Exploration of Optimal Product Innovation Strategy Using Decision Tree Analysis: A Data-mining Approach

Insu Cho*

Abstract

Recently, global competition in the manufacturing sector is driving firms in the manufacturing sector to conduct product innovation projects to maintain their competitive edge. The key points of product innovation projects are 1) what the purpose of the project is and 2) what expected results in the target market can be achieved by implementing the innovation. Therefore, this study focuses on the performance of innovation projects with a business viewpoint. In this respect, this study proposes the "achievement rate" of product innovation projects as a measurement of project performance. Then, this study finds the best strategies from various innovation activities to optimize the achievement rate of product innovation projects. There are three major innovation activities for the projects, including three types of R&D activities: Internal, joint and external R&D, and five types of non-R&D activities — acquisition of machines, equipment and software, purchasing external knowledge, job education and training, market research and design. This study applies decision tree modeling, a kind of data-mining methodology, to explore effective innovation activities. This study employs the data from the 'Korean Innovation Survey (KIS) 2014: Manufacturing Sector.' The KIS 2014 gathered information about innovation activities in the manufacturing sector over three years (2011-2013). This study gives some practical implication for managing the activities. First, innovation activities that increased the achievement rate of product diversification projects included a combination of market research, new product design, and job training. Second, our results show that a combination of internal R&D, job training and training, and market research increases the project achievement most for the replacement of outdated products. Third, new market creation or extension of market share indicates that launching replacement products and continuously upgrading products are most important.

Keywords
product innovation project, achievement rate, innovation activities, Decision Tree (DT) analysis

* Assistant Professor, Department of Industrial & Management Engineering, Sun Moon University, Asan-si, South Korea, incho@sunmoon.ac.kr

1. INTRODUCTION

Recently, global competition in the manufacturing sector has been intensified by the pursuit of emerging countries including China. This environment is driving firms in the manufacturing sector to conduct product innovation projects to maintain their competitive edge (Nieto & Santamaría, 2007). However, it is complex and difficult to successfully reach innovation goals using product innovation projects in the target market (Balachandra & Friar, 1997). Two key points of the product innovation project are 1) what the purpose of the product innovation project is and 2) what expected results in the target market can be achieved by implementing the innovation. Previous literature related to innovation projects has used patent counts, patent citations, or counts of new product announcements to capture the innovation performance of the firms (Hagedoorn & Cloodt, 2003). These factors are somewhat inadequate to directly evaluate product innovation project performance. As mentioned above, because the project has a defined purpose, the key evaluation metric of the project's performance is to what degree the project accomplished its initial purpose.

This study proposes the "achievement rate" of product innovation projects as a practical business concept. To calculate the achievement rate, this study focuses on two points: The importance of the purpose of the product innovation project, and the actual effect of product innovation.

For many product innovation projects, particularly those with a non-trivial level of technology and in sectors with market uncertainty, it is not easy for a firm to identify the key activities that must be undertaken to achieve the product innovation project (Ciarapica, Bevilacqua, & Mazzuto, 2016).

Therefore, this study identifies major innovation activities that can influence the achievement rate. In previous research, a firm's R&D has been the most common activity serving as a key determinant of product innovation. However, to meet rapidly changing technology trends and customer needs, firms should simultaneously conduct not only R&D activities but also various innovation activities such as acquisition of machines, equipment, and software, purchasing external knowledge, job training, and market research.

This study finds the best strategies used in various innovation activities for the achievement rate of product innovation projects. To do this, this study applies the decision tree model, a kind of data-mining methodology.

