad \varepsilon_i \sim N(0,\Sigma) \tag{4.7}$$

where

$$\begin{aligned} &U_i = (U_{i1},...,U_{ij},...,U_{iJ})', \\ &\varepsilon_i = (\varepsilon_{i1},...,\varepsilon_{ij},...,\varepsilon_{iJ})', \quad \text{and } X_i = (x_i' \otimes I_J) = \begin{pmatrix} x_{i1}' & 0 & \cdots & 0 \\ 0 & x_{i2}' & \cdots & 0 \\ \vdots & \vdots & x_{ij}' & \vdots \\ 0 & 0 & \cdots & x_{iJ}' \end{pmatrix} \\ &\beta_i = (\beta_1,...,\beta_j,...,\beta_J)', \end{aligned}$$

The relationship between U_{ij} and y_{ij} is given by:

$$y_{ij} = \begin{cases} 1 \ , \ if \ U_{ij} > 0 \\ 0 \ , \ \text{otherwise} \end{cases} \tag{4.8}$$

In order to estimate parameter (β,Σ), the Bayesian approach allows researchers to

argue probability density function about parameters (i.e. the posterior distributions) conditional on the sample (i.e. the likelihood function) and prior information (i.e. the prior distributions) based on the Bayes' rule. We can construct model structure by applying Bayes' rule for above multivariate regression model and obtain following equation.

$$P(\beta,\Sigma^{-1}\,|\,U)\propto P(\beta,\Sigma^{-1})P(U\,|\,\beta,\Sigma^{-1}) \tag{4.9}$$

where $P(\beta,\Sigma^{-1}\,|\,U)$ is the posterior distributions of parameters, $P(\beta,\Sigma^{-1})$ is the prior distributions of parameters and $P(U\,|\,\beta,\Sigma^{-1})$ is the likelihood function.

Assuming β and Σ are priori independent and the prior density of β and Σ^{-1} follow the k -dimensional multivariate normal distribution and Wishart distribution, respectively, the prior distribution can be represented as follows:

$$\begin{aligned} P(\beta,\Sigma^{-1}) &= P(\beta)P(\Sigma^{-1}) \\ &= (2\pi)^{-\frac{k}{2}}\,|\,C\,|^{-\frac{1}{2}}\exp(-\frac{1}{2}(\beta-B)'C^{-1}(\beta-B)) \\ &\quad\times|\,\Sigma^{-1}\,|^{\frac{s-J-1}{2}}\,etr(-\frac{1}{2}\Sigma^{-1}V) \end{aligned} \tag{4.10}$$

where $\beta\sim N(B,C)$ and $\Sigma^{-1}\sim W(s,V)$.

The likelihood function for the multivariate probit model is given by

$$
\begin{aligned}
L(\beta,\Sigma^{-1}) &= P(U \mid \beta,\Sigma^{-1}) \\
&= \prod_{i=1}^{N}(2\pi)^{-\frac{J}{2}} |\Sigma|^{-\frac{1}{2}} \exp(-\frac{1}{2}(U_i - x_i'\beta)'\Sigma^{-1}(U_i - x_i'\beta)) \\
&= (2\pi)^{-\frac{NJ}{2}} |\Sigma|^{-\frac{N}{2}} \exp(-\frac{1}{2}\sum_{i=1}^{N}(U_i - x_i'\beta)'\Sigma^{-1}(U_i - x_i'\beta))
\end{aligned} \tag{4.11}
$$

Then, the posterior distribution is expressed as follows.

$$
\begin{aligned}
P(\beta,\Sigma^{-1} \mid U) &\propto P(\beta)P(\Sigma^{-1})P(U \mid \beta,\Sigma^{-1}) \\
&= (2\pi)^{-\frac{k}{2}} |C|^{-\frac{1}{2}} \exp(-\frac{1}{2}(\beta - B)'C^{-1}(\beta - B)) \\
&\quad \times |\Sigma^{-1}|^{\frac{s-J-1}{2}} etr(-\frac{1}{2}\Sigma^{-1}V) \\
&\quad \times (2\pi)^{-\frac{NJ}{2}} |\Sigma|^{-\frac{N}{2}} \exp(-\frac{1}{2}\sum_{i=1}^{N}(U_i - x_i'\beta)'\Sigma^{-1}(U_i - x_i'\beta)) \\
&= |\Sigma^{-1}|^{\frac{s-J-1}{2}} etr(-\frac{1}{2}\Sigma^{-1}V) \\
&\quad \times (2\pi)^{-\frac{NJ}{2}-\frac{k}{2}} |C|^{-\frac{1}{2}} |\Sigma|^{-\frac{N}{2}} \exp(-\frac{1}{2}(\beta - \hat{\beta})'\Sigma_{\beta}^{-1}(\beta - \hat{\beta}))
\end{aligned} \tag{4.12}
$$

where $\Sigma_{\beta} = \left(\sum_{i=1}^{N} x_i'\Sigma^{-1}x_i + C^{-1}\right)$ and $\hat{\beta} = \Sigma_{\beta}\left(\sum_{i=1}^{N} x_i'\Sigma^{-1}U_i + C^{-1}B\right)$

Since above posterior density is not well-known probability density function, it is very hard to directly compute from the formula. In this situation, MCMC method is very useful to estimate parameters in posterior distribution. The basic idea of MCMC method is to construct Markov chain in the parameter space. A Markov chain is a chain generating a sequence of random variable whose conditional distribution depends only on the one step ahead, i.e. $\theta_{r+1} \mid \theta_r \sim F(\theta_r)$. The state of the chain after a number of steps is then used as a

sample of the desired posterior distribution. Thus, we are not directly sampling from the posterior distribution itself. Rather, we simulate samples by sweeping through all the posterior conditionals, one random variable at a time.

As one of the MCMC methods, Gibbs sampling formulates a Markov chain obtained by iterative sampling from conditional distributions of m set of parameters, i.e. $\theta' = (\theta_1, \theta_2, ..., \theta_m)$. The general procedures of Gibbs sampling from m set of parameters can be expressed as follows.

1st step: Set initial value, θ_0

2nd step: Sample from

$$\begin{aligned}
&\theta_{11} \sim f_1(\theta_1 \mid \theta_{02}, ..., \theta_{0m}) \\
&\theta_{12} \sim f_2(\theta_2 \mid \theta_{11}, \theta_{03}, ..., \theta_{0m}) \\
&\vdots \\
&\theta_{1m} \sim f_m(\theta_m \mid \theta_{11}, ..., \theta_{1,m-1})
\end{aligned}$$

3rd step: Repeat as necessary.

Through the above iterative process, the samples approximately become close to the joint distribution of all variables and the marginal distribution of any subset of variables can be approximated by simply considering the samples for that subset of variables.

We use the multivariate probit Gibbs sampler implemented in *bayesm* given by Rossi et al (2005).

1st step: Set initial value for each parameter: U_0, β_0, Σ_0

2nd step: Draw $U_1 \mid \beta_0, \Sigma_0, y$

i.e. sampling U_1 from $P(U \mid \beta, \Sigma^{-1})$ ~ truncated $N(x_i^{'}\beta, \Sigma)$

The sampling procedure of latent utility is described in Appendix B

3rd step: Draw $\beta_1 \mid U_1, \Sigma_0 \sim N(\tilde{B}, \tilde{C})$

where $\tilde{C} = (X^{*'}X^{*} + C^{-1})^{-1}$, $\tilde{B} = \tilde{C}(X^{*'}U^{'} + C^{-1}B)$

$\Sigma_0 = C'C, \quad x_i^{*} = C'x_i, \; U_i^{*} = C^{'}U_i$ and $X = \begin{bmatrix} x_i \\ \vdots \\ x_N \end{bmatrix}$

4th step: Draw $\Sigma_1 \mid U_1, \beta_1$ using $\Sigma^{-1} \mid U, \beta \sim W(s + N, (V + S)^{-1})$

where $S = \sum_{i=1}^{N} \varepsilon_i \varepsilon_i^{'}$ and $\varepsilon_i = U_i - x_i\beta$

5th step: Repeat as necessary

4.5 Empirical analysis

To estimate the Bayesian multivariate probit model, we ran 20,000 draws from the conditional posterior distributions using the MCMC-Gibbs sampling method. We discarded initial 10,000 draws as burn-in period. After burn-in period every 10th value was chosen from draws for parameter inference. The results of the multivariate probit estimation are shown in Table 12.

One need to note that demographic variables were included as control variables since these significantly influence adoption behavior in high-tech product. For instance, the younger are more likely to have interest on innovative products. Therefore, these will not be interpreted. Gender is dummy variable where 1 represents male whereas 0 indicates female. Age is continuous variables. Single is also dummy variable where 1 represents single-person household while 0 represents non single-person household.

Table 12. Estimation results

Dependent variable / Independent variable	Stage1	Stage 2	Stage 3
	Cognitive	**Affective**	**Behavioral**
Demographics			
Gender	0.156 (0.111)	-0.082 (0.099)	**-0.229* (0.103)**
Age	**-0.031* (0.008)**	**-0.038* (0.006)**	**-0.035* (0.005)**
Single	**-0.198* (0.148)**	**-0.401* (0.136)**	**-0.428* (0.201)**
Perceived innovation characteristics			
Relative Advantage	0.017 (0.063)	**0.130* (0.061)**	0.069 (0.067)
Compatibility	-0.019 (0.063)	0.042 (0.046)	**0.102* (0.054)**
Complexity	**-0.175* (0.051)**	**-0.202* (0.056)**	**-0.186* (0.056)**
Observability	**0.273*(0.058)**	**0.242* (0.064)**	**0.146* (0.066)**
Trialability	-0.003 (0.062)	0.029 (0.057)	0.068 (0.060)
Innovativeness			
Functional	**0.141* (0.064)**	**0.148* (0.066)**	**0.148* (0.067)**
Hedonic	-0.052 (0.053)	**-0.137* (0.051)**	**-0.259* (0.056)**
Social	**-0.156* (0.071)**	**-0.147* (0.060)**	**-0.151* (0.065)**
Cognitive	0.080 (0.074)	**0.126* (0.072)**	**0.288* (0.084)**
Message characteristics			
Information	0.059 (0.069)	0.019 (0.067)	0.022 (0.067)
Transformation	0.071 (0.072)	0.076 (0.068)	0.070 (0.075)
Expertise	0.005 (0.079)	0.046 (0.089)	-0.042 (0.082)
Trustworthiness	0.059 (0.091)	-0.112 (0.079)	-0.105 (0.093)
Variance-Covariance matrix (Correlation matrix)			
Cognitive	1	0.999033	0.998877
Affective	0.999033	1	0.998871
Behavioral	0.998877	0.998871	1

Note 1) * represents a significance level < 0.1

First, we found that the impact of perceived innovation characteristics on consumers' cognitive, affective, and behavioral reactions differs across stages. This finding is directly linked to the main research question of this study. Specifically, the relative advantage ($\beta = 0.130$ on affective) is the only statistically significant factor in the affective stage, whereas the variable is not significant in the cognitive or behavioral stage. Thus, the relative advantage of E-book readers drives consumers who are aware of the use of the device and are interested in it. The result also reveals that compatibility ($\beta = 0.102$ on behavioral) is significant in increasing behavioral intention, implying that low compatibility with alternative ways of reading a book can hinder the adoption of E-book readers. Accordingly, those who favor E-book readers may not have an intention to purchase them if they judge that reading an E-book with a dedicated E-book reader is incompatible with their reading habits. It is also notable that both complexity ($\beta = -0.175$ on cognitive, $\beta = -0.202$ on affective, $\beta = -0.186$ on behavioral) and observability ($\beta = 0.273$ on cognitive, $\beta = 0.242$ on affective, $\beta = 0.146$ on behavioral) are statistically significant characteristics affecting every stage of decision-making, while trialability is not significant at all.

