경영학석사학위논문

The Impact of Technological Relatedness and Learning Capabilities on Exploitative and Exploratory Innovation in Technological M&A

기술적 **M&A**에서 기술 관련성과 학습 역량이 탐색적 혁신과 활용적 혁신에 미치는 영향

July 2022

College of Business Administration
Seoul National University
Strategy and International Management Major

HYUNJEE JUNG

The Impact of Technological Relatedness and Learning Capabilities on Exploitative and Exploratory Innovation in Technological M&A

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이 논문을 경영학석사 학위논문으로 제출함
2022년 5월

서울대학교 대학원
경영학과 경영학전공

정 현 지

정현지의 경영학석사 학위논문을 인준함
2022년 6월

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Abstract

This study investigates how technological mergers and acquisitions (M&A) affect the innovation performance of firms and focuses on the technological relatedness between the acquirer and the target as well as acquirers' learning capabilities. Moreover, it categorizes innovation into exploitative and exploratory innovation depending on whether it is incremental innovation that follows the existing technology trajectory or radical innovation that involves moving into a new technology trajectory and investigated how the key factors affect these two types of innovation. To test the hypotheses, this study used technological M&A of knowledge-intensive industries such as the semiconductor, bio, and ICT industries as the subject of analysis and conducted negative binomial regression and Tobit regression using the United States patent database. As a result, technological similarity and technological complementarity showed an inverted-U relationship with post-M&A quantitative innovation performance, while technological similarity showed an inverted-U relationship with exploitative performance and technological complementarity with exploratory performance. Meanwhile, higher technological similarity led to a higher exploitative innovation performance ratio than exploratory innovation performance, whereas higher technological complementarity led to a higher exploratory innovation performance ratio than exploitative innovation performance. This result increases the understanding of how technological relatedness between the target and the acquirer affects follow-on innovation performance. Furthermore, this study reveals the importance of "learning capabilities" as a factor that increases innovation performance in the integration process after technological M&A. Active learning capabilities through R&D investment and passive learning capabilities through M&A experience had a positive effect on both exploitative and exploratory innovation performance, and this result proved that learning capabilities of firms serve as the source of their competitive advantage.

Keyword : Technological M&A, Post M&A Innovation, Knowledge Relatedness, Knowledge Similarity, Knowledge complementarity, Heterogenous Learning Capability

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TABLE OF CONTENTS

LIST OF TABLES

1. Introduction

The importance of innovation is being emphasized as a method for firms to achieve and maintain sustainable competitive advantage (Cassiman et al., 2005). To survive in the rapidly changing environment, modern firms must constantly obtain new knowledge and achieve advanced technological innovation (Bollinger & Smith, 2001; Jin et al., 2017). However, accelerated global competition and technological changes show how difficult it is for firms to achieve innovation with just internal resources (Gunday et al., 2011; Jo et al., 2016). The strategic means for firms to obtain external knowledge include foreign direct investment, mergers and acquisitions (M&A), strategic alliance, and learning-by-hiring (Shan & Song, 1997; Song et al., 2003), and the share of M&A is gradually increasing in these knowledge sourcing activities (Valentini & Dawson, 2010).

M&A enables access to external sources of innovation and provides the ability to respond to rapid technological changes, which is why the number has increased rapidly and constantly over the last few years (de Man & Duysters, 2005; Ganzaroli et al., 2016). Corporate managers in R&D-intensive industries actively use M&A as a growth strategy and are expected to produce innovative results based on acquired technological knowledge and know-how (Cloodt et al., 2006; Kapoor & Lim, 2017). However, against the expectations, the failure rate of M&A in actual settings was high from 65% to 90% (Ganzaroli et al., 2016; Orsi et al., 2015).

To reduce the gap between theory and practice, previous studies have strived to investigate factors affecting post-M&A innovation performance. They focused on factors such as whether the purpose of M&A is the acquisition of technology (Ahuja & Katila, 2001), acquirers' characteristics (Prabhu et al., 2018; Desyllas & Hughes, 2010), targets' characteristics (Datta & Roumani, 2015), or differences in technological relatedness and technological knowledge bases among firms (Colombo & Rabbiosi, 2014; Miozzo et al., 2016; Sears & Hoetker, 2014) and analyzed how each factor affects post-M&A technological innovation performance. However, they have not examined in detail which field of innovation is affected by new knowledge obtained by firms through M&A.