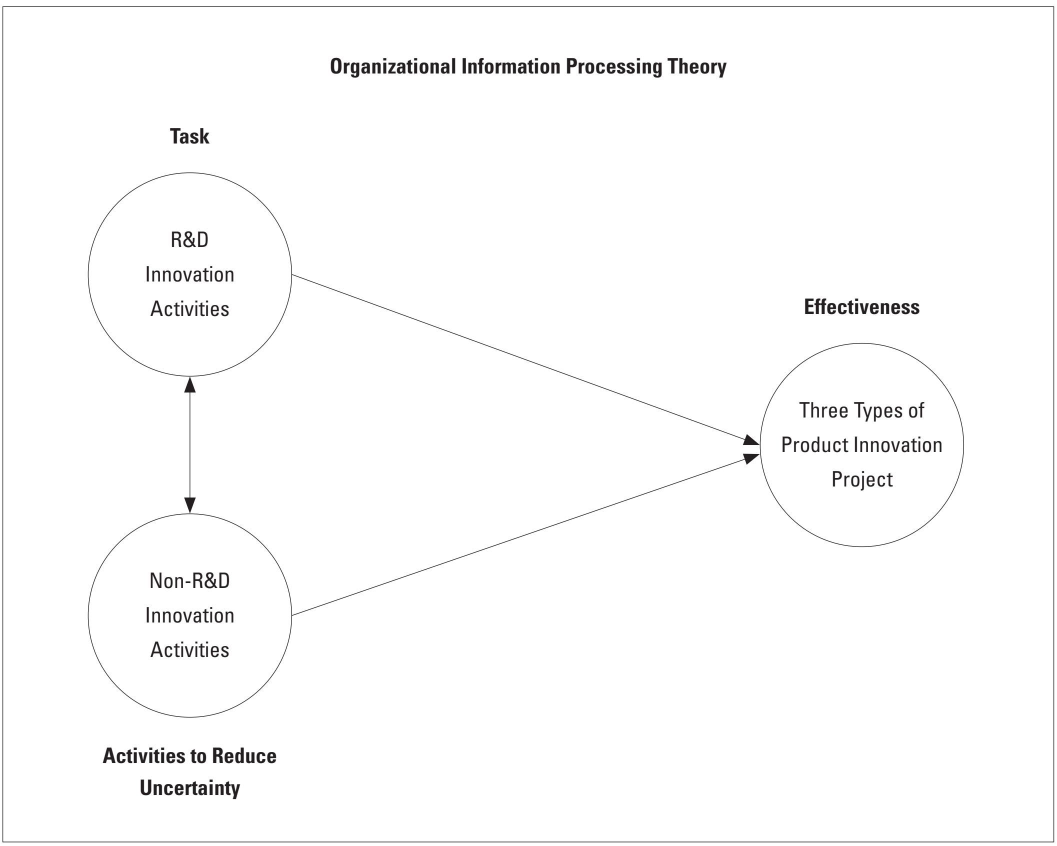
2. PRODUCT INNOVATION PROJECT AND INNOVATION ACTIVITIES

Product innovation projects are frequently composed of information processing activities (Tatikonda & Rosenthal, 2000). There are many work elements such as 1) responding to information received, 2) altering, rearranging, or recomposing information or things, and 3) converting information into products (Burns & Stalker, 1961). This study applied 'organizational information processing theory' to view product innovation project and innovation activities. It can be useful to describe the relationships among uncertainty, tasks, and effectiveness (Tatikonda & Rosenthal, 2000). In this study, task refers to the main R&D activities of firms toward successful innovation projects.

Firms conduct non-R&D activities, such as job training or market research, at the same time as R&D activities to reduce market uncertainty. Firms can ensure a competitive edge when the value from the products released by their innovation activities is consistent with the value of the market, to reflect customers' needs. Engaging in non-R&D activities helps firms to meet customer needs (Danneels, 2002).

There are, then, a number of factors which can influence the effectiveness of a project. To assess effectiveness, this study focuses on market-oriented terms such as product diversity, renewal of original products, customer satisfaction, new market creation, and market share.

FIGURE 1. Conceptual Model Based on Organizational Information Processing Theory



2.1. Achievement Rate of Product Innovation Project

Kogut and Zander (1992) explained innovation as a concept of competition between innovator and imitator. Various innovation technologies, especially those linked to new products on the market, can be quickly and easily imitated by competitors. Although it is possible to reduce the damage caused by imitation through innovation protection mechanisms such as patents, a rapid speed to market, and complementary resources, competitors eventually catch up with the first mover (Cho, Park, & Kim, 2012). From this point of view, a product innovation ability that continuously releases new products to market or adds new features to existing ones is important to commercially meet customer and market needs (Utterback & Abernathy, 1975). In other words, strengthening product competitiveness by continuous new product launches and improvement of existing products is one of the keys to growth of manufacturing firms (Relich & Bzdyra, 2014). Therefore, manufacturing firms have conducted various projects to support continuous product innovation. Each project has a specific goal and performs various activities to achieve it. In this process, it is important to identify whether the project result met the original goal (Loch, Stein, & Terwiesch, 1996).

Several approaches to evaluating product innovation project performance have been proposed in the literature. First, Lettice, Roth, and Forstenlechner (2006) measured performance of product innovation projects as the extent to which the project is meeting stakeholder expectations. Verworn, Herstatt, and Nagahira (2008) evaluated new product development projects by using four metrics: project goals on sales, profit margin, return on assets, and return on investment. Recently, Ramezani and Lu (2014) suggested a fuzzy multiple attribute-based group decision-support system (FMAGDSS) based on a fuzzy ranking method and sensitivity analysis system to evaluate the effectiveness of projects in achieving organizational goals.

In all of the previous research, the common and primary issue of a product innovation project is to achieve the project goals under the existing constraints (Teimoury, Fesharaki, & Bazyar, 2011).

In the case of the manufacturing industry, product innovation project goals can usually be divided into three types: 1) product diversification, 2) replacement of outdated products, and 3) new market creation or extension of market share via the before-mentioned two types (Cooper & Kleinschmidt, 1995).

The first goal of product diversification is a competitive edge to quickly meet various customer needs. Especially in the market where trends are rapidly changing, firms should continuously launch various product lines to become the key product in the current trend. In this regard, product diversification is one of the growth strategies of a firm (Alesón & Escuer, 2002). Product diversification itself can be considered innovation performance by generating economic benefits (Luo, 2002). Product diversification also contributes to new market creation or existing market expansion.

Second, replacement of outdated products is an innovation project that overcomes the limitation of existing products by introducing upgraded products with improved performance and design. As a product lifecycle is shortened, especially for IT products, many firms have introduced upgraded products to attract customers' attention. Thus, they conduct the project with core products being central. In a rapidly changing market for technology and product environments, firms should constantly upgrade products by aggressively adopting new changes in market or technology for their competitive edge. Despite the importance of replacing outdated products as an innovation goal, there is no active discussion on it in the research.

Finally, firms innovate to develop new markets and increase market share. Due to the recent economic recession, there is excessive competition among firms in certain industries. In this context, Zhou, Yim, and Tse (2005) mentioned that the ability to find a new market or customer base has a significant impact on the performance of a firm. When a firm's product innovation projects are superior to its competitors, it has relevance to find a new market (Zhou, et al., 2005). Product innovation projects for new market creation or market share expansion could be sequentially achieved based on product diversification or replacement of outdated products.

Three 'new product success measures' are used to assess the outcomes of a portfolio of new product projects: The percentage of launched products that are successful by company assessment criteria, the level of profit, and the level of revenue from new products (products introduced in the past three years) (Brown & Eisenhardt, 1995).

2.2. Innovation Activities for the Projects

Recognizing the importance of product innovation projects, firms are conducting a variety of innovation activities to successfully lead these projects. Product innovation activities include the technical design, R&D, manufacturing, management and commercial activities involved in the marketing of a new (or improved) product. According to organizational information processing theory, 'task' and other activities to reduce 'uncertainty' is necessary for success of a product innovation project as 'effectiveness of innovation (Tatikonda & Rosenthal, 2000).' It means that product innovation activities undertaken by firms can be divided into R&D as the main task and non-R&D activities as other activities aiming to reduce 'uncertainty.'