Second, all innovativeness variables are significant but show differences depending on the stage. It is especially interesting that functional innovativeness ($\beta = 0.148$ on affective, $\beta = 0.148$ on behavioral) and cognitive innovativeness ($\beta = 0.126$ on affective, $\beta = 0.288$ on behavioral) are significantly positive in the affective and behavioral stages, whereas hedonic innovativeness ($\beta = -0.137$ on affective, $\beta = -0.259$ on behavioral)

and social innovativeness ($\beta = -0.147$ on affective, $\beta = -0.151$ on behavioral) are significantly negative in the affective and behavioral stages. Given that the literature argues that innovativeness must be distinguished depending on its motivation (Vandecasteele & Geuens, 2010), our empirical result strongly supports the view that the impacts of different motivations or sources of innovativeness are much more related to innovation adoption behavior than is innate innovativeness. In particular, a high hedonic innovativeness and social innovativeness, which are closely related to hedonic activities such as playing games and communication, reduce the possibility that consumers will experience affective and behavioral intention during E-book reader adoption. On the other hand, the result shows that consumers with a high cognitive and functional innovativeness are likely to react in the affective and behavioral stages of decision-making, perhaps because reading a book is a kind of mental and intellectual activity. Therefore, people with a high cognitive and functional innovativeness are more likely to have an interest in and intention to purchase E-book readers. In other words, E-book readers are so closely related to paper-based books (unlike other smart devices with E-book applications as well as other uses such as viewing video clips, chatting, and playing games) that cognitive and functional innovativeness stimulates their adoption.

Third, every variable related to message characteristics were found to be insignificant across all dependent variables. There was no apparent relationship between either the nature of a message and E-book reader-related cognitive, affective, and behavioral responses. Consequently, the message characteristics of E-book readers do not affect

Korean consumers' adoption decisions. However, given that the message characteristics of innovation are especially influential and meaningful when a new product has been launched on the market, one possible explanation for our result could be that respondents might have been affected by the credibility and nature of the communication when E-book readers first appeared but that the effect disappeared over the years (E-book readers were released in the Korean market in 2010). Publishing companies recently released multiple new E-book readers on the market and promoted them through different communication strategies. Accordingly, message characteristics may influence consumers' decision-making at the brand level but not at the product level.

4.6 Conclusion

4.6.1 Lessons from empirical analysis

Through empirical application of the proposed model, this study has successfully identified the meaningful factors that influence the decision-making process for the adoption of E-book readers. The results of empirical analysis provide a few useful implications to marketers and product engineers of E-book readers.

First, complexity was a main bottleneck affecting all stages of the E-book reader adoption process in the Korean E-book market, consistent with the results of previous research (Hwang & Lim, 2015). The issue of complexity is especially important for the

market acceptance of high-tech consumer products. Our result demonstrates that the fear of technological complexity acts as a barrier to acceptance and that Korean consumers' concerns about the difficulty of using E-book readers have a significant impact. Additionally, consumers may face a backlash from overly complex E-book readers. Therefore, product engineers need to design E-book readers in a way that guarantees ease of use, and marketers must then explain to consumers how easily the readers can be used.

Second, the results also showed that high observability is positively related to the cognitive, affective, and behavioral stages. From the marketer's perspective, then, enhancing the observability of E-book readers is an essential strategy in Korea, since increased observability makes consumers aware of, feel interested in, and have the intention to use E-book readers. For example, one practical strategy for increasing observability is to display and exhibit E-book readers in offline stores and on websites frequently, making them easily recognizable to visitors.

Third, issues of compatibility arise at the behavioral stage. Compatibility indicates how well the use of E-book reader fits with that of paper-based books. One possible explanation of this result is that people tend to think that they cannot read with an E-book reader as comfortably as they can with a paper-based book. The underlying cause may be that Korean consumers are unfamiliar with reading a book using electronic devices and therefore perceive it as something that requires learning. A strategic implication of this observation is that product engineers have to make an effort to develop E-book readers that provide a seamless reading experience and one that is similar to reading a paper-based book.

Marketers have to emphasize to potential buyers that there is no great difference between reading an E-book reader and reading a paper-based book. Marketers should also communicate that E-book readers do not require additional learning. Thus, marketers have to foster the perception in customers' minds that using E-book readers is as easy as using paper-based books.

Fourth, we found that the demand for E-book readers is segmented by kinds of innovativeness: functional and cognitive innovativeness have a positive effect on both affective and behavioral stages, while hedonic and social innovativeness have a negative effect on affective and behavioral responses, respectively. By identifying the motivated innovative consumers in the Korean E-book reader market, we offer insights different from the general consensus in the extant literature, which has indicated that innovativeness is usually innate and that motivations do not differ among innovative consumers. Our results indicate that consumers, who have different motivational innovativeness, should be targeted with effective marketing communications that address their specific motivation.

To put it shortly, by applying the suggested model to survey set on dedicated E-book reader, we could draw some meaningful implications for Korean E-book device market, where its sales was not as high as what experts expected. Finally, we believe that these implications will be guide for those who are thinking to design next generation E-book device.

4.6.2 Contribution to extant studies

Even though there are still arguments among advertising academics and marketers about the theory of how advertising works and how consumers perceive it, the hierarchy of effect models are clearly useful and practical. There is no doubt that they bring some implications for practitioners such as helping to predict behavior regardless of how imperfect those predictions are.

In the same vein, this study represents pioneering research in terms of its research framework, which allowed us to capture the hierarchical decision-making stages described by Lavidge and Steiner (1961) and to observe how significantly innovation attributes influence transition of each decision-making stage.

In fact, the proposed model based on hierarchy of effect theory is an appropriate framework for evaluating not only innovation attributes but also any forms of communications. This is because potential buyers may be at different stages in the hierarchy so the marketers face different sets of communication problems. In this perspective, we found that the proposed model is useful to promotional planners from several perspectives because they describe a series of steps which potential purchasers must be taken through to move them from unawareness of a product to readiness to purchase it.

In sum, the proposed model provides practitioners with information on what marketing communication strategies should be implemented for given decision-making stage and eventually provides planners with a good planning, training and conceptual framework.

4.6.3 Limitation and outlook

Despite its meaningful strategic implications, this study has a few limitations. First of all, the proposed research framework assumes that consumers experience cognitive, affective, and behavioral stages sequentially, based on the theory of traditional consumer behavior and the innovation adoption literature. However, some researchers have pointed out that consumers can follow different decision-making paths when purchasing new products (Ratchford, 1987). For example, in impulse purchasing situations, consumers first experience a behavioral intention to purchase and then follow the affective and cognitive stages. There is high possibility that the order of the decision-making process might be different across individual customers; however, there seems to be no research that addresses individual heterogeneity in purchase decision-making path for the same product and connects it to innovation attribute factors. Thus, future research must shed light on determining which decision-making paths consumers follow in innovation adoption and identifying key messages to stimulate innovation adoption for a given decision-making path.

Lastly, as dedicated E-book readers and contents (i.e., E-books) can also be bundled, firms may consider a promotional strategy that is especially based on a price strategy. Considering Amazon's sales strategy of Amazon Kindle, for example, there are indications that Amazon-Kindle is not sold as a profit-generating product but rather as an element in Amazon's promotional strategy for E-books and video. In other words, the Kindle is a loss-

leader promoted at a price that is lower than its cost, in order to attract consumers' adoption of revenue-generating items such as E-books. Due to this reason, it is conceivable that people's adoption of dedicated E-book readers can be influenced by promotional strategies that bundle device and contents into one product. In this case, the sales of the bundle (i.e., device and contents) are more important than the sales of the single device. Thus, our future research may include an in-depth investigation concerning how low-price promotional strategy influences consumer's adoption of E-book readers and, furthermore, the net sales of E-book readers and E-books.

Nonetheless, this study reveals that people make decisions in three sequential steps rather than in a simple dichotomous way (i.e., adoption vs. non-adoption). From a theoretical perspective, our research framework makes it possible to address the hierarchical decision-making stages and how innovation characteristics, consumer innovativeness, and message characteristics affect each one. In the management domain, our empirical results provide useful implications to marketers and product engineers.

Chapter 5. Strategic Management of Market Segment and New Product Positioning Considering Consumer Heterogeneity on Decision-Making Path

5.1 Introduction

Understanding of impact of communication message in consumer purchase decision-making has long been an important research topic in marketing. Since the pioneering study called hierarchy of effect model by Lavidge and Steiner (1961), the hierarchy framework has been widely cited and applied in audience behavior study. Essence of the traditional hierarchy framework claims that consumers of a variety of marketing communications respond to those messages in a very ordered way of three stages: cognitively first ('thinking'), affectively second ('feeling') and conatively third ('doing') (Barry & Howard, 1990). While there is little disagreement, however, about three components of the hierarchy of effects model, there has been a lot of critiques in order of three stages in hierarchy and there is no clear-cut evidence about sequence. This critique is directly linked to following question: Does awareness always lead to preference toward a product and then to purchasing behavior (Barry, 1987)? Academically, this has been the area of the most intense criticism and debate concerning the hierarchy of effect and a lot of researchers debated.

This stage model in consumer behavior is also referred to as the decision-making perspective in consumer research. From this decision-making perspective, prior works have been claiming that there may exist different sequence of three decision-making stages other than traditional hierarchy of effects model (Barry & Howard, 1990; Vakratsas & Ambler, 1999). For example, Krugman (1965) argued that, in low involvement situation, massive repetition of advertisements eventually leads to a modified cognitive structure in those consumers, who may purchase a product on that cognition alone, and afterwards decide whether they prefer it or not. The result of the work of Krugman appears to suggest a cognition-conation-affect sequence. Further, Ray et al. (1973) suggested that any stage can be initial processing at consumer decision-making process. They argued that all three order hierarchies are feasible and can be correct because consumer responses are likely to be individual and situation specific. And they found that three distinguished hierarchy models (three orders model) were valid. Despite evidence that consumers may follow different order of three stages, little attention has been given to empirical research that address individual heterogeneity with respect to different decision-making process.

Thus, the objective of third empirical essay is to investigate a transferal process for high-tech product adoption that allows for consumer heterogeneity in decision-making path. One may ask following question. Why is it important to incorporate heterogeneity in decision-making process while studying adoption behavior of high-tech product? Answers can be twofold. First, while traditional hierarchy of effect model has been heavily citied to describe consumers' new product adoption, there has been much critique in its sequence.

Thus this study provides flexible pattern for decision-making path empirically. Further, the research model enables us to explain which paths are reliable but which are not. Second, more importantly, exploring and understanding different decision-making paths provides information on what communication strategy and message has to be implemented according to each path when marketers plan communication strategies and implement them. In other words, once marketers identify individual specific different path, they are able to learn different essential key drivers and bottleneck in the new product adoption and establish different communication strategy by targeting those who follow same decision-making path. Consequently, understanding of individual different decision-making path can help marketers plan communication message and persuasion strategy in order to stimulate consumers to reach adoption behavior as fast as possible. Hence, we aim at, in this third essay, capturing all possible different orders of three hierarchical stages over individuals and furthermore identifying key drivers and bottleneck according to the difference of decision-making path.

5.2 Theoretical background

In the real world, it is well known that consumers do not immediately decide whether to purchase new products or not, when they learn information on them. Rather, they experience a series of hierarchical and sequential stage in order to reach actual adoption decision. Namely, 'Hierarchy of effects model' was theoretically developed to explain such

a sequential stage. This is a theoretical model proposed by Lavidge and Steiner (1961) who described accumulated effect of communication message on consumer's purchase decision and it is basically about there being different sequential stages involved from the product first coming into target customers' awareness to having a purchase intention. The term 'hierarchy' precisely represents sequence of multiple steps a consumer passes through from the initial exposure to a product or advertisement to the purchase decision. Researchers found that consumers went through a series of stages as they moved from awareness-knowledge to decision to adopt (Beal & Rogers, 1960). Therefore, adoption behavior is a process that contains stages, and three stages (cognitive, affective and conative) occur over time. According to the hierarchy of effect model, at cognitive stage, consumers form beliefs about a product by accumulating knowledge regarding relevant attributes. Next, at affective stage, the consumers evaluate these beliefs and forms a feeling about the new product. Over time, at the conative stage, consumers engage in a relevant behavior, such as adoption or rejection of new product based on their evaluation. No one doubts the existence of the cognitive, affective and conative reactions to communication message. While all three components of an attitude are important, their relative impact may vary depending upon a consumer's level of motivation with regard to the object. That is, the challenge is whether cognitive reactions must precede affective which must precede conative. Many literatures both in psychology and marketing communication indicated that cognitive response is often not a measurable precedent to either affect or conation. Similarly, the affective-conative link was questioned by a numerous studies of the attitude behavior relationship. Clearly, if

we knew nothing about hierarchy, it would be reasonable to assume that they could be ordered in all six possible permutations of three stages. In fact, some researchers pointed out that the response of marketing communication message were represented by each six path including standard learning model. Thus, there is possibility that individual can take different path in decision-making process. Next, we will take a look at alternative decision-making paths briefly.