Innovation is categorized into two types, exploitative and exploratory innovation, depending on whether it is incremental innovation that follows the existing technology trajectory or radical innovation that involves moving into a new technology trajectory (Benner & Tushman, 2003). This innovation performance is presumed to have a close relationship with technological relatedness between the acquirer and the target, but previous studies have not investigated this effect in detail. Moreover, few studies have been conducted on which characteristics of acquirers affect the improvement or deterioration of exploratory/exploitative innovation performance in the post-M&A or post-merger integration (PMI) process.

Therefore, based on the knowledge-based view, this study examines knowledge obtained according to the relatedness of technological knowledge bases between targets and acquirers in technological M&A and which innovation type of new knowledge it is transformed into. In particular, this study subdivided the relatedness of technological knowledge bases into technological similarity and complementarity among firms and investigated how the knowledge difference between these two types is connected to exploratory/exploitative innovation. The goal is to determine how technological M&A affects exploratory and exploitative innovation and verify whether M&A functions effectively as a strategy that mitigates the tradeoff between exploration and exploitation.

Furthermore, this study examines factors affecting follow-on innovation performance in PMI. Previous studies have focused on factors affecting the acquisition of new knowledge through M&A, but few have studied factors affecting knowledge assimilation, transformation, and exploitation processes (Jo et al., 2016). Technological relatedness only defines the potential benefits that can be gained by acquirers through the acquisition of external knowledge, when, in fact, the benefits depend on the capabilities of acquirers to support new knowledge production through absorptive capacity (Deng, 2010; Ganzaroli et al., 2016). Accordingly, this study focuses on learning capabilities as a factor affecting follow-on innovation performance in PMI in addition to the technological relatedness between two firms before M&A acquisition. Applying knowledge to innovation necessitates assimilation, transformation, and exploitation (Zahra & George, 2002), and learning capabilities contribute to post-M&A innovation performance by transforming certain resources into excellent innovation performance (Zollo and Singh, 2004; Prabhu, Chandy and Ellis, 2018; Cefis, Marsili and Rigamonti, 2020). Learning capabilities related to M&A are classified into "active learning (or learning by search)" as the result of internal R&D and "passive learning (or learning by doing)" as the result of M&A experience (Cefis et al., 2020). This study increases the understanding of the difference in performance between technological M&A transactions by examining how firms' heterogeneous learning capabilities affect follow-on innovation performance.

This study is expected to make the following contributions to research on technological M&A and innovation performance by providing a theoretically extended analysis. First, it empirically verifies the effectiveness of M&A by examining whether technological M&A serves as a strategy for firms to achieve both exploitative and exploratory innovation. Second, it specifies the direction of follow-on innovation led by the difference in technological knowledge bases of the target and the acquirer by subdividing the relatedness of technological knowledge bases between the two into similarity and complementarity for measurement. Third, this study contributes to a better understanding that can improve expected innovation performance in technological M&A transactions by revealing heterogeneous learning capabilities as a factor that improves the performance of exploratory and exploitative innovation in PMI. In addition to broadening the scope of understanding of the field of study, this study provides significant implications by presenting factors affecting technological M&A and suggesting practical plans to improve follow-on innovation performance to managers.

II Theoretical Background And Hypothesis

2.1. Technological M&A and Post M&A Innovation Performance

Most M&As were non-technological M&As that are not motivated for technological reasons such as M&As for horizontal integration that aim for increased market share and economy of scale, M&As for vertical integration to establish an integrated production system, or M&As for diversification to enter a new business (Berkovitch & Narayanan, 1993; Chakrabarti et al., 1994; Jo et al., 2016; Trautwein, 1990). Meanwhile, many M&As are recently executed for firms to obtain knowledge, know-how, and technologies to deal with rapidly changing technologies (Hagedoorn & Duysters, 2002; Rossi et al., 2013). Ahuja & Katila (2001) focused on this phenomenon and classified M&As into technological and non-technological acquisitions and studied how technological innovation performance varies among the types.

Technological M&A is an M&A driven by a motivation to acquire technology through which the acquirer can absorb the technological knowledge base of the target, increasing the possibility of economies of scale, scope, and recombination by expanding its knowledge base and producing innovative results (Ahuja & Katila, 2001; Fleming, 2001; Henderson & Cockburn, 1993). Here, innovation is defined as applying new ideas to a different aspect of products, processes, or corporate activities, which is the process of adopting new ideas and improving corporate performance (Rogers, 1998). Meanwhile, non-technological M&A does not have much effect on the acquirer's technological knowledge base. Further, the innovation performance due to the acquisition is also not significant (Ahuja & Katila, 2001). Technological M&As are mostly executed to acquire the target firm's technology in a high-tech industry that values R&D such as ICT, electronics and communications, and biotechnology (Hagedoorn & Duysters, 2002), and knowledge is a key resource that brings competitive advantage in high-tech industries, which is why research on this is important (Makri et al., 2010). Many researchers are emphasizing the relative lack of research despite the constant increase in technological M&A (Valentini, 2012; Rossi, Tarba and Raviv, 2013; Bena and Li, 2014; Lodh and Battaggion, 2015;).