I reviewed previous research to explore the relationship among types of product innovation projects and innovation activities, as shown in Table 1. This study examined the three R&D activities and four non-R&D activities for all three types of product innovation projects.

TABLE 1. Review of Relationship between Types of Product Innovation Project and Innovation Activities

Innovation Activities		Types of Product Innovation Project			Researchers
		Product Diversification	Replacement of Outdated Product	New Market Creation or Extension of Market Share	
R&D Activities	Internal R&D	–	V	V	Cassiman and Veugelers (2006) O'Connor and Rice (2013)
	Joint R&D	–	V	V	White & Bruton, (2010) Parida, Westerberg, and Frishammar (2012)
	External R&D	V	V	–	Berchicci (2013)
Non-R&D Activities	Acquired Technology Externally	V	V	V	Cassiman and Veugelers (2006) Luo (2002) O'Connor and Rice (2013)
	Market Research	–	V	V	White and Bruton (2010) O'Connor and Rice (2013)
	Job Training	V	V	–	Lau and Ngo (2004)
	Design	V		V	O'Connor and Rice (2013)

2.2.1. R&D Activities

Internal R&D resources can serve as appropriation capacity, e.g., by increasing the complexity of the new product/process (Cassiman & Veugelers, 2006). In particular, the higher uncertainty and transaction-specific transaction-costs that come with new products and processes drive firms to choose internal R&D. Internal R&D capability of a firm is determined by the firm's entrepreneurial orientation, technological capabilities, and the financial resources invested during the development period (Lee, Lee, & Pennings, 2001). R&D in small and medium enterprise (SME) especially emphasizes innovativeness and proactiveness to find market opportunities and generate new ideas. These activities of internal R&D can develop a market niche with new or upgraded products.

Some research on product innovation activities through utilization of external resources or collaboration with other research institutes has also been conducted. In the current business environment, where the convergence of technology information and knowledge is the source of a competitive edge, firms should pursue rapid technology development strategies. This requirement is challenging for SMEs not only because of their limited size, but also because they have less internal resources and a more restricted competence base, which affect their ability to engage in innovative efforts (White & Bruton, 2010). Therefore, collaborative innovation activities with external entities are important in promoting complementary asset sharing and mutual learning of insufficient technical knowledge in response to rapid technological change (Ahuja, 2000).

Cohen (1995), who highlights the absorptive capacity of firms, suggest SMEs need to actively utilize external resources from suppliers, customers, universities, public institutions, industry associations, and so forth to supplement relatively insufficient internal resources. Similarly, Hauschildt (1992) presented four types of external resources such as 1) the market, including customers and partners, 2) scientific organizations including universities and research institutes, 3) government or public institutions including patent and financial support agencies, and 4) consultants or science and technology expositions.

One of the R&D types that utilizes the above resources is the joint R&D. Joint R&D refers to R&D activities conducted jointly with external organizations (other companies or institutions) for the same purpose as internal R&D. In general, joint R&D is conducted as a horizontal type of collaboration with external partners that have key knowledge and expertise of the technology development of interest. Their expertise helps SMEs to precisely identify potential technical problems, develop new product development methods, and change product design effectively (Kessler & Chakrabarti, 1996).

Another type of collaboration R&D model is external R&D such as outsourcing. Firms choose a collaboration type that will maximize their core value or complement their competencies. It is necessary to connect with or be open to external knowledge or resources in order to achieve their purpose. In this context, contract research or R&D outsourcing plays a key role in enhancing the core competencies and competitive edge of firms. Generally, this external R&D is conducted as a vertical type between contractors.

Keeping with the above-mentioned R&D types, an important task in R&D innovation activities is to optimally integrate internal and external knowledge or resources within the firm's innovation process to be able to benefit from the positive effects each innovative activity has on the other.

2.2.2. Non-R&D Activities

Non-R&D innovation activities as well as R&D activities are also important for product innovation projects. First, it is necessary to establish a direction for product development and improvement based on consumer needs through market research. In order to succeed with a product innovation project, firms should identify the market situation, and then analyze the possibilities of the niche market and the new market. This starts with a clear understanding of the internal and external conditions of firms. Firms must understand the product life cycle, market situation, and customer needs so they can develop and launch new products in time. Also, marketing activities such as launching advertisements are essential to launch new products and improve existing market share.

Recently, the aesthetic and emotional aspects in product innovation are becoming new key values, in addition to function and quality. Therefore, the differentiation of product value by innovative design is recognized as an important core competence in creating innovation performance of SMEs.

As a non-R&D activity, it is also necessary to acquire the machines, equipment, and software for the process of developing and producing new products resulting from R&D activities. Lastly, training and education are required for employees to use new knowledge, equipment, and production processes smoothly.

3. RESEARCH METHODOLOGY

This study employs Decision Tree (DT) analysis as a data mining approach. DT analysis is a powerful tool for classification and prediction by finding out the rules, patterns, or relationships between data and is therefore is one of the most frequently used data mining methods (Berry & Linoff, 2000). Classification means to group subjects based on several predictor variables, like grading customers as good or bad according to their credit rating. Prediction means to forecast future events based on rules discovered from a pool of data. DT is represented in the form of a tree, and a full tree is built by making child-nodes until each branch reaches the terminal node. In DT, there are two main types of trees, which are differentiated according to the measurement level of variables. When target variables are a discrete type, they make a classification tree, and if they are continuous types, they build a regression tree (Bala, De Jong, Huang, Vafaie, & Wechsler, 1996; Hunt, 1993).