1) Cognitive-Affective-Conative: Traditional hierarchy of effect model

This describes consumer's approach to product decision as a problem-solving process. First, he or she forms a belief about a product by accumulating knowledge (beliefs) regarding relevant attributes. Next, the customer evaluates these beliefs and forms a feeling about the product. Over time, the customer integrated information about alternative products. Finally, based on the evaluation, the consumer engages in a relevant behavior. This hierarchy assumes that a consumer is highly involved in making a purchase decision. The person is motivated to seek out a lot of information, carefully weight alternatives, and come to a thoughtful decision. This process is likely to occur if the decision is important to the consumer.

2) Cognitive-Conative-Affective: (Krugman, 1965, 1966)

This decision making path was frequently labelled 'low involvement' hierarchy. In this perspective, the consumer does not have a strong preference for a product, but acts on the

basis of limited knowledge and then decide whether they like it or not. Following the finding of Krugman (1965), In the wake of overwhelming repetition of television advertising, consumers may be better able to recall the concept of product. Then in a situation where they are in purchasing, that product comes to mind, they buy after all. Preference is subsequently changed as a result of experience with the product.

3) Affective-Cognitive-Conative: (Vaughn, 1980, 1986)

The idea of this sequence is that affect usually, if not always, precedes cognition. In other words, this sequence is thought to typify the response of feeling consumers who respond more to emotion than information in making purchase decisions resulting from communication message. Vaughn (1986) posited that this hierarchy is applicable to highly involving and feeling purchase and the model is the priority for buying emotional products such as cosmetics, jewelry, and fashion clothing.

4) Affective-Conative-Cognitive: (Zajonc, 1980, 1984; Zajonc & Markus, 1982)

Zajonc (1980) has begun to stress the significance of affect as central aspect of a product and found that affective response do not always require prior cognitions, but instead are primarily affectively based. The fact that preference can be decided by affective basis alone presents the potential for an affect and conative path. If an individual later saw need to justify on preferred product then affect, conation and cognition path could arise. This hierarchy can explain purchase of song listed in billboard charts which may possess

the same attributes as many other songs (e.g., dominant bass guitar, raspy vocal), but belief about this attributes cannot explain why one song became classic while another disappeared in the chart leaving many people unaware of their presence.

5) Conative-Cognitive-Affective: (Kiesler, 1971)

Kiesler (1971) states that a choice behavior often wields a power of commitment which results in the reorganization of cognitions to be consistent with that commitment. Then affective formation follows commitment with both behavior and cognition. In marketing context, for instance, a purchase of a product may cause one to think about it in a manner that supports the choice and then feelings are developed consistent with those choice behavior and thoughts.

6) Conative-Affective-Cognitive: (Bem, 1972; Kelley, 1973)

This decision making path was labelled 'Dissonance-Attribution hierarchy' which is exact reverse of the standard learning hierarchy. This typically occurs in the situation where audience has been involved but the alternatives have been almost indistinguishable. In this situation, a consumer first purchase, preference is then formed to bolster the choice, and selective learning follows to further support that behavior. Ray et al. (1973) explained that when consumer is forced to make a choice on the basis of some non-media or non-marketing communication source, the conative response, a choice among undifferentiated alternatives, is made then attitude and cognitive responses are supposed to follow.

5.3 Research design

Prior works consistently argued a variety of decision-making paths may be reliable in real world. With this background, this empirical research investigates all possible transferal process in decision-making through cognitive, affective and conative stage. Specifically, we gathered survey data of cognitive, affective and conative response regarding attitude on dedicated E-book reader device. Additionally, we measured five perceived attributes of innovation toward dedicated E-book reader in order to identify significant key innovation attributes affecting E-book reader adoption behavior according to the specific transferal process.

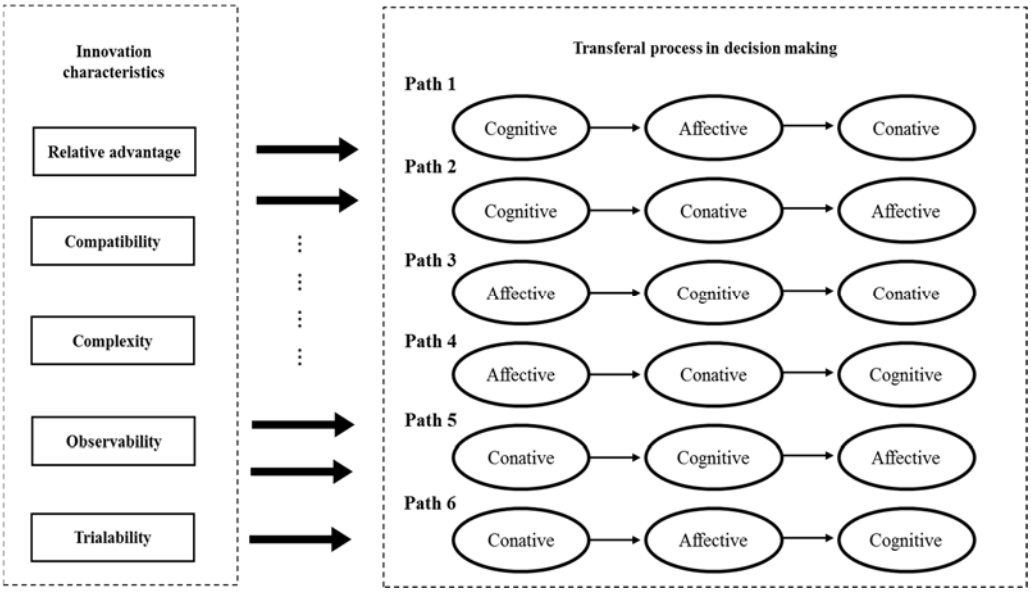


Figure 14. The proposed theoretical research framework

Data were collected through a structured survey questionnaire with a Likert scales in order to measure the research variables. This survey allows us gauge component of attitude and perceived innovation attributes that otherwise would not be directly quantified. Particularly, a Likert scale of seven points was used to measure the construct. The number 1 indicates that the respondent completely disagrees with the statement, and the number 7 indicates that the respondent strongly agrees with the statement. The survey was conducted through a Web-based survey system with specialized company which have more than 200,000 panel in Korea. Respondents were offered a small amount of electronic cash as payment for participating in the survey. The survey was targeted for 536 respondents aged 20 years or older during the months of September and October 2014.

Table 13. Variable measurement items

Variable (# of item)	Meaning and measurement	Mean (Variance)
Component of Attitude		
Cognitive response (1)	I know about E-BR device	4.2994 (2.1254)
Affective response (1)	I am a favorite with E-BR device	3.9683 (1.8255)
Conative response (1)	I have intention to use E-BR device	4.0933 (2.0211)
Perceived innovation attributes		
Relative advantage (1)	Using E-BR makes it easier to read text than paper based book	4.1940 (1.925)
Compatibility (1)	Using E-BR is compatible with my life style	3.7761 (2.0282)
Complexity (1)	E-BR is not easy to use	3.6063 (1.1753)
Observability (1)	I have seen E-BR demonstrations at stores	3.3731 (1.9541)
Trialability (1)	I would have an opportunity to try E-BR	3.4235 (1.9046)

5.4 Methodology

Following the research framework described in Figure 14, we can generally represent transferal process of individual depending on the specific decision-making path type. For instance, if one follows traditional hierarchy of effect decision-making path through cognitive, affective and conative path, the regression model is given in (5.1)

$$\begin{aligned} y_{cog,i} &= \alpha_{cog} + \delta' x_i + \varepsilon_{cog} \\ y_{aff,i} &= \alpha_{aff} + \gamma_{ca} y_{cog,i} + \varepsilon_{aff} \\ y_{con,i} &= \alpha_{be} + \gamma_{ac} y_{aff,i} + \varepsilon_{be} \end{aligned} \tag{5.1}$$

Where $y_{cog,i}, y_{aff,i}, y_{con,i}$ are variable with respect to cognitive, affective and conative response respectively from each respondent $i(i=1,...,I)$. x_i is variables of perceived innovation characteristics from each respondent. $\alpha_{cog}, \alpha_{aff}, \alpha_{aff}$ are constant of each linear regression and $\delta, \gamma_{ca}, \gamma_{ac}$ represent regression coefficients of equation. Especially, δ indicates regression coefficients of perceived innovation characteristics and γ_{ca}, γ_{ac} indicates transition weight of prior stage respectively. Similarly, we can express all six decision-making paths mathematically in a form of regression.

The decision-making path is accounted for individually. The equation (5.1) can be expressed again as following equation (5.2) in a vector form.

$$for \;\; \tau_i = j \qquad Y_i = X_i^{(j)} \beta_j + \varepsilon_i \tag{5.2}$$

Where τ_i is discrete latent variable indicating individual i 'decision-making path j ($j = 1...J$). X_i^j are explanatory variables corresponding linear regression model of (5.1) whose dimension is $(3 \times (3+5+2))$. ε_i is error distribution and it follows normal distribution with mean zero and variance covariance matrix Σ_j. And we assumed that variance-covariance matrix has only diagonal elements leaving off diagonal elements zeros for identification and it has a form of $diag(\sigma_{cog}^2, \sigma_{aff}^2, \sigma_{con}^2)$. Consequently, the model is traditional parametric Gaussian mixture model of six different types. Note that this equation is used only for individual transferal path. When we aggregate data over same path type group, the model identifies path specific parameters of regression coefficients and error disturbance. We extend model to tell us what portion ($\pi = (\pi_1, \pi_2, \ldots, \pi_J)$) of the each transferal process can be obtained over whole population by introducing hierarchical specification with respect to τ_i.

In order to complete model construction, we assume prior distribution for each parameter set. By considering conjugate priors for some parameters, we can easily draw samples for them.

The prior distributions for each parameter are given as follow.

$$\beta_j \sim MVN(\mathrm{B},\mathrm{C}) \quad \text{for } \forall j$$

$$\Sigma_j \sim IW(\mathrm{s},\mathrm{V}) \quad \text{for } \forall j$$

where $\Sigma \sim IW(\mathrm{s},\mathrm{V})$ Σ is assumed to follow inverse Wishart distribution with degree of freedom 's' and symmetric positive-defined $\mathrm{m}\times\mathrm{m}$ scale matrix 'V', that is,

$$P(\Sigma) = \frac{|\mathrm{V}|^{\frac{s}{2}}}{2^{\frac{sm}{2}}\Gamma_p(\frac{s}{2})}|\Sigma|^{-\frac{s+m+1}{2}}\exp(-\frac{1}{2}\mathrm{tr}(\mathrm{V}\Sigma^{-1}))$$

$$\tau_i \sim Multinomial(\pi) \qquad where\ \pi = \{\pi_1 \ldots \pi_6\}$$

$$\pi \sim Dir(\mathrm{a}) \quad \text{for } \forall i$$

Thus, we can express full posterior as a result of product between likelihood function and prior of unknown parameters.

$$\begin{aligned}
P(\beta,\Sigma,\tau,\pi \mid \mathrm{y},\mathrm{x}) &\propto \{\prod_{i=1}^{I}\mathrm{P}(\mathrm{y}_i \mid \beta,\Sigma,\tau_i)\}\times\{\prod_{j=1}^{J}\mathrm{P}(\beta_j)\}\times\{\prod_{j=1}^{J}\mathrm{P}(\Sigma_j)\}\times\{\prod_{i=1}^{I}\mathrm{P}(\tau_i \mid \pi)\}\times\mathrm{P}(\pi) \\
&\propto \left[\prod_{i=1}^{I}\prod_{j=1}^{J}|\Sigma|^{-n_j/2}\exp\{-\frac{1}{2}\sum_{i\in Q_j}(\mathrm{Y}_i-\mathrm{X}_i^{(\mathrm{j})}\beta)'\Sigma^{-1}(\mathrm{Y}_i-\mathrm{X}_i^{(\mathrm{j})}\beta)\}\right] \\
&\times\left[\prod_{j=1}^{J}|\mathrm{C}|^{-\frac{1}{2}}\exp\{\sum_{i\in Q_j}-\frac{1}{2}(\beta_j-\mathrm{B})'\mathrm{C}^{-1}(\beta_j-\mathrm{B})\}\right] \\
&\times\left[\prod_{j=1}^{J}|\Sigma|^{-(\mathrm{s}+m+1)/2}\exp\{-\frac{1}{2}\mathrm{tr}(\mathrm{V}\Sigma_j^{-1})\}\right]\times\left[\prod_{i=1}^{I}\prod_{j=1}^{J}\pi_j^{I_{\tau_i=j}}\right]\times\left[\pi_1^{a_1-1}\pi_2^{a_2-1}\cdots\pi_J^{a_J-1}\right]
\end{aligned}$$

(5.3)

where $P(y_i \mid \beta, \Sigma, \tau_i)$ is individual likelihood function which has multivariate linear regression, n_j is the number of observation fitted to path j, Q_j is homogeneous path type group defined as $Q_j = \{i \mid \tau_i = j, i = 1,...,I\}$, and $\pi = \{\pi_1,...,\pi_j\}$ is hyper-parameter of τ_i indicating proportion of each path type over total individual. The full posterior is not analytically tractable and we used MCMC method. As one of the MCMC methods, Gibbs sampling formulates a Markov chain obtained by iterative sampling from conditional distributions of m set of parameters, i.e. $\theta' = (\theta_1, \theta_2, ..., \theta_m)$. As we did in Chapter 4, the samples approximately become close to the joint distribution of all variables and the marginal distribution of any subset of variables can be approximated by simply considering the samples for that subset of variables.