Previous studies on the relationship between technological M&A and innovation performance have strived to find and investigate factors affecting post-M&A innovation performance (Jo et al., 2016). First, technological M&A itself affects follow-on innovation. Wagner (2011) argued that M&A brings efficiency to the invention process through economies of scale and scope and has a positive effect on applying for patents of R&D outcomes by increasing access to various channels. Additionally, from the knowledge-based view, acquirers can obtain external knowledge and combine new knowledge with old knowledge through technological M&A, thereby contributing to creating R&D innovation (Argote & Ingram, 2000; Valentini, 2012).

Meanwhile, many researchers regarded acquisition as a combination of knowledge bases between firms and confirmed that the characteristics of technological knowledge bases of the target and the acquirer, as well as technological relatedness between firms, are key factors that determine post-M&A innovation performance(Ahuja & Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006; Kapoor & Lim, 2007; Colombo & Rabbiosi, 2014; Sears & Hoetker, 2014; Orsi et al., 2015; Miozzo et al., 2016;). Studies focusing on the characteristics of each firm's knowledge base claimed that the size of the target's knowledge base (Datta & Roumani, 2015), the scope and depth of the acquirer's knowledge (Prabhu et al., 2018), and the size of the acquirer's knowledge base (Desyllas & Hughes, 2010) affect innovation performance. On the other hand, studies focusing on the relative difference in technological knowledge bases between the target and the acquirer analyzed how factors such as relatedness of acquired and acquiring knowledge bases and relative size of acquired knowledge base affect innovation performance(Ahuja & Katila, 2001). The relative size of the acquired knowledge base represents the size of technology and knowledge owned by the target compared to the acquirer. According to Ahuja et al. (2001), the bigger the relative size of the knowledge base to be integrated, the more difficult the acquirer's integration process becomes, and the impact on post-M&A innovation performance also turns out to be more negative. Meanwhile, higher relatedness of the acquired knowledge base does not simply lead to more positive innovation performance, but it rather decreases when the relatedness exceeds a certain point, showing an inverted-U relationship.

Accordingly, the characteristics of each firm's technological knowledge base and the technological relatedness between the target and the acquirer are the key factors affecting post-M&A technological innovation performance. Many studies aimed to investigate how the technological knowledge bases of both firms affect innovation performance.

2.2. Explorative Innovation and Exploitative Innovation

In general, exploration and exploitation are regarded as two forms of organizational learning competing over the organization's resources and interests (Belussi & Orsi, 2015; Levinthal & March, 1993). Exploration is related to "exploring new technologies to develop new products and services that meet the needs of new customers in a new market", while exploitation is about "improving existing technologies to improve product performance, quality, and efficiency to meet the needs of existing customers in the current market" (March, 1991). Based on this concept, previous studies have categorized innovation into two types. While exploratory innovation is the radical innovation that involves moving into a new technology trajectory beyond existing knowledge, exploitative innovation is incremental innovation that increases the efficiency of existing processes and structures by expanding based on existing knowledge and technology (Belussi & Orsi, 2015; Benner & Tushman, 2003; He & Wong, 2004; Jansen et al., 2006).

According to March (1991), when a firm conducts search activities to respond to the changing environment, it may fall behind due to learning myopia if it focuses on the existing course of success; therefore, to prevent this, a firm's search process must maintain a balance between exploitation and exploration. In other words, firms must seek both incremental and discontinuous innovation at the same time and must become "ambidextrous organizations" that can explore new fields while also exploiting existing fields to achieve sustainable growth (Tushman & O'Reilly, 1996)

Technological M&A is a strategy that can support both exploratory and exploitative innovation in terms of the dilemma of balancing the two (Belussi & Orsi, 2015). Firms can obtain external knowledge through technological M&A and achieve both exploration and exploitation depending on the trajectory of how they obtain new knowledge(Ahuja & Katila, 2001). If firms use new knowledge obtained by increasing resources and capabilities through M&A to improve existing technologies, competencies, products, and processes, they would be able to achieve exploitative innovation. Meanwhile, firms can promote exploratory innovation if they intend to develop new technologies and markets by overcoming the peripheral search scope and securing technological diversity through M&A.