Nevertheless, all DT trees have the same structure. The formation process of DT is affected by split criterion, stopping rule, and pruning rule. Split criterion set the tree into subsets based on an attribute value test with raw data. This process is repeated on each derived subset in a recursive manner called recursive partitioning. Stopping rule decides when the tree stops splitting certain branches. Pruning rule is algorithm to reduce the effect of noise is to delete the subtrees that incorrectly classify examples. The most popular algorithms for DT are Chi-squared Automatic Interaction Detection (CHAID) (Kass, 1980), Classification and Regression Trees (CART) (Breiman, Friedman, Olshen, & Stone, 1984), and C4.5 (Quinlan, 1993). The CHAID is an algorithm performing a multiway split using a chi-square test for discrete target variables, or using a F-test for continuous ones. The CHAID procedure begins by finding independent variables that have statistically significant influence on the target variables (Thomas & Galambos, 2004). Then, it assesses the category groupings to find the most significant combination. The independent variable that has the greatest effect on the target variable becomes the first branch in the tree to divide subgroups to different outcome. This process is repeated to find the predictor variable on each leaf most significantly related to the outcome, until no significant variables remain.

The CART makes a binary split by using the Gini index for discrete target variables, whereas it uses the variance reduction for continuous ones (Quinlan, 2014). The Gini index is an index that measures the impurity in each node. It selects the explanatory variable that minimizes the Gini index and the optimal separation of the variable as a child node. The reduction of variance is a measure of the variability of each node, which forms the child node by optimal separation of the criterion maximizing the reduction of variance while minimizing the prediction error.

When comparing other statistical analysis methods such as cluster analysis or regression analysis, a DT is easily understood and features a simple top–down tree structure where decisions are made at each node (Jin & Yong, 2011). Also, owing to the non-parametric method of this model, there is no need for the assumptions of linearity, normality, and homoscedasticity to be met. Even if data types are different, the model can be analyzed only through rank regardless of the responsiveness of outliers. Thus, it can be used effectively when there is an issue of data quality (Jin & Yong, 2011).

This study mainly deals with the combinations of innovation activities, which means that it analyzes the interaction effects of them. In this case, the DT model is more efficient than other parametric methods such as regression analysis or logit analysis (Jin & Yong, 2011). Finally, regardless of specific modelling such as structural equation modeling or multiple linear regression, DT model as a data mining method can find new possible combinations of R&D and non-R&D activities.

This study uses the CHAID algorithm based on the chi-square and CART algorithm based on the Gini index performing a binary split. The achievement rate of product innovation projects is used as a target variable. According to project purpose, this study divided product innovation projects into three different types including product diversification, replacement of outdated products, and new market creation or extension of market share. This study applied the CHAID algorithm for the product diversification and replacement of outdated products and the CART algorithm for the New market creation or extension of market share.

This study sets R&D and non-R&D innovation activities as a predictor variable for the achievement rate of product innovation projects. In R&D innovation activities, there are three types of R&D activities (internal R&D, joint R&D, and external R&D (outsourcing)).

This study employs the data from 'Korean Innovation Survey (KIS) 2014: Manufacturing Sector' of STEPI. The KIS 2014 gathered the information of innovation activities in the manufacturing sector for three years (2011-2013). The original dataset included 1251 manufacturing firms. This study filtered data to delete firms that do not have information on product innovation projects or innovation activities resulting in data on 1,245 firms for training and test sets.

This study extracts the types of product innovation project as output variables and R&D and non R&D innovation activities as input variables, as shown in Table 2. To measure the achievement rate of all three types of product innovation projects, this study checked the main purpose and importance of product innovation projects in small to medium manufacturing. Then, this study checked the actual effects of the innovation project and calculated the degree of achievement against the original project purpose.

TABLE 2. Output and Input Variables of This Study

	Types of Achievement Rate of Product Innovation Project	Measure (2011-2013)
Output Variables	- Product diversification	Achievement rate (%)
	- Replacement of outdated products	Achievement rate (%)
	- New market creation or extension of market share	Achievement rate (%)
Input Variables	R&D activities	
	- Internal R&D	'Yes' or 'No'
	- Joint R&D	'Yes' or 'No'
	- External R&D (outsourcing)	'Yes' or 'No'

	Non R&D activities	
Input Variables	- Acquisition of machine, equipment, and software	'Yes' or 'No'
	- Purchasing external knowledge	'Yes' or 'No'
	- Job education and training	'Yes' or 'No'
	- Market research	'Yes' or 'No'
	- Design	'Yes' or 'No'

This study applies the three main R&D activities: 1) internal R&D, 2) joint R&D, and 3) external R&D (outsourcing). Also this study applies five different non R&D activities: 1) acquisition of machines, equipment, and software; 2) purchasing external knowledge, 3) job education and training, 4) market research, and 5) design. These activities are measured in two types, yes or no, by whether they have been conducted for product innovation projects in small and medium manufacturing.

4. RESULTS OF DECISION TREE MODELING

This section describes the results of decision tree modeling for three different product innovation projects. The results show the model summary and decision tree modeling.