To put it short, Gibbs sampling is a MCMC method typically used when direct sampling of the joint posterior distribution is intractable, but sampling from the full conditional distribution of each parameter is reasonably straightforward. By iteratively sampling from each conditional distribution in turn, samples of the joint posterior distribution are indirectly obtained. In this way, parameter samples are repeatedly drawn, until it is decided that a reasonable representation of the joint posterior distribution has been obtained.

The Gibbs sampling for estimation of each parameter can be completed as follows.

1st step: β_j draw for each $j = 1,...,J$

$$P(\beta_j \mid \Sigma, \mathrm{Y}, \tau_i) \propto \prod_{i \in Q_j} P(\mathrm{Y}_i \mid \beta, \Sigma, \tau_i) \times P(\beta_j)$$

$$\propto \left|\Sigma_j\right|^{-n_j/2} \exp\{-\frac{1}{2}\sum_{i \in Q_j}(\mathrm{Y}_i - \mathrm{X}_i^{(j)}\beta_j)'\Sigma_j^{-1}(\mathrm{Y}_i - \mathrm{X}_i^{(j)}\beta_j)\} \times \left|\mathrm{C}\right|^{-1/2} \exp\{-\frac{1}{2}(\beta_j - \mathrm{B})'\mathrm{C}^{-1}(\beta_j - \mathrm{B})\}$$

$$\propto MVN(\bar{\mathrm{B}}_j, \bar{\mathrm{C}}_j)$$

where

$$\bar{\mathrm{B}}_j = \bar{\mathrm{C}}_j\,(\mathrm{C}^{-1}\mathrm{B} + \sum_{i \in Q_j} \mathrm{X}_i^{(j)\prime}\Sigma_j^{-1}\mathrm{Y}_i)$$

$$\bar{\mathrm{C}}_j = (\mathrm{C}^{-1} + \sum_{i \in Q_j} \mathrm{X}_i^{(j)\prime}\Sigma_j^{-1}\mathrm{X}_i^{(j)})^{-1}$$

2nd step: Σ_j draw for each $j = 1,...,J$

$$P(\Sigma_j \mid \beta, \mathrm{Y}, \tau_i) \propto \prod_{i \in Q_j} P(\mathrm{Y}_i \mid \beta, \Sigma, \tau_i) \times P(\Sigma_j)$$

$$\propto \left[\left|\Sigma_j\right|^{-n_j/2} \exp\{-\frac{1}{2}\sum_{i \in Q_j}(\mathrm{Y}_i - \mathrm{X}_i^{(j)}\beta)'\Sigma_j^{-1}(\mathrm{Y}_i - \mathrm{X}_i^{(j)}\beta)\}\right]$$

$$\times \left[\frac{\left|\mathrm{V}\right|^{\frac{s}{2}}}{2^{\frac{sm}{2}}\Gamma_p(\frac{s}{2})}\left|\Sigma_j\right|^{-\frac{(s+m+1)}{2}} \exp(-\frac{1}{2}\mathrm{tr}(\mathrm{V}\Sigma_j^{-1}))\right]$$

$$\sim IW(\bar{s}, \bar{\mathrm{V}})$$

where

$$\bar{s} = s + n_j$$

$$\bar{\mathrm{V}} = \mathrm{V} + \sum_{i \in Q_j}(\mathrm{Y}_i - \mathrm{X}_i^{(j)}\beta)(\mathrm{Y}_i - \mathrm{X}_i^{(j)}\beta)'$$

3rd step: τ_i draw for each individual i

$$P(\tau \mid \beta, \Sigma, y) \propto \{P(y_i \mid \beta, \Sigma, \tau_i)\} \times \{P(\tau_i \mid \pi)\}$$

Since there is no analytically tractable solution for above conditional posterior, M-H (Metropolis-Hastings) algorithm can work successfully.

1) $k = 0$ *Set initial value for* $\tau_i = j \sim$ *random draw* $(j = 1, \ldots, 6)$ *for* $\forall i$

2) *Draw* $\tau_i^{(new)} (\neq \tau_i) = \bar{j} \sim MN\{\pi\}, \quad \pi = \{\pi_1, \ldots, \pi_6\}$ *for* $\forall i$ *and accept* $\tau_i^{(new)}$ *with prob.* α

where $\alpha = \min\{\dfrac{P(y_i \mid \beta, \Sigma, \tau_i^{(new)})}{P(y_i \mid \beta, \Sigma, \tau_i)}, 1\}$

$$= \min\{\frac{\left|\Sigma_{\bar{j}}\right|^{-1/2} \exp\{-\frac{1}{2}(Y_i - X_i^{(\bar{j})} \beta_{\bar{j}})' \Sigma_{\bar{j}}^{-1} (Y_i - X_i^{(\bar{j})} \beta_{\bar{j}})\}}{\left|\Sigma_j\right|^{-1/2} \exp\{-\frac{1}{2}(Y_i - X_i^{(j)} \beta_j)' \Sigma_j^{-1} (Y_i - X_i^{(j)} \beta_j)\}}, 1\}$$

4) *Let* $k = k + 1$, *go back* 1) *step*

4th step: π draw from Dirichlet- multinomial distribution

$$P(\pi \mid \tau_i) \propto \{\prod_{i=1}^{I} P(\tau_i \mid \pi)\} \times P(\pi)$$

$$\propto [\pi_1^{n_1} \pi_2^{n_2} \cdots \pi_6^{n_6}] \times [\pi_1^{a_1 - 1} \pi_2^{a_2 - 1} \cdots \pi_6^{a_6 - 1}]$$

n_j *is the number of observation where* $\tau_i = j$

$$\propto \pi_1^{n_1 + a_1 - 1} \pi_2^{n_2 + a_2 - 1} \cdots \pi_6^{n_6 + a_6 - 1}$$

$$= dir(n_1 + a_1, \cdots, n_6 + a_6)$$

5th step: Repeat 1-4

5.5 Empirical analysis

To estimate the suggested Bayesian model, we ran 80,000 draws from the conditional posterior distributions using the MCMC method; every 10th value was chosen from draws for parameter inference after discarding initial 40,000 draws as burn-in period. The estimation results are shown in Table 14.

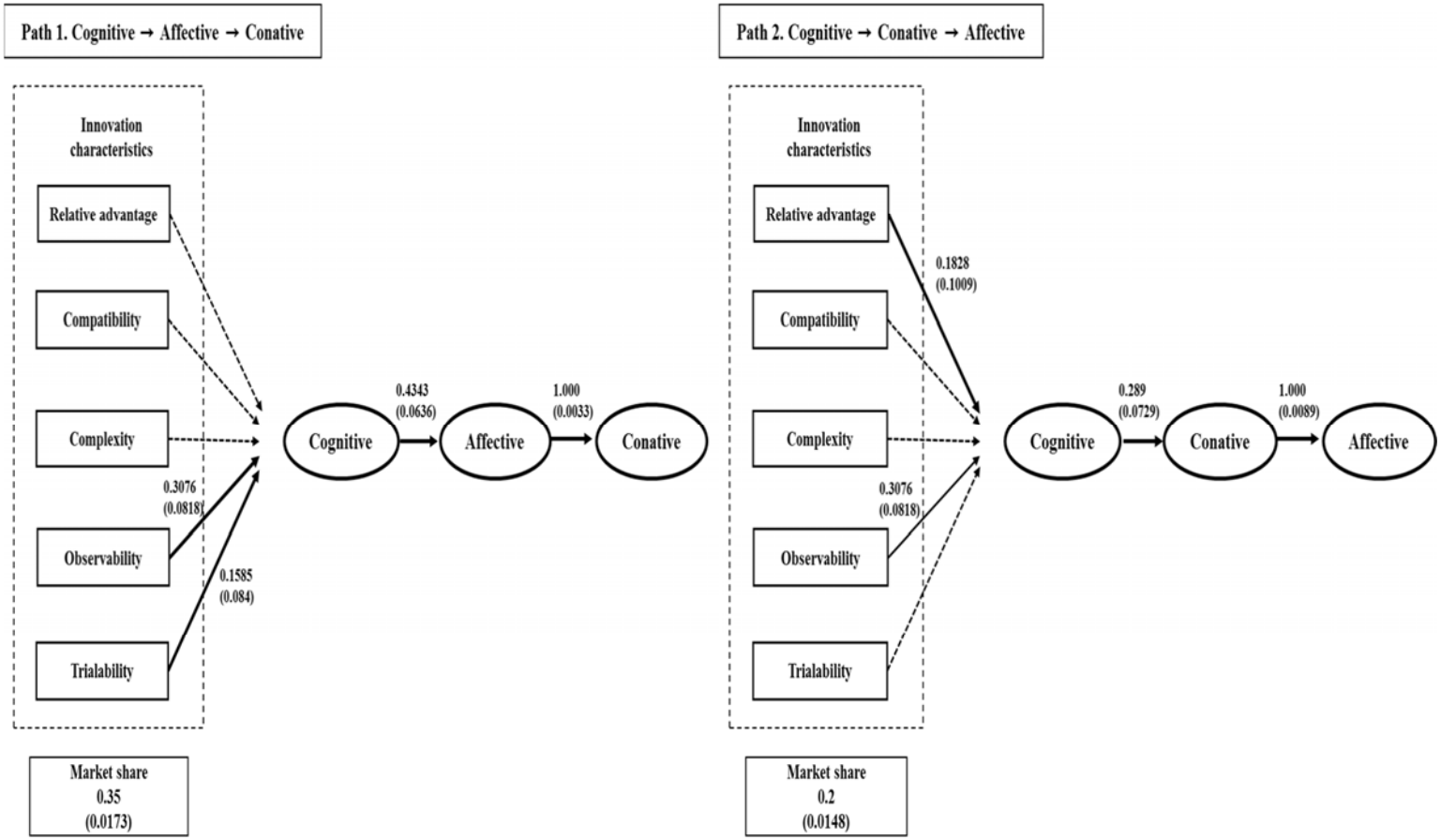
Table 14..Estimation results

	Path 1 (Cognitive→Affective→Conative)			Path 2 (Cognitive→Conative→Affective)		
	Cognitive	**Affective**	**Conative**	**Cognitive**	**Affective**	**Conative**
Constant	**2.6565*** **(0.4166)** **[1.971,3.341]**			**1.8251*** **(0.6118)** **[0.817,2.838]**		
Constant		**2.2707*** **(0.2716)** **[1.824,2.717]**			**-1.0002*** **(0.0435)** **[-1.071,-0.928]**	
Constant			0 (0.0144) [-0.024,0.024]			**3.597*** **(0.3212)** **[3.073,4.127]**
Relative Advantage	0.0179 (0.0811) [-0.115,0.152]			**0.1828*** **(0.1009)** **[0.018,0.350]**		
Compatibility	0.1253 (0.0796) [-0.006,0.257]			0.0017 (0.096) [-0.157,0.160]		
Complexity	-0.1245 (0.0828) [-0.261,0.012]			-0.0039 (0.1084) [-0.181,0.176]		
Observability	**0.3076*** **(0.0818)** **[0.172,0.443]**			**0.2812*** **(0.1007)** **[0.115,0.446]**		
Trialability	**0.1585*** **(0.084)** **[0.020,0.296]**			0.1739 (0.1061) [-0.002,0.347]		
Transition weight		**0.4343*** **(0.0603)** **[0.335,0.5331]**				**0.289*** **(0.0729)** **[0.169,0.408]**
Transition weight			**1*** **(0.0033)** **[0.995,1.005]**		**1*** **(0.0089)** **[0.985,1.015]**	
Sigma	**0.5334*** **(0.7597)**	**0.4704*** **(0.6715)**	**0.0015*** **(0.0021)**	**0.4639*** **(0.6664)**	**0.003*** **(0.0043)**	**0.2932*** **(0.4214)**
Phi (Market share)		**0.35 (0.0173) ***			**0.2 (0.0148) ***	