Exploitative Innovation

Firms can achieve exploitative innovation through M&A so that they can improve existing technologies, competencies, products, and processes and expand the current market. Acquirers can share R&D costs and risks in collaboration with targets or obtain complementary know-how to avoid redundant efforts (Ahuja & Katila, 2001; Kogut & Zander, 1992; Lane & Lubatkin, 1998). They can also accelerate the R&D process in industries where the speed of technological development is important (Li & Yeh, 2017). Moreover, R&D also increases the depth of knowledge about the current technologies and markets and improves efficiency by promoting the experience curve effects in existing businesses and reducing production and transaction costs (Wang & Lam, 2019). Through exploitation, acquirers can achieve incremental innovation based on existing resources and knowledge.

Explorative Innovation

Meanwhile, the acquirer and the target can obtain technological diversity through post-M&A exploration and achieve innovative performance in a new field by combining complementary resources that had not been exploited in the past with a focus on finding new technology-based business opportunities (Capron et al., 1998; Graff et al., 2003). When the acquirer absorbs a greater amount of new knowledge, more technology combinations occur for the firm to diversify into new fields (Graebner et al., 2010; Karim & Mitchell, 2000; Sears & Hoetker, 2014). When more new external knowledge flows in, the firm can achieve radical innovation through open and flexible learning (Atuahene-Gima, 2005). By learning things that are far from conventional organizational activities such as developing new technologies, identifying the needs of potential customers, and developing new markets (Li & Yeh, 2017), firms can obtain new knowledge, processes, and routines, which have a positive effect on the knowledge creation process and thus improves the innovation performance of firms (Phene et al., 2010).

Considering the above, firms can make a significant contribution to exploratory and exploitative innovation through technological M&A, and this innovation performance may vary depending on the level of relatedness of technological knowledge bases between the acquirer and the target.

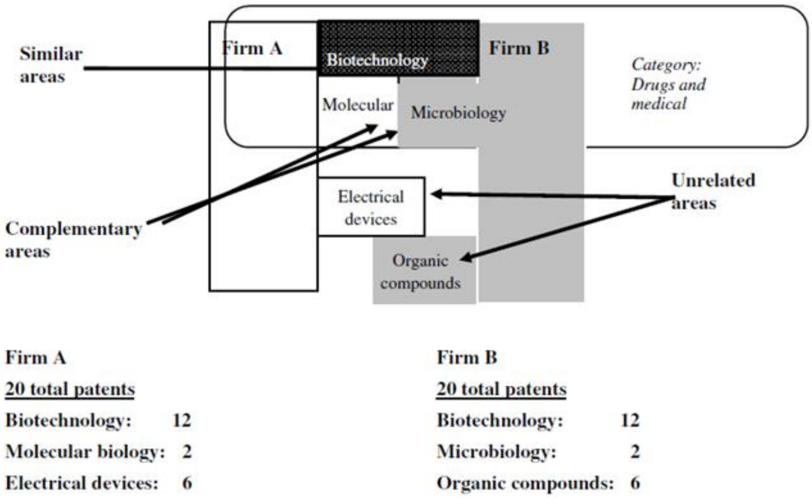
2.3. Technological Relatedness, Technological Similarity, Technological Complementarity

Previous studies focus on the relatedness of technological knowledge bases between the acquirer and the target as a key factor that affects post-M&A innovation performance. Cloodt et al. (2006) and Cassiman et al. (2005) argued that higher technological relatedness facilitates the integration of acquired knowledge bases, which reduces the lead time of innovation and enables large-scale collaborative projects, thereby showing the effect of economies of scale and scope in R&D (Cloodt et al., 2006; Gerpott, 1995; Hagedoorn & Duysters, 2010). Ahuja & Katila (2001) claimed that while the relatedness of the target's knowledge base has a positive effect on innovation outputs, extremely high relatedness that exceeds a certain level does not have much effect on the existing knowledge base since it is too similar to the acquired knowledge base, thereby reducing contribution to innovation outputs and showing an inverted-U relationship.

Meanwhile, Makri et al. (2010) pointed out that previous studies have limitations in that they merely analyzed knowledge relatedness as a single dimension. When the acquirer and the target have relatedness, it has been generally regarded that there is a similarity in knowledge. However, there is also relatedness when the two firm's knowledge is complementary. In other words, even though there could be two meanings connoted by relatedness, previous studies extensively defined knowledge relatedness, mixing the use of the two concepts or overlooking the aspect of complementarities altogether. Therefore, Makri et al. (2010) emphasized the need to analyze technological relatedness from multiple aspects by dividing it into technological similarity and technological complementarity and defining them as follows.