4.1. Product Diversification Project

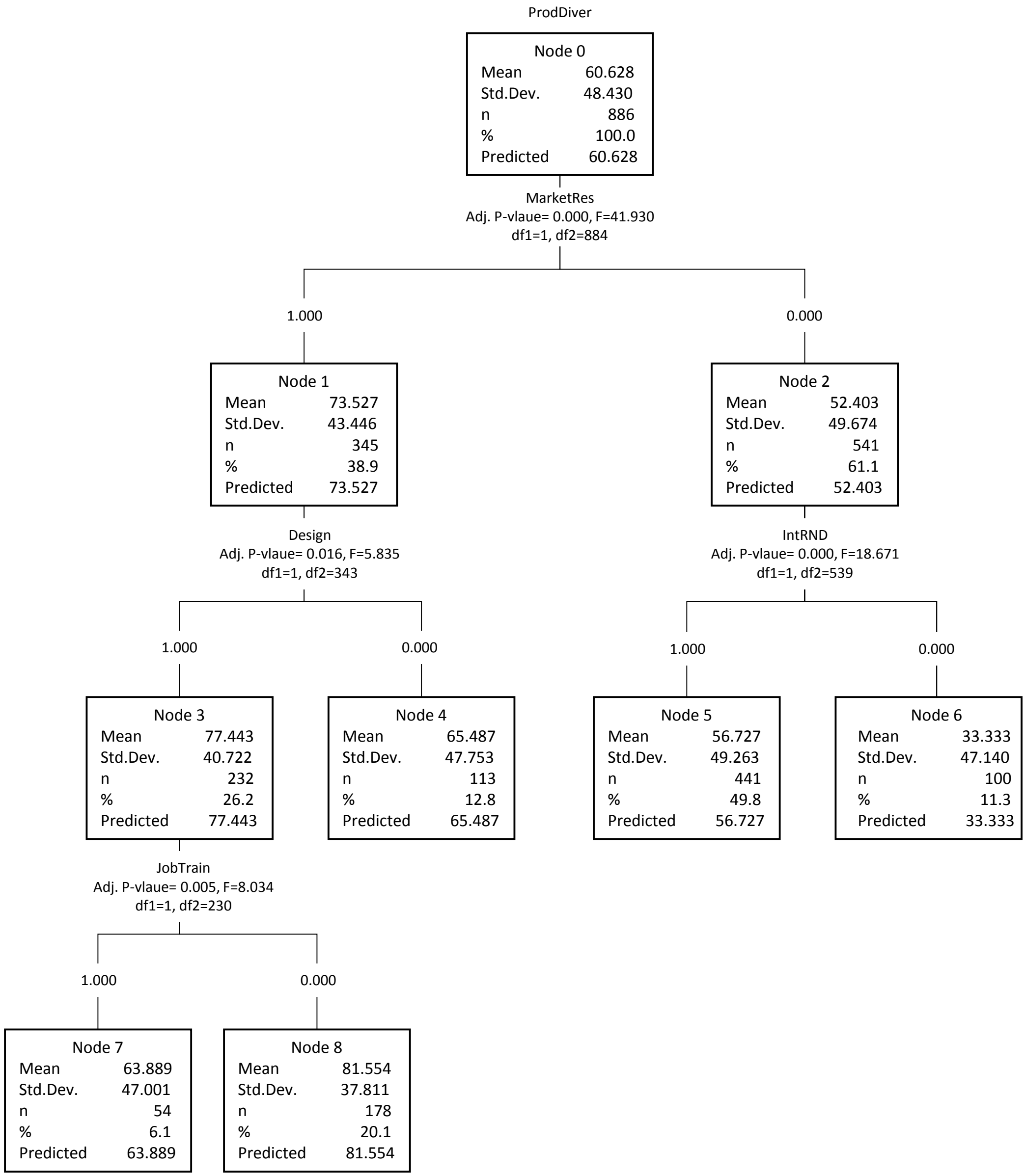
TABLE 3. Model Summary of Product Diversification Project

Model Summarization		
Specification	Growing Method	CHAID
	Dependent Variables	ProdDiver
	Independent Variables	IntRND, ColRND, ExtRND, Mach_SW, ExtKnowl, JobTrain, MarketRes, Design
	Maximum Tree Depth	3
	Maximum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables	MarketRes, Design, JobTrain, IntRND
	Number of Nodes	9
	Number of Terminal Nodes	5
	Depth	3

Note: ProdDiver = Product diversification, IntRND = Internal R&D, ColRND = Joint R&D, ExtRND = External R&D, Mach_SW = Acquisition of machine, equipment, and software, ExtKnowl = Purchasing external knowledge, JobTrain= Job education and training, MarketRes = Market research, Design = Design

The CHAID procedure for Product diversification project generated a tree containing five terminal nodes (see Figure 1). The percentage of achievement rate for product diversification within the past three years ranged from 33.333% to 81.554% in these five combinations. The first variable selected for splitting was market research. When firms conduct market research, the achievement rate of replacement of outdated products is improved to 73.527%. Next, when firms conduct new project with design, the achievement rate of replacement of outdated products is slightly improved to 77.443%. Finally, job training slightly improves the achievement rate of target variable to 81.554%. Therefore, according to the highest prediction of achievement rate, the best combination is market research + design + job training.

FIGURE 2. Decision Tree Modeling Result of Product Diversification Project



Note: ProdDiver = Product diversification, MarketRes = Market research, Design = Design, JobTrain= Job training, IntRND = Internal R&D

4.2. Replacement of Outdated Products Project

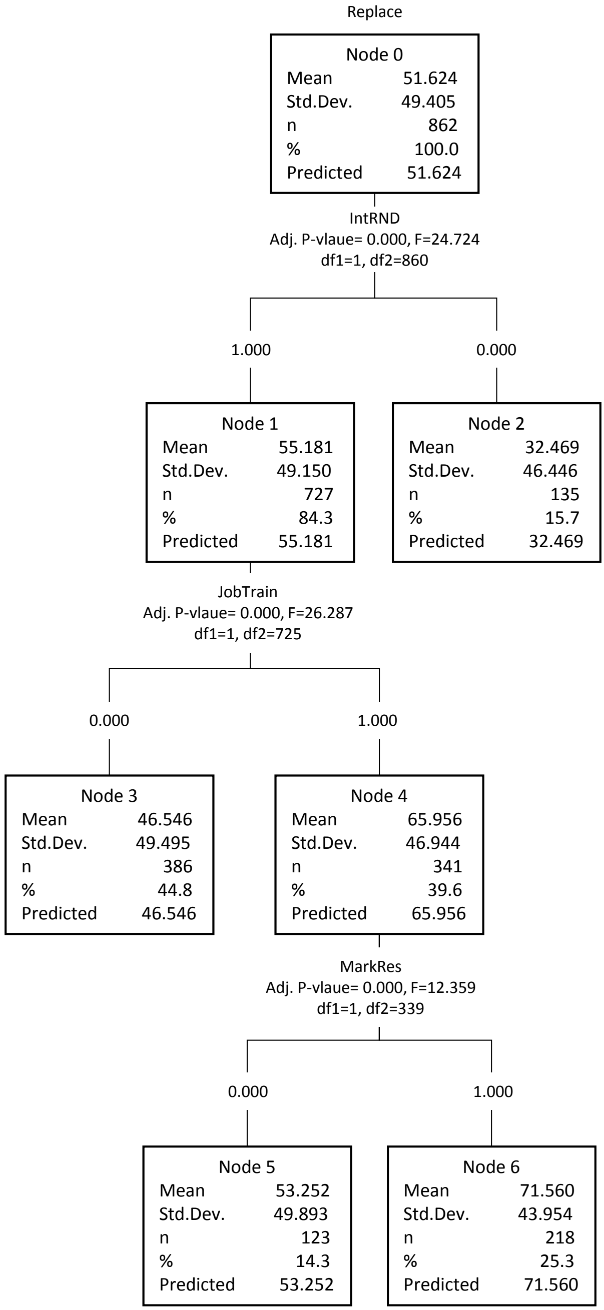
TABLE 4. Model Summarization of Replacement of Outdated Products Project