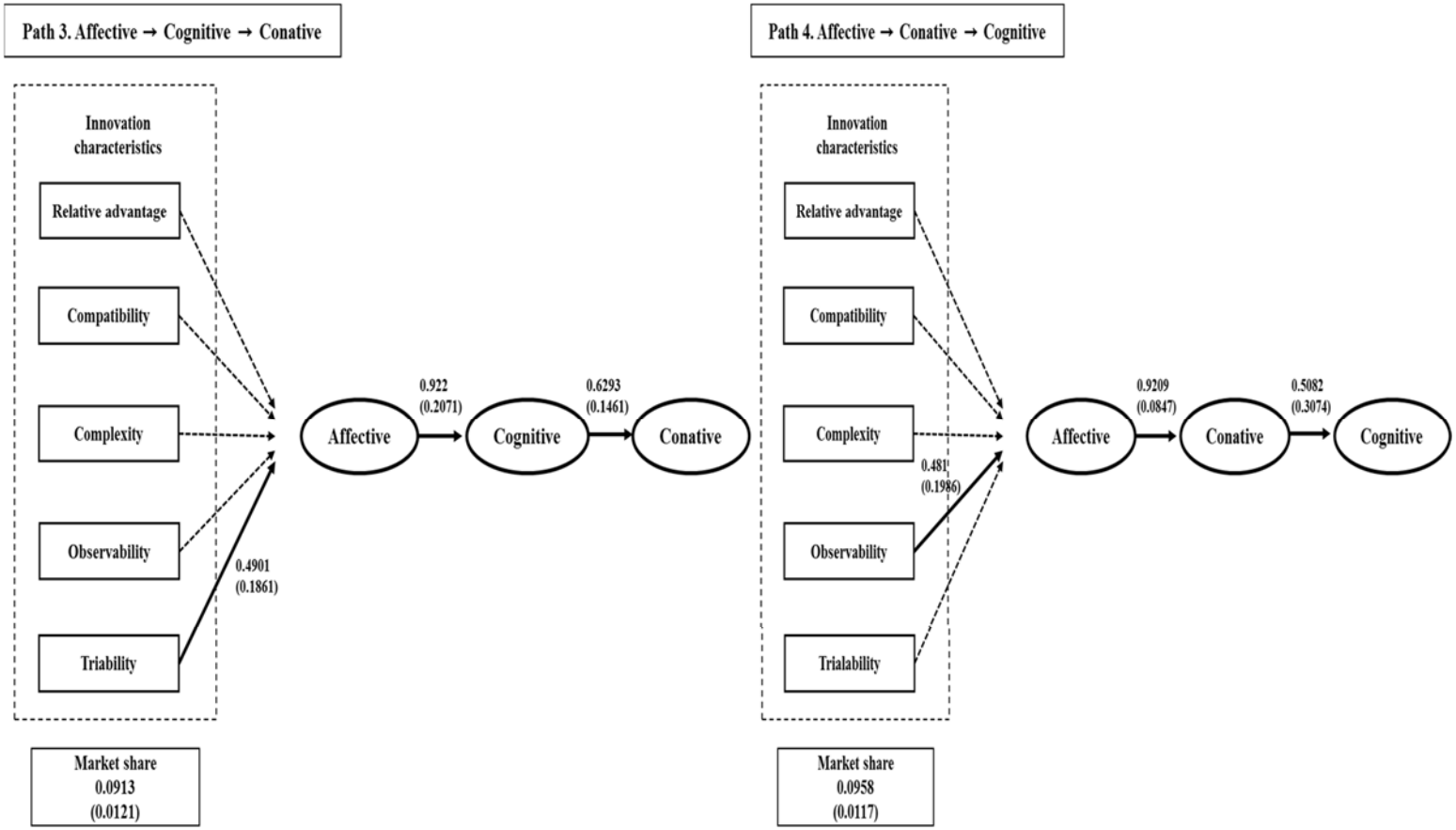
	Path 3 (Affective→Cognitive→Conative)			Path 4 (Affective→Conative→Cognitive)		
	Cognitive	**Affective**	**Conative**	**Cognitive**	**Affective**	**Conative**
Constant	**1.326* (0.561) [0.444,2.272]**			**2.662* (0.980) [0.993,4.203]**		
Constant		0.008 (0.894) [-1.419,1.502]			**3.105* (1.074) [1.376,4.873]**	
Constant			**2.176* (0.5766) [1.428,3.2373]**			**-1.786* (0.418) [-2.449,-1.085]**
Relative Advantage		0.116 (0.237) [-0.245,0.529]			0.217 (0.208) [-0.130,0.552]	
Compatibility		-0.079 (0.286) [-0.578,0.358]			0.012 (0.246) [-0.376,0.433]	
Complexity		0.174 (0.225) [-0.203,0.538]			-0.089 (0.210) [-0.428,0.256]	
Observability		0.087 (0.203) [-0.241,0.423]			**0.481* (0.198) [0.152,0.802]**	
Trialability		**0.490* (0.186) [0.207,0.805]**			-0.101 (0.228) [-0.484,0.267]	
Transition weight	**0.922* (0.207) [0.564,1.251]**					**0.921* (0.085) [0.780,1.055]**
Transition weight			**0.6293* (0.1461) [0.3539,0.81]**	**0.5082* (0.3074) [0.010,1.021]**		
Sigma	**0.3072* (0.5007)**	**0.3273* (0.5205)**	**0.1579* (0.3167)**	**0.807* (1.2291)**	**0.3204* (0.5084)**	**0.0845* (0.1316)**
Phi (Market share)		**0.0913 (0.021)***			**0.0958(0.0117)***	

	Path 5 (Conative → Cognitive → Affective)			Path 6 (Cognitive → Affective → Cognitive)		
	Cognitive	**Affective**	**Conative**	**Cognitive**	**Affective**	**Conative**
Constant	**7.186* (0.453) [6.447,7.900]**			**1.7311* (0.5265) [0.865,2.6032]**		
Constant		**3.459* (0.521) [2.600,4.310]**			**1.0001* (0.0366) [0.9402,1.0604]**	
Constant			1.852 (1.325) [-0.306,4.050]			0.543 (0.5085) [-0.2907,1.38]
Relative Advantage			**0.576* (0.298) [0.095,1.071]**			**0.2773* (0.0989) [0.114,0.438]**
Compatibility			0.134 (0.283) [-0.324,0.598]			**0.183* (0.0969) [0.0228,0.3404]**
Complexity			-0.023 (0.292) [-0.488,0.471]			**-0.2084* (0.1197) [-0.402,-0.0086]**
Observability			0.073 (0.262) [-0.352,0.502]			**0.3599* (0.0976) [0.1979,0.5203]**
Trialability			-0.297 (0.279) [-0.759,0.148]			0.136 (0.1057) [-0.0375,0.3105]
Transition weight	**-0.797* (0.096) [-0.949,-0.641]**				**1* (0.0103) [0.9831,1.017]**	
Transition weight		-0.188 (0.128) [-0.394,0.022]		**0.6393* (0.1156) [0.4471,0.8292]**		
Sigma	**0.3338* (0.5062)**	**0.4942* (0.7866)**	**1.0898* (1.6553)**	**0.495* (0.7152)**	**0.0043* (0.0062)**	**0.2606* (0.3771)**
Phi (Market share)		**0.1058 (0.0134)***			**0.1558 (0.0132)***	

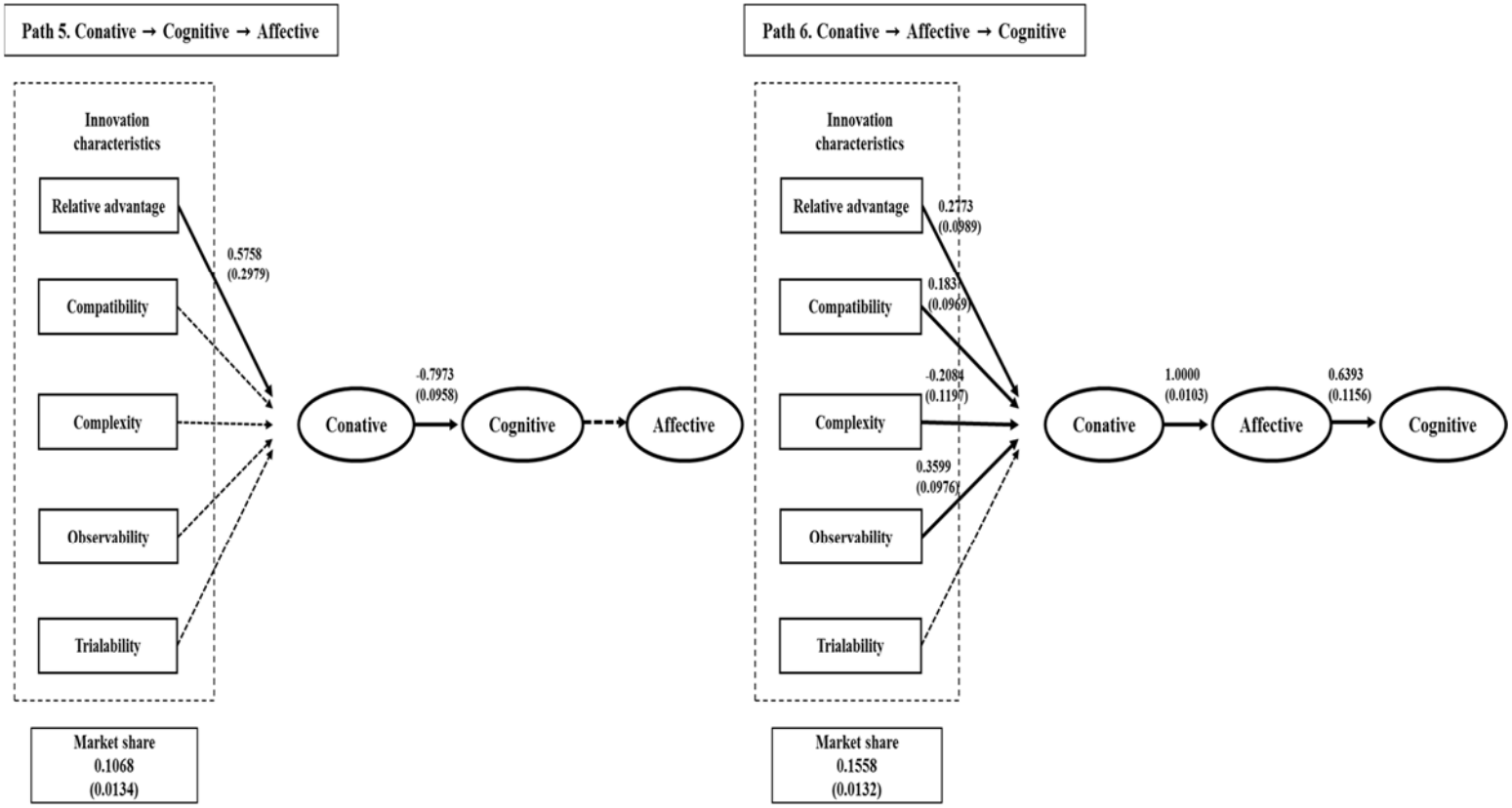
Note) * significant at 10% interval; parentheses is standard error; square bracket is 90% confidence interval



Note) Solid line is significant at 10% interval; Dashed line is insignificant



Note) Solid line is significant at 10% interval; Dashed line is insignificant



Note) Solid line is significant at 10% interval; Dashed line is insignificant

Figure 15. Path diagram of estimated results

Path 1 depicts standard hierarchy of learning model. Those who follow this path may consider dedicated E-book reader as highly involving product where thinking and economic considerations prevail (Vaughn, 1986). As a result of estimation, it turned out that observability and trialability had positive significant impact on cognitive stage in this path, which implies that emphasizing observability and trialability in communication message stimulates purchase for those who follow Path 1. Besides, the fact that observability and trialability are key factors that have to be emphasized in marketing communication means that E-book reader is still so unfamiliar product in the market that consumers do not aware the usage and feature of this product. Additionally, the potential market size of Path 1 was estimated to be 35% which is the biggest figure among six different paths. Accordingly, we can state that potential buyers are most likely to follow standard learning path in their E-book reader adoption.