Model Summarization		
Specification	Growing Method	CHAID
	Dependent Variables	Replace
	Independent Variables	IntRND, ColRND, ExtRND, Mach_SW, ExtKnowl, JobTrain, MarketRes, Design, CustInvol
	Maximum Tree Depth	3
	Maximum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables	IntRND, JobTrain, MarketRes
	Number of Nodes	7
	Number of Terminal Nodes	4
	Depth	3

Note: Replace = Replacement of outdated products, IntRND = Internal R&D, ColRND = Joint R&D, ExtRND = External R&D, Mach_SW = Acquisition of machine, equipment, and software, ExtKnowl = Purchasing external knowledge, JobTrain= Job education and training, MarketRes = Market research, Design = Design

The CHAID procedure for replacement of outdated products project generated a tree containing four terminal nodes (see Figure 2). The percentage of achievement rate for replacement of outdated products within the past three years ranged from 32.469% to 71.580% in these four combinations. The first variable selected for splitting was internal R&D. When firms conduct internal R&D, the achievement rate for replacement of outdated products is improved to 55.181%. Next, when firms train employees for new projects, the achievement rate of replacement of outdated products is improved to 64.956%. In addition, market research slightly improves the achievement rate of target variable to 71.560%. Therefore, according to the highest prediction of achievement rate, the best combination is internal R&D + job training + market research.

FIGURE 3. Decision Tree Modeling Result of Replacement of Outdated Products Project



Note: Replace = Replacement of outdated products, IntRND = Internal R&D, JobTrain= Job training, MarketRes = Market research

4.3. New Market Creation or Extension of Market Share Project

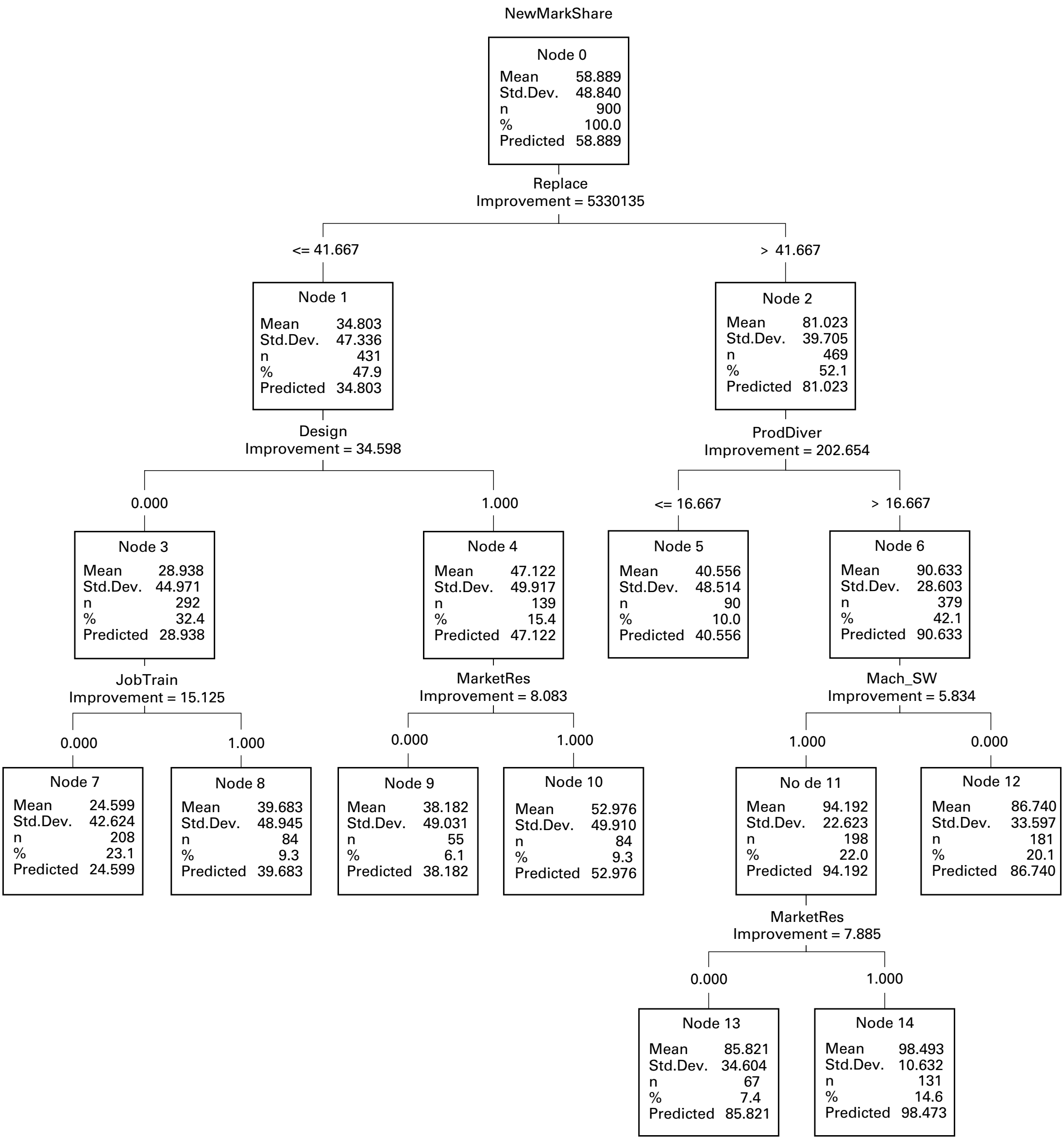
TABLE 5. Model Summarization of New Market Creation or Extension of Market Share Project