Path 2 depicts purchase decision making is sequentially made by order of cognitive, conative and affective reaction which means that, after consumer understand usage of E-book reader, they feel intention to use and then they rationalize their intention by construction preference on it. In empirical analysis, not only transferal process between cognitive and conative but also transferal process between conative and affective in Path 2 were all statistically significant. This confirms that Path 2 is reliable decision-making path for a portion of population in E-book reader adoption occasion. Relative advantage and observability were statistically significant as factors affecting cognitive stage in Path 2. In terms of proportion, market size of Path 2 was estimated to be 20%. This figure is ranked

at second in all decision-making paths.

Path 3 describes decision-making process of affective, cognitive and conative sequence. This path was found statistically significant by showing that transition between affective and cognitive, and cognitive and conative were all statistically significant. Traialability is only significant factor influencing affective stage in Path 3 among five innovation characteristics. One possible interpretation of this result is that allowing trying E-book reader device makes consumers have a positive attitude toward an E-book reader and stimulate adoption of device for those who follow affective, cognitive and conative decision-making path. The market size of path 3 in terms of proportion among the respondents was 9.13%. This figure is the smallest but not negligible.

Path 4 depicts sequence of affective, conative and cognitive reaction. Result of empirical analysis found that Path 4 was also feasible decision-making path by confirming that transition between affective and conative and transition between conative and cognitive were statistically significant. Essence of this process is that affective response do not always require prior cognition so one is able to adopt a product without belief about usage and features. Given that preference can be decided by affective basis alone and it directly influence conative reaction without cognition in Path 4, the E-book reader is perceived as primarily expressive or delivers sensory pleasure rather than utilitarian benefit for those who experiencing this type of holistic processing. Observability is only significant factor among five innovation characteristics affecting affective stage in path 4. Simply, enhancing observability in offline store and online shop stimulate decision-making for

those who follow path 4 since this group would not want to understand specific utilitarian benefits related to feature and usage. The proportion of path 4 over population is 9.58%. This figure is small but cannot be ignored in market segmentation.

Path 5 represents conative, cognitive and affective sequence whereas path 6 represents conative, affective and cognitive sequence. Assumption that affective first coms into consumer's mind is same in Path 5 and Path 6. The difference between two paths is that the next is cognitive in Path 5 and conative in Path 6. In the result of empirical analysis, the decision-making process of Path 5 was not supported while Path 6 was supported. In Path 5, the transition between conative and cognitive is negatively significant and transition between cognitive and affective is not statistically significant. Given that Berger (1986) said Path 5: conative → cognitive → affective is more likely to happen for habitual product for which deeper learning is not necessary for such commodity decisions as household cleaners or gasoline, E-book reader purchase has nothing to do routinized consumer and their purchase decision making. Therefore, we can state that this decision-making path is not feasible in E-book reader adoption. It is notable that conative → affective → cognitive of path 6 is supported even though both path 5 and path 6 begin with conative stage. The fact that transferal process of path 5 is insignificant can be interpreted in a manner. If consumers feel intention to use E-book reader first then it is more likely to transfer to affective stage rather than cognitive stage since consumers tend to form attitudes to bolster action, and selective learning follows to support that behavior.

In summary, among six possible transferal process in decision-making path, we prove

that every path was statistically significant process except Path 5: conative → cognitive → affective. Path 5 is understandable and logical for low involvement and thinking products with routinized consumer behavior which does not require deep learning about a product. This decision-making process may not be fitted to E-book adoption behavior. In terms of proportion of population, much take the Path 1: cognitive → affective → conative process followed by Path 2 in terms of size. 55.02% of population forms belief about a product by accumulating knowledge regarding relevant attributes of E-book reader. In other words, cognitive stage first comes in to mind for more than half over respondents.

Additionally, we identified key innovation characteristics as important message which marketers have to emphasize depending on the type of decision-making path. For instance, enhancing observability and trialability in market is effective communication strategy for those who follow traditional learning model.

5.6 Conclusion

We investigated a model of transferal path in high-tech product adoption occasion. Consumers' individual decision-making paths are explicitly accounted for in the model. Potential market size of each path are also obtained by aggregating individual result. This study contributes to the marketing literature along both academic and substantive dimension. Along the academic dimension, we developed an estimable model for capturing transferal process in decision-making path. Accordingly, we show there exist heterogeneity

in individual decision-making path empirically using survey data. In substantive domain, we are able to obtain insights into the communication message for high-tech product that has managerial implication. We demonstrate that the impact of perceived innovation characteristics in high-tech product adoption occasion can be varying according to the one's decision-making path.

However, our study has several limitations. First, the model only includes perceived innovation characteristics in order to revel the impact of innovation attributes in high technology marketing context. However, not only innovation attributes but also source credibility such as reliability and expert may influence decision-making path as message characteristics. Extensive collection of data related to message characteristics will contribute attitude research. Second, we do not model motivation for selecting different path, i.e., what makes one to follow such attitude formation path than others. Including underlying motivation determining different decision-making path would be a good avenue for future research since little has been known about reason of individual heterogeneity in decision-making path.

In summary, we have taken the initial steps to accounting for consumers' heterogeneity in decision-making path when considering adoption behavior of a high-tech new product. We hope that this encourages future researchers to address some of the unresolved issues raised here.

Chapter 6. Concluding Remarks

6.1 Summary

The objective of this dissertation is to solve the decision-making problems that managers frequently face in the product development and management areas, particularly focusing on the high-tech industry, which has both high technological and high market uncertainties. Technological uncertainty is associated with how a new product can satisfy consumers' specific needs on new product functionality, and market uncertainty is related to consumers' demand heterogeneity. In this circumstance, this dissertation suggests models based on statistical methodologies for effectively overcoming both uncertainties. The following summary is based on empirical analyses of the proposed models and illustrates the noticeable results from these analyses.

The first essay identifies factors of successful new product development without any parametric assumption on model specification and finds the optimal configuration of significant resources, which maximize product performance, by conducting a Monte Carlo simulation. The results of the empirical analysis in the first essay are summarized as follows: First, the impact of R&D and marketing integration on new product performance is not linear but nonlinear. Second, the resource and capability utilized by the firm in the new product development process are not independent and, thus, have interaction effects during

the development process. As a result, it is natural to conclude that there is optimal configuration between resources, which maximizes new product performance. Third, if the R&D-marketing integration is emphasized too much, it may lead to inefficient and negative results on time to market and product sales. Therefore, from a managerial perspective, it is not always optimal to integrate R&D and marketing to the highest level. The interesting finding of the first essay is that the marginal response function of time to market and that of product sales look very similar, but the marginal response function of technological innovation is different from others. This fact points out that time to market performance may be more associated with financial performance rather than with technological innovation. Additionally, this result implies that new product development teams achieve technological innovation by pursuing high level of R&D and marketing integration, but at the same time, they would be more likely to fail in the market by missing time to market.

The second essay evaluates the impact of the innovation characteristic, consumer characteristic, and message characteristic on the transition between the decision-making stages in innovation adoption by applying the multivariate probit model. Application of the suggested model to the survey data set on an E-book reader showed that complexity has a negative effect throughout the process, whereas observability has a positive effect on all stages. The relative advantage has a positive effect on the transition from the cognitive stage to the affective stage, and compatibility turns out to be the most important factor affecting transition from the affective stage to the behavioral stage. An interesting point in the empirical results is that functional innovativeness and cognitive innovativeness have

positive effects and, on the other hand, hedonic innovativeness and social innovativeness have negative effects on adoption. We speculate that, in this study, this result comes from the targeted product category. Dedicated E-book readers are an alternative to paper-based books, and, at the same time, reading a book is deeply associated with consumers' cognitive activities. The characteristic of product category explains why consumers with high functional and high cognitive innovativeness have higher intention to adopt.

The third essay identifies reliable decision-making paths or attitude formation paths in consumers' innovation adoption by applying the Gaussian mixture model. Using the proposed model, we were able to successfully identify reliable decision-making paths with a survey data set on a dedicated E-book reader. In our analysis, all paths were feasible except the conation→cognition→affection path. Looking into the market share, the traditional hierarchy response model (i.e., the cognition→affection→conation path) ranked at the top with 35% while the affection→cognition→conation path ranked at the bottom with 9.13%. Finally, we provided an efficient marketing communication strategy given a decision-making path. For example, enhancing observability and trialability is an effective strategy for those who follow the cognition→affection→conation path in order to stimulate consumers to formulate a positive attitude toward the new product. An interesting point of the empirical results is that the conation→cognition→affection path is not reliable; the fact that this path is not significant implies that consumers do not perceive the E-book reader as a habitual product, such as food or household cleaning items. This decision-making path was often named "passive learning hierarchy," because it does not require cognitive effort

and is often selected out of habit. Therefore, passive learning has nothing to do with the occasion on which people purchase an E-book reader. Additionally, another possible interpretation of this result is that when consumers experience an impulsive purchasing intention regarding an E-book reader in which conation comes first, they are more likely to follow it with the affective and cognitive stages, sequentially, rather than the cognitive and affective stages, sequentially.

6.2 Contribution and Implications

This dissertation has both theoretical and practical implications. The academic implication is that the dissertation proposes effective methodologies to solve major problems related to new product development and management, which other researchers could use in the future. The practical implication is that this dissertation gives a strategic guideline for decision making in the process of new product development and management regarding the market segment and the corresponding new product positioning. In detail, the contributions toward prior works and implications of each essay within the dissertation are as follows:

The contribution and implication of the first essay can be summarized as follows. First, to our best knowledge, this research is the first study that identified the change of marginal impact of R&D and marketing integration on new product performance by applying the nonparametric regression model. Most previous studies utilized a parametric method on model specification, which was partly determined by the researchers' prior beliefs and is

inherently linked to the model misspecification problem. We found that the nonparametric regression model could be applied successfully to solve this problem. We expect that academics can utilize the MARS methodology to capture the marginal response function or marginal response surface to solve similar decision-making problems in new product development areas. Second, this research identified the interaction effects between key resources deployed during the new product development process. Eventually, we found the optimal combination that can maximize the new product's performance. This implies that new product development team leaders must consider not only the main effect of each resource but also the joint effect between different resources. In particular, when leaders decide how intensively R&D and marketing departments should jointly cooperate or how many team members should hold a joint meeting, they must consider the current level of the R&D and marketing resources owned by the team, because the impact of R&D and marketing collaboration on a new product is seriously influenced by each R&D and marketing resource, respectively. Lastly, this study looked into the multi-dimensional performance of a new product when evaluating the impact of R&D and marketing integration. When the level of R&D and marketing integration becomes higher, the technological innovativeness of a new product continuously increases, but its effect on launch on time or profit is negative. This implies that too much integration may harm the performance of the new product. With respect to time to market and product sales, the impact of R&D and marketing integration increases until a certain point but decreases after its peaks. This finding contradicts previous arguments, which stated that more is always

better. Our results showed that not all projects should aim at the highest level of integration between R&D and marketing and suggest that project leaders must always keep in mind that too many integration activities may lead to a reverse effect in development results by delaying the launch of new products and, in turn, badly influencing product sales.