Model Summarization		
Specification	Growing Method	CART
	Dependent Variables	NewMarkShare
	Independent Variables	IntRND, ColRND, ExtRND, Mach_SW, ExtKnowl, JobTrain, MarketRes, Design, ProdDiver, Replace
	Maximum Tree Depth	5
	Maximum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables	Replace, ProdDiver, JobTrain, MarketRes, IntRND, Design, Mach_SW, ColRND, ExtKnowl, ExtRND
	Number of Nodes	15
	Number of Terminal Nodes	8
	Depth	4

Note: NewMarkShare = New market creation or extension of market share, ProdDiver = Product diversification, Replace = Replacement of outdated products, IntRND = Internal R&D, ColRND = Joint R&D, ExtRND = External R&D, Mach_SW = Acquisition of machine, equipment, and software, ExtKnowl = Purchasing external knowledge, JobTrain= Job education and training, MarketRes = Market research, Design = Design

The CART procedure for a new market creation or extension of market share project generated a tree containing eight terminal nodes (see Figure 3). The percentage of achievement rate of new market creation or extension of market share within the past year ranged from 24.60% to 98.47% in these eight combinations. The first variable selected for splitting was replacement of outdated products. When the achievement rate of projects for replacement of outdated products is over 41.667%, the achievement rate of new market creation or extension of market share is improved to 81.023%. Next, the product diversification project is the second variable for increasing the target variable. Finally, the activities of acquisition of machines, equipment, and software and market research slightly improve the achievement rate of the target variable. Therefore, according to the highest prediction of achievement rate, the best combination is replacement of outdated products over the 41.667% + product diversification over the 16.667% + acquisition of machines, equipment, and software + market research.

FIGURE 4. Decision Tree Modeling Result of New Market Creation or Extension of Market Share Project



Note: NewMarkShare = New market creation or extension of market share, Replace = Replacement of outdated products, Design = Design, ProdDiver = Product diversification, JobTrain= Job training, MarketRes = Market research, Mach_SW = Acquisition of machine, equipment, and software

5. DISCUSSION AND CONCLUSION

This study proposes measuring the achievement rate on product innovation project by evaluating the purpose of the project and actual effect. To do this, this study applied organizational information processing theory to develop a conceptual model. Also, this study identifies empirically the important innovation activities for the achievement rate and gives some practical implication for managing the activities.

The innovation activities that contributed most to an increase in the achievement rate of product diversification project were combination of market research, new product design, and job training. These results mean that design differentiation based on market research and employee education and training for producing new products resulted in a high project achievement rate. In the case of domestic small and medium-sized manufacturing, they have focused on product diversification through design to meet consumer needs rather than technological diversification, due to limitations of their R&D capacities.

These results show that a combination of internal R&D, job training and training, and market research drive the greatest increase in project achievement for the replacement of outdated products. Internal R&D, in particular, is the most effective innovation activity because functional upgrading is the key success factor to replace outdated products. It is also necessary to carry out job training in parallel to manage improving function of outdated products by internal R&D activities.

Decision tree analysis results for exploitation of a new market and increasing market share indicates that launching replacement products and continuous product upgrading is most important. In addition, acquisition of machines, equipment, and software and market research are needed to exploit a new market and increase market share. In other words, this study confirmed that each innovation project activity to replace outdated products and launch various products is the basis for improving market share.

Also, it was confirmed that the interaction effects of non-R&D activities such as acquisition of machines, equipment, and software and market research are significant among the combinations of innovation activities.

This study investigated optimal combinations of innovation activities to increase the achievement rate of three types of product innovation projects in small and medium manufacturing by applying decision tree analysis. However, this study has some limitations. First, product innovation is the most important point in becoming a first mover to cope with rapidly changing product trends and the chase of competitors. In addition, process innovation is needed to achieve standardization and efficiency of product. This means that the process innovation after the product innovation could help to flexibly and strategically cope with industry change. However, this study only focused on product innovation project to simplify the models, the results, and implications. In the follow-up research, I will deal with not only product innovation performance but also process innovation performance. In addition, the product price is also an important factor in the success rate of product innovation projects, but it is not addressed in this study due to limitations of acquired panel data.

Finally, this study does not consider the level of each innovation activity, only making binary ‘yes’ or ‘no’ categorizations about them. Further research is needed to build strategies for specific innovation activities.

REFERENCES

Ahuja, G. (2000). The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal, 21*(3), 317-343.

Alesón, M. R., & Escuer, M. E. (2002). The impact of product diversification strategy on the corporate performance of large Spanish firms. *Spanish Economic Review, 4*(2), 119-137.

Bala, J., De Jong, K., Huang, J., Vafaie, H., & Wechsler, H. (1996). Using learning to facilitate the evolution of features for recognizing visual concepts. *Evolutionary Computation, 4*(3), 297-311.

Balachandra, R., & Friar, J. H. (1997). Factors for success in R&D projects and new product innovation: A contextual framework. *IEEE Transactions on Engineering Management, 44*(3), 276-287.

Berchicci, L. (2013). Towards an open R&D system: Internal R&D investment, external knowledge acquisition and innovative performance. *Research Policy, 42*(1), 117-127.

Berry, M., & Linoff, G. (2000). *Mastering data mining: The art and science of customer*. NY: John Willey and Sons.

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees*. Belmont, CA: Wadsworth.

Brown, S. L., & Eisenhardt, K. M. (1995). Product development: Past research, present findings, and future directions. *Academy of Management Review, 20*(2), 343-378.

Burns, T. E., & Stalker, G. M. (1961). *The management of innovation*. London: Tavistock Publication; Champaign IL: University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship

Cassiman, B., & Veugelers, R. (2006). In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. *Management Science, 52*(1), 68-82.

Cho, I., Park, H., & Kim, J. K. (2012). The moderating effect of innovation protection mechanisms on the competitiveness of service firms. *Service Business, 6*(3), 369-386.

Ciarapica, F. E., Bevilacqua, M., & Mazzuto, G. (2016). Performance analysis of new product development projects: An approach based on value stream mapping. *International Journal of Productivity and Performance Management, 65*(2), 177-206.

Cohen, W. M. (1995). CH. 4: Fifty years of empirical studies of innovative activity and performance. In P. Stoneman (Ed.), *Handbook of the economics of innovation and technological change* (pp. 129-213). Oxford: Blackwell.

Cooper, R. G., & Kleinschmidt, E. J. (1995). Benchmarking the firm's critical success factors in new product development. *Journal of Product Innovation Management, 12*(5), 374-391.

Danneels, E. (2002). The dynamics of product innovation and firm competences. *Strategic Management Journal, 23*(12), 1095-1121.

Hagedoorn, J., & Cloodt, M. (2003). Measuring innovative performance: Is there an advantage in using multiple indicators? *Research Policy, 32*(8), 1365-1379.

Hauschildt, J. (1992). External acquisition of knowledge for innovations—a research agenda. *R&D Management, 22*(2), 105-110.

Hunt, K. (1993). Classification by induction: Application to modelling and control of non-linear dynamical systems. *Intelligent Systems Engineering, 2*(4), 231-245.

Jin, H. J., & Yong, K. B. (2011). Analysis for consumers' opinion regarding domestic wheat bread. *Journal of Consumer Policy Studies, 40*, 205-222.

Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. *Applied Statistics, 29*(2), 119-127.

Kessler, E. H., & Chakrabarti, A. K. (1996). Innovation speed: A conceptual model of context, antecedents, and outcomes. *Academy of Management Review, 21*(4), 1143-1191.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*(3), 383-397.

Lau, C. M., & Ngo, H. Y. (2004). The HR system, organizational culture, and product innovation. *International Business Review, 13*(6), 685-703. doi: http://dx.doi.org/10.1016/j.ibusrev.2004.08.001

Lee, C., Lee, K., & Pennings, J. M. (2001). Internal capabilities, external networks, and performance: A study on technology-based ventures. *Strategic Management Journal, 22*(6-7), 615-640.

Lettice, F., Roth, N., & Forstenlechner, I. (2006). Measuring knowledge in the new product development process. *International Journal of Productivity and Performance Management, 55*(3/4), 217-241.

Loch, C., Stein, L., & Terwiesch, C. (1996). Measuring development performance in the electronics industry. *Journal of Product Innovation Management, 13*(1), 3-20.

Luo, Y. (2002). Product diversification in international joint ventures: Performance implications in an emerging market. *Strategic Management Journal, 23*(1), 1-20.

Nieto, M. J., & Santamaría, L. (2007). The importance of diverse collaborative networks for the novelty of product innovation. *Technovation, 27*(6), 367-377.

O'Connor, G. C., & Rice, M. P. (2013). New market creation for breakthrough innovations: Enabling and constraining mechanisms. *Journal of Product Innovation Management, 30*(2), 209-227.

Parida, V., Westerberg, M., & Frishammar, J. (2012). Inbound open innovation activities in high-tech SMEs: The impact on innovation performance. *Journal of Small Business Management, 50*(2), 283-309.

Quinlan, J. R. (2014). C4. 5: *Programs for machine learning*. San Francisco: Morgan Kaufmann.

Ramezani, F., & Lu, J. (2014). An intelligent group decision-support system and its application for project performance evaluation. *Journal of Enterprise Information Management, 27*(3), 278-291.

Relich, M., & Bzdyra, K. (2014). Estimating new product success with the use of intelligent systems. *Foundations of Management, 6*(2), 7-20.

Tatikonda, M. V., & Rosenthal, S. R. (2000). Technology novelty, project complexity, and product development project execution success: A deeper look at task uncertainty in product innovation. *IEEE Transactions on Engineering Management, 47*(1), 74-87.

Teimoury, E., Fesharaki, M., & Bazyar, A. (2011). The relationship between governance and NPD performance and the mediating role of tie strength. *International Journal of Productivity and Performance Management, 60*(6), 622-641.

Thomas, E. H., & Galambos, N. (2004). What satisfies students? Mining student-opinion data with regression and decision tree analysis. *Research in Higher Education, 45*(3), 251-269.

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

Verworn, B., Herstatt, C., & Nagahira, A. (2008). The fuzzy front end of Japanese new product development projects: Impact on success and differences between incremental and radical projects. *R&D Management, 38*(1), 1-19.

White, M. A., & Bruton, G. D. (2010). *The management of technology and innovation: A strategic approach*: Cengage Learning (2nd Edition). Mason OH: Cengage learning.

Zhou, K. Z., Yim, C. K., & Tse, D. K. (2005). The effects of strategic orientations on technology-and market-based breakthrough innovations. *Journal of Marketing, 69*(2), 42-60.