The second essay has the following contributions and implications. From the theoretical perspective, to the best of our knowledge, this is the first study to provide a statistical model for capturing the theoretical model for the innovation decision process, or the consumer attitude formation process. Extant studies ignored the theoretical evidence on the hierarchical decision-making process and estimated the cognitive, affective, and behavioral response independently. Therefore, they could not identify key factors affecting transition between decision-making stages precisely. In the second essay, however, we identify successfully them by applying the multivariate probit model. Through this study, we prove that the key factors affecting the transferal process can be different and that the communication strategy must differ depending on where potential buyers are now in the innovation decision process. From the marketers' perspective, implementation of the communication strategy should be differentiated according to the stage of the potential buyer. For example, if a group of potential buyers is aware of the functionality of a newly introduced product and even has an interest in it, but hesitates to purchase it, then it is a helpful approach for marketers to persuade the group by emphasizing the product's compatibility with extant devices or services. Similarly, delivering a message that highlights relative advantages of the new product will be effective for those who are aware

of the new product but are not interested in it. In short, marketers should keep in mind that an effective marketing communication strategy regarding the key message should consider the potential consumers' status.

The third essay has the following implications. First, the research proposes a general and flexible Bayesian multivariate regression model based on the Gaussian mixture to be able to identify reliable decision-making paths; the model is fitted to a survey data set for empirical application of the proposed model. Although some previous studies raised a question doubting the working mechanism of the traditional hierarchy response model, they were silent on the identification of possible decision-making paths. Thus, the major contribution of the third essay is that it provides a model that can reflect consumers' heterogeneous decision-making paths. Utilizing this model, we can easily identify market segments and implement corresponding new product positioning strategies. Two important implications can be drawn from the results of the third essay. Within the academic domain, the traditional hierarchy of effect framework had been used as a planning tool, but often created problems because the order of key components was controversial among scholars. The proposed model in the third essay explains the heterogeneous decision-making paths. Furthermore, the model implies that the alternative views are not competing within the same product category; instead, they only deal with a different situation. In the same vein, the third essay proves that the decision-making paths of consumers are different from each other even within the same product category. Within the substantive domain, this research helps marketers to implement efficient marketing strategies according to the different

decision-making paths by identifying the key message to simulate the adoption process for a given path. In other words, the third essay implies that marketers should pay attention to all possible decision-making paths and differentiate the marketing strategy for a given path.

Through the three essays, this dissertation provides a few philosophical lessons in the new product innovation and management areas. The following Figure 16 describes the integrated process of new product development and market management.

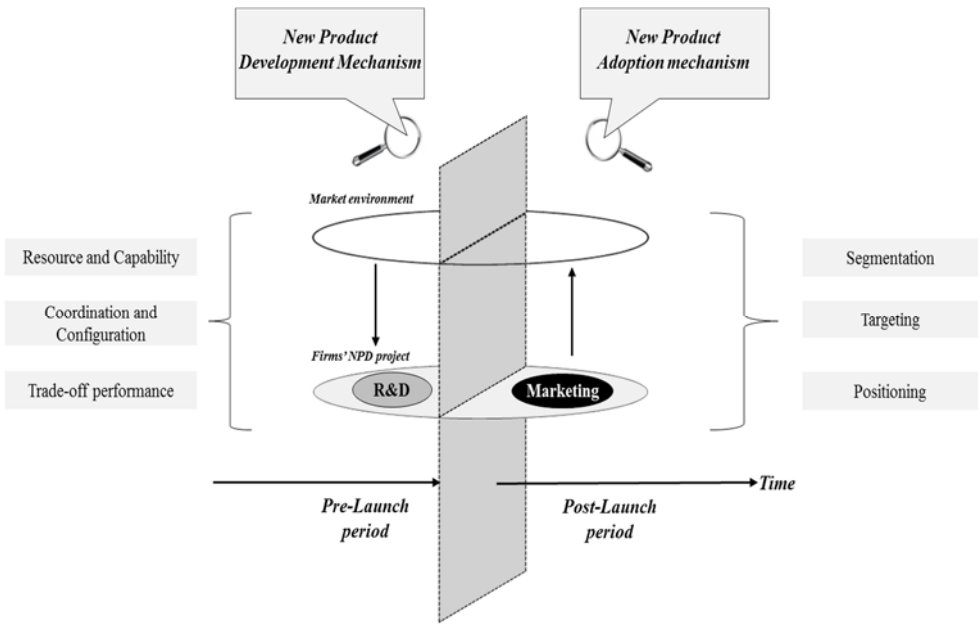


Figure 16. An integrated process of new product development and market development

In the new product development domain, new product development teams collect the data from multiple sources and integrate it to extract meaningful knowledge assets. Arno Penzias, the 1978 Nobel laureate in physics and vice president of research at AT&T Bell

Laboratories, stated, "*Knowledge is not chunks of information, it is a belief about how the world works*." In this regard, the first essay of the dissertation says that reaching this state of a shared belief system requires achieving a shared interpretation of the information and its implication for innovation development. Shared interpretation goes far beyond simply sharing the information. Consider this variation in the following statements.

Marketing: The glass is half full.

R&D: The glass is half empty.

Each perspective carries substantially different views of what a particular piece of information means, and, by extension, different implications for what the firm should do. Integrating information and intelligence in order to achieve a shared objective is vital.

Indeed, firms in the high-tech industry must strive for internal consensus in order to successfully develop a new product that has technological advantage. However, prior to achieving consensus, firms may benefit from a relatively high level of disagreement among researchers in interpreting the information they have gathered. Such disagreement allows closer inspection of the validity of different assumptions and alternatives, as well as an assessment of the relative importance of the firm's objectives and competitive methods. Consequently, the first essay emphasizes that not all perspectives can prevail in the debate, but all opinions have value in shaping the right answers, though it takes a lot of time.

In the market development domain, one of the most important issues that high-tech firms wrestle with is the choice of an initial target market to pursue with their promising innovative new product. Yet, the segmenting and targeting, which seem obvious in

hindsight, are rarely clear at the time of decision making. The rationale behind segmenting markets and selecting a target is to identify groups of customers who share similar needs and buyer behavior characteristics and who are responsive to the firm's offering. Directing marketing effort toward a specific target is both more effective and more efficient than loosely attempting to reach as many customers as possible in the hope that some of them might be interested and respond. This submarket analysis process is implemented through segmentation, targeting, and positioning.

In this context, the second and third essays provide insights that traditional segmentation variables such as age, gender, and income may not; these are consumers' decision-making stage and heterogeneous decision-making path with three stages. Through this approach, firms are able to evaluate the attractiveness of the various segments in order to narrow the choice of which segment to pursue. Two important criteria for evaluating each segment were useful in this study: (1) market size and (2) key message to serve the needs of each segment. With these criteria, the submarket can be targeted strategically. As a final step of the segmentation process, firms can create a meaningful positioning strategy for the innovation. A firm's positioning is the image of the product in the eyes of the customers, relative to competitors, on critical attributes of importance. In other words, positioning is based on customers' perceptions. After all, customers will make the decision to adopt the new innovation, and what they believe about the new product matters. In this regard, firms must effectively communicate their value proposition to customers to create the positioning they desire.

6.3 Limitation and Outlook

This dissertation sheds light on three major issues associated with new product development and management practice in the high-tech industry. Combining the literature on innovation, marketing, and psychology, the dissertation provides decision support models for solving major problems in the new product innovation and management areas. However, this dissertation does have limitations, which provide an opportunity for future extensions. These are briefly discussed in the following paragraphs.

In the first essay, which evaluates the effect of the new product development team's resource and capability on product development performance, a twofold limitation underlies the empirical research. First, we considered only the impact of firm's internal resources and capabilities for product performance in the proposed theoretical model. Recently, firms' collaboration activities with governmental institutions, university labs, or even rival firms are very common in the new product development process. Given this fact, not only internal resource and capability but also firms' external activities may influence new product performance. If we measured the network activity of firms in the process of new product development and quantified them in an empirical model using the social network theory, then the study would bring more beneficial results and implications for product innovation. Therefore, we expect that future research will address the change of marginal impact of firms' network activities, such as technological alliance on new product performance.

Additionally, the realistic approach that connects managerial practice to results of the first essay of this dissertation should be improved. Majority of new product research studies share this weakness. Though there have been countless studies about the success factors of new products for the past 50 years, the practical success rate of new product development is not increasing. It seems the academic findings are difficult to apply in practical issues. Therefore, future research must try to focus on solving practical issues.

The second and third essays, which analyze consumers' decision-making process and its heterogeneity by addressing major criticisms raised by previous literature, also have limitations. First, analyses were conducted at the group level by applying cross-sectional survey data; it was not individual-level analysis. This was due to data availability. It is not easy to access and collect individual-level panel data regarding the decision-making process. Yet, a more in-depth analysis could have been conducted with individual-level panel data, if we had collected them. For example, individual-level panel data allow us to identify the transition between different decision-making paths and key factors affecting such a transition between different paths in individual level by applying methodology such as the Hidden-Markov model.

Secondly, the second and third essays utilize and conceptualize the five innovation characteristics suggested by Rogers' research when analyzing new product adoption behavior. Though countless studies have built upon Rogers' diffusion of innovation theory, it is hard to correctly evaluate and explain consumer response on recently launched innovative products using this conceptual framework. In fact, the importance of aesthetic

value and creativity has grown expeditiously in recent high-tech innovation. However, it is impossible to reflect these attributes in the traditional framework. Therefore, in the future, a general framework that can reflect these characteristics of high-tech innovation should be developed.

Finally, we should note that the models proposed in this dissertation can be applied in any industry and product category to help marketers' decision making. For example, application to environmental-friendly goods can be a good extension. Not surprisingly, some consumers are willing to pay more for green products, whereas others are not. According to the research conducted by Royne, Levy, and Martinez (2011), although the majority of U.S. consumers indicate that they are "environmentalists," this mindset does not necessarily translate into pro-environmental behavior such as purchasing eco-friendly detergents. In other words, there is a significant gap between consumers' environmental concerns and willingness to pay for eco-friendly products. However, little is known so far about what messages should be provided to translate interest in environmental goods to purchase intention. Alternatively, the decision-making path that the majority of consumers follow in eco-friendly product purchasing occasions has not been explored yet. Given this fact, the models we developed in the second and third essay can be applied successfully and will guide an effective and efficient marketing communication strategy to make consumers willing to spend more on eco-friendly products

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Appendix A: Questionnaire of the first essay

Ⅰ. Organizational capability	
R&D and marketing integration	NPD team members evenly consisted of people from R&D and marketing departments. When problems arise during the project period, R&D and marketing departments successfully search for solutions that are agreeable to both departments. All R&D and marketing members were involved in the decision-making process for this project. R&D and marketing team members actively shared information about this project.
Formality of NPD project	We had a well-defined NPD process, which include role and responsibility for this project. We clearly followed the procedure described in the protocol for this project. All tasks were conducted following the official procedure, described in the protocol for this project.
Support of Top Management Team	The impetus for this project came from top management team's recognition of a short-term and long-term distinctive goal. Top management team provided enough financial and non-financial resources for this project. Top management team was willing to accept the possibility of failure in the initial stage of this project. Top management team willingly took a risk in the middle of the project.
Ⅱ. Technological capability	
Research	The preliminary technical assessment in the initial stage of the project was greatly successful. The preliminary appraisal of the new product development plan was carefully conducted, to identify the probable technical route at the initial

	stage of the project.
Development	Our scientific research activities were fully utilized in the evaluation of the possibility of the success of the new product development for this project.
	We were completely familiar with the technology used for the development.
	The technological aspects for the development for this project were well-known to us.
	When a technical problem rose within this project, we had a database of information to draw from.
	Our development skills on design and interface specification were at ideal level for this project.
Ⅲ. Marketing capability	
Consumer need analysis	Customers' needs were well-defined.
	We actively contacted customers and gathered information about their desired product features for this project.
	The customers' needs could be readily translated into a new product specification.
	We updated information related to customers' responses and made it available to all project members.
Market research	Our marketing research skills were at ideal level for this project.
	Our perceived marketing research expertise in this project area was very high.
	Our forecast of the market demand for this new product was accurate.
	We quantitatively observed external environmental changes for this project.
Competition analysis	We could accurately analyze competitors' product attribute changes.
	We could accurately analyze competitors' price changes.
	We could accurately analyze competitors' product strategy changes.
	We could accurately analyze consumer's loyalty and satisfaction toward competitors' products.

Ⅳ. Success dimension	
Time to market	Did the top management team satisfy the project launching time? Did the project adhere to a time schedule? Was the project undertaken quickly and in a time efficient manner?
Technological innovation	Did the product offer unique attributes not available from competing products? Were the product's technological performance characteristics useful for solving customers' inconveniences that they felt with extant products? Was the product superior to competing products in terms of technological sophistication? Was the product outstanding to competing products in terms of compatibility?
Product sales	Was the new product's sales record a noticeable financial success? Did the product's sales bring a large positive impact on the company? Did the product's sales contribute to an increase of market share in the same product market?

Appendix B: Sampling from Truncated Multivariate Normal Distribution

Since it is difficult to draw latent utility (U_i) directly from truncated multivariate normal distribution, it is recommended to construct a Gibbs sampler by breaking each draw of U_i into sequence of univariate truncated normal draws by cycling through the U_i vector.

$$U_{ij} \mid U_{i,-j}, y_i, \beta, \Sigma \sim N(m_{ij}, \tau_{jj}^2) \times [I(y_{ij} = 1) I(U_{ij} > 0) + I(y_{ij} = 0) I(U_{ij} < 0)]$$

Where $m_{ij} = x_{ij}^{'} \beta + F'(U_{i,-j} - X_{i,-j}\beta)$,

$F = -\sigma^{ij} \gamma_{j,-j}$,

$\tau_{jj}^2 = 1/\sigma^{ij}$

Such that

σ^{ij} : denotes the (i, j) th element of Σ^{-1}, and $\Sigma^{-1} = \begin{bmatrix} \gamma_1^{'} \\ \vdots \\ \gamma_J^{'} \end{bmatrix}$

$\gamma_{j,-j}$: refers to the j th row of Σ^{-1} with j th element deleted

$X_{i,-j}$: X_i with j th column deleted.

Abstract (Korean)

지난 수십 년 동안 많은 연구자들이 다양한 연구를 통해 성공적인 신제품 개발 및 확산을 위한 연구를 진행하였고 그 결과가 상당히 축적되어 왔다. 그럼에도 불구하고 기업들에게 신제품 개발 및 확산은 여전히 실패위험성이 높은 불확실한 분야로 인식되고 있다. 이러한 현실은 기존 연구들이 신제품 개발 및 확산영역에서 상당한 기여를 하였지만 여전히 해결해야 할 과제가 많이 남아 있음을 의미한다. 따라서 본 논문에서는 신제품 개발 및 확산과 관련하여 수행된 기존의 연구모형 및 연구결과들을 충분히 고려한 후, 현재까지 의문으로 남아있는 다음의 세 가지 주요 문제를 중심으로 해결책을 제시하고자 하였다.

첫 번째 에세이에서는, 신제품 개발과정에서 필요한 다양한 자원과 능력에 대하여, 자원투입대비 성과 향상 정도를 포착 하였다. 신제품 성공요인을 규명하는 기존의 많은 연구들은 산업 및 제품의 종류, 국가, 문화 등등을 세분화하여 분석의 단위를 달리하면서 제품혁신에 필요한 자원과 역량이 달라질 수 있음을 보이는데 주 관심을 쏟았다. 그런데 절대다수의 기존 연구들은 실증분석과정에서 설명변수가 되는 기업이 보유한 자원과 반응변수가 되는 성과변수 사이의 관계식을 도출하는데 있어 선형회귀분석과 같은 모수적인 방법론을 적용하여 분석을 시도하였다. 그런데 이와 같은 모수적회귀모형들은 투입자원의 효과를 정확히 측정할 수 없을 뿐만 아니라, 연구모형에 연구자가 임의적 제약을 가함으로써 실증모형에서 현실의 정확한 관계를 포착

하기 어렵고 그 결과 왜곡되거나 상반된 연구결과를 도출 할 수 있는 여지가 있다. 결과적으로, 방법론의 제약으로 인하여 신제품 개발 과정에서 투입되는 자원들의 강도 증가에 따른 성과의 변화를 보다 정확히 관찰 하는 데 소홀 한 것이다. 실제로 신제품 개발과정에서 성과를 극대화하기 위한 연구개발과 마케팅의 협력 정도에 대한 기존의 연구결과들이 상반된 결과를 보이는 것 또한 같은 이유에 기인한다고 볼 수 있다. 일부의 연구들에서는 협력의 정도가 강하면 강할수록 신제품개발의 성과가 증가한다고 주장하는 반면 일부 연구자들은 신제품 성과의 극대화를 위한 최적수준의 협력 정도가 있다고 주장하고 있다. 이와 같은 문제는 신제품개발과정의 효과적인 관리를 위해서 반드시 해결되어야 할 연구문제 중의 하나이다. 이러한 한계점을 극복하고자 첫 번째 에세이에서는 비모수 함수추정 방법론중의 하나인 다변량적응회귀분석 모형을 적용하여 모형 모수에 대한 제약 없이 회귀식을 추정함으로써 신제품 혁신의 결정요인을 모형 스스로 판별하도록 하였으며, 나아가 각 요인들 사이에 상호효과가 존재하고 있음을 보여주었다. 실증분석을 통해 도출된 결과는 다음과 같이 요약될 수 있다. 첫째, 연구개발과 마케팅 통합수준을 포함한 신제품개발팀에 투입되는 각 자원들이 신제품성과에 미치는 영향은 선형이 아니라 비선형이라는 점이다. 둘째, 기업이 투입하는 자원과 역량은 서로 독립적인 것이 아니라 제품개발 과정 중에서 상호간 교차효과가 존재함이 밝혀졌다. 이를 통해 기업의 신제품 개발에 있어 혁신성과를 극대화하는 자원들 사이의 최적조합이 존재함을 알 수 있었다. 셋째, 연구개발과 마케팅의 통합이 과도하게 강조되었을 때 목표하는 성과(시장적기출시, 신제품기술혁신, 신제품매출)에 따라서 비효과적이거나 신제품의 성공에 부정적인 영향을 미칠 수 있다는 점이다. 따라서 모든 관리자들이 높은 수준의 통합을 항상 달성해야만 하는 것이 아님

을 알 수 있었다. 결과적으로 첫 번째 에세이는 기존의 신제품 성공요인 분석 연구의 한계로 지적되어 온 모수적 접근을 통한 모형설정 오류의 가능성을 비모수함수추정 방법론을 적용하여 성공적으로 극복함으로써 연구개발과 마케팅의 통합효과에 대한 기존의 상반된 연구결과들을 재해석할 수 있는 실마리를 제공하였다는데 의의가 있다.

두 번째 에세이에서는, 혁신제품의 시장확산과정에서 기업들이 직면하는 주요 의사결정 문제 중 하나인 소비자들의 의사결정 단계를 고려한 신제품의 마케팅전략 수립에 대해서 살펴 보았다. 전통적인 혁신확산이론에 따르면 소비자들은 '지식-설득-구매의도'와 같은 위계적인 단계를 거쳐 혁신제품 구매에 이른다고 알려져 있다. 소비자심리학에서도 혁신이론과 마찬가지로 소비자들의 상품구매에 대한 의사결정이 계층적이고 순차적으로 이루어진다는 사실이 오래 전부터 널리 입증되어 사실로 받아들여져 왔다. 이러한 소비자들의 의사결정경로를 고려해볼 때 혁신제품을 채 인지하지 못한 그룹, 혁신제품을 인지하지만 관심을 갖지 않는 그룹, 관심을 갖고 있으나 구매의사가 없는 그룹 각각에 대하여 이들을 다음단계로 이동 시킬 수 있는 최적화된 마케팅 커뮤니케이션전략이 구축되어야 한다. 하지만 소비자들의 이러한 계층적 의사결정 과정을 실증모형에 적용하여 제품채택에 영향을 미치는 요인들을 판별하고 이를 토대로 마케팅 커뮤니케이션 전략을 제시한 연구들은 거의 찾아볼 수 없다. 몇몇의 연구들이 소비자들의 계층적 의사결정에 대한 언급을 하며 혁신제품 채택에 영향을 미치는 요인들이 해당 신제품에 대한 인지, 관심, 구매의도와 같은 다차원의 반응에 어떻게 영향을 미치지는 살펴보기는 하였으나, 계층적 의사결정과정을 엄밀히 실증모형에 반영 하는 데는 실패하였다. 이처럼 소비자 의사결정과정에 대한 이론모형의 학술적 기여에도 불구하고, 이를 실증연구모형에 반영함으로써 신제품채택에 영향을 미

치는 요인을 의사결정단계별로 식별한 연구는 거의 없다. 이러한 기존연구의 한계점을 보완 하고자 두 번째 에세이에서는 다변량프로빗 모형을 적용하여 제품특성, 소비자특성, 메시지특성이 소비자의 제품채택 각 단계(인지-관심·흥미-구매의도)에 있어 다음 단계로의 전이에 미치는 영향력을 평가하였다. 결과적으로 두 번째 에세이는 소비자들의 혁신제품 채택과정에서 나타나는 의사결정 단계를 모형화 하고 각 단계의 전이에 영향을 미치는 요인들을 성공적으로 판별할 수 있는 의사결정 모형을 제시하였다는데 의의가 있다.

끝으로 세 번째 에세이에서는 혁신제품 채택에 대한 소비자들의 이질적인 의사결정 경로와 이를 고려한 시장세분화와 마케팅커뮤니케이션 전략수립에 대해서 살펴보았다. 앞서 언급했다시피, 오래 전부터 소비자심리학 연구자들은 소비자들이 신제품에 대한 정보 또는 광고를 접하자마자 그 즉시 제품을 구매하는 것이 아니라 인지→관심→구매의향과 같은 계층적 의사결정을 통해 이루어진다는 사실은 발견하였다. 소비들의 신제품 구매과정에서 이와 같은 위계적 의사결정을 구성하는 세 단계 과정(인지, 정서, 행동의도)에 대해서는 큰 이견이 없었으나, 실제로 그 과정의 구현이 인지→정서→행동의도를 통해서 나타나는지 혹은 다른 대안적 경로가 존재하는지에 관해서는 꾸준히 비판과 의문이 제기되어 왔었다. 일부 연구자들은 신제품의 특성 또는 제품의 관여 정도에 따라 다양한 의사결정 경로가 존재할 수 있음을 주장하여왔다. 그럼에도 불구하고 소비자들의 이질적인 의사결정 경로에 대한 가능성과 이들의 차이를 식별한 연구는 거의 없다. 이와 같은 기존연구의 한계점을 해결하고자 세 번째 에세이에서는 가우시안혼합 모형을 응용하여 혁신제품 채택에 대한 소비자들의 이질적인 의사결정과정을 모델링 하였다. 그리고 제안된 수리모형을 전자책 단말기에 대한

서베이 자료에 적용하여 현실 가능한 의사결정 경로를 포착하고 해당 경로를 따르는 하위시장의 특성을 식별하였다. 결과적으로 세 번째 에세이는 가우시안혼합 모형을 응용하여 소비자들의 이질적인 의사결정 경로에 따른 하위시장을 식별하고, 각 의사결정 경로를 따르는 소비자들이 보다 빠르게 긍정적인 태도를 형성하게끔 하는 주요 메시지를 식별하였다는데 의의가 있다.

세편의 에세이로 구성 된 본 논문은 학술적으로 실무적으로 풍부한 시사점을 제공한다. 본 논문의 학술적 시사점은 그 동안 신제품개발 및 확산 분야에서 제기되어 온 여러 문제점 및 비판들과 관련하여 이를 효과적으로 해결할 수 있는 통계모형을 제시하고 이를 실증적용 하였다는데 있다. 실무적으로는 바람직한 신제품개발 프로세스 관리에 대한 전략적 가이드라인을 제공하였으며, 새로운 혁신제품의 시장확산과 관련하여 소비자들의 제품구매 의사결정의 전이경로를 고려한 마케팅 커뮤니케이션 전략을 제시하였다. 나아가 소비자들의 이질적인 의사결정 경로에 따른 하위시장 분석 및 표적시장선정의 적용가능성을 살펴보고 각 경로에 따른 바람직한 커뮤니케이션 전략을 제안하였다는데 의의가 있다.

주요어: 신제품개발 및 확산, 연구개발과 마케팅 통합관리, 소비자 의사결정 단계, 다변량적응회귀 모형, 다변량프로빗 모형, 가우시안혼합 모형
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