Technological similarity is "the degree of focus on the same narrowly defined knowledge area in solving technological problems" (Makri, Hitt and Lane, 2010). In other words, if two firms have the same patent class within the same industry section, they are considered to be using similar technological knowledge, which is represented as "similar areas" in Figure 1. Moreover, technological complementarity is "the degree of focus on the different narrowly defined knowledge areas within the broadly defined knowledge area they share in solving technological problems" (Makri, Hitt and Lane, 2010). In other words, two firms have complementarity when their patents belong to the same industry section but different patent classes and they are considered to have integrative potential, which is represented as "complementary areas" in Figure 1.

As such, technological similarity and technological complementarity are concepts clearly distinguished from technological relatedness, and each area can have different effects on post-M&A innovation performance. Therefore, this study subdivides the relatedness of technological knowledge bases into technological similarity and complementarity for analysis and examines how each characteristic affects post-M&A quantitative/exploratory/exploitative innovation performance.



[Figure 1] Technology relatedness aggregated across areas (Makri et al., 2010)

2.4. Technological Similarity and Post M&A Innovation Performance, The Relationship between Explorative Innovation and Exploitative Innovation

High similarity of technological knowledge bases between firms has a positive effect on the acquirer's absorptive capacity, enabling the acquirer to quickly obtain and assimilate into the target's knowledge and commercially exploit it (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998). This facilitates the transfer of explicit and tacit knowledge and enables high-quality knowledge transfer (Phene et al., 2010). Moreover, similar technological knowledge bases enable the two firms to share the same language and way of thinking, which increases learning (Lane & Lubatkin, 1998) and enables them to quickly grasp the value of each other's technology, resources, and capabilities, and exploit their strengths (Colombo & Rabbiosi, 2014). By successfully exchanging and obtaining information and know-how, there is a positive effect on knowledge integration between the two firms (Grant, 1996; Kogut & Zander, 1992). Furthermore, by repeatedly using technological and knowledge know-how in certain areas, firms can build expertise and reduce trial and error based on accumulated experience, thereby achieving follow-on innovation in an organized way (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998).

Meanwhile, if the similarity of technological knowledge bases between the acquirer and the target is too high, it causes path dependence in existing areas and limits the scope of innovation since it is difficult to perceive new information and stimulation from the outside (Makri et al., 2010). Since new knowledge is not obtained, the mutual learning effect among group members decreases (Sapienza et al., 2004; Shenkar & Li, 1999). In other words, higher technological similarity reduces incentives for various research opportunities and the scope of potential learning that the firm can gain from M&A, thereby limiting the benefits (Cassiman et al., 2005). On the other hand, there is also an issue when the similarity is too low. New, completely different knowledge hinders knowledge transfer within the organization, therefore acquirers face difficulties in absorbing the newly acquired knowledge (Mowery et al., 1998). This also decreases the level of knowledge integration between the acquirer and the target, requiring high costs in organizational transformation thereby causing a negative effect on innovation (Ganzaroli et al., 2016; Jo et al., 2016).

As such, technological similarity has an ambivalent effect on post-M&A technological innovation performance, and post-M&A innovation performance requires an adequate level of technological similarity. Accordingly, the following hypothesis can be set up.

Hypothesis 1. In technological M&As, there is a curvilinear (inverted u-shape) relationship between technological similarity and post-M&A quantitative innovation performance.

With higher similarity of technological knowledge bases between firms, a firm can integrate their R&D activities efforts in less time and with less effort, which increases their inventive productivity and enables them to create valuable and high-quality inventions in the firm's present technology fields after M&A (Colombo & Rabbiosi, 2014; Makri et al., 2010). In other words, the similarity of technological knowledge bases has a positive effect on exploitative innovation performance. Firms can prevent errors based on the target's cumulative know-how obtained through M&A and correct the wrong direction of innovation to increase efficiency by preventing unpredictable experimental failures (Ahuja & Katila, 2001; Lane & Lubatkin, 1998). Moreover, the target and the acquirer have similar cognitive bases and language in skills , which facilitates the recombination of existing technologies (Cohen & Levinthal, 1990; Makri et al., 2010).

However, when the similarity of technological knowledge bases is too high, it reduces the possibility of new recombination since it is difficult to encounter new knowledge necessary for innovation and there is a high redundancy of resources (Sears & Hoetker, 2014). There are also limitations in creating new technological knowledge since the same knowledge base is used, and the high similarity between the two firms causes assimilation of related knowledge, thereby having a negative effect on the acquirer's learning (Ahuja & Katila, 2001; Makri et al., 2010; Schildt et al., 2005). Furthermore, overlapping knowledge hinders the firm's progress in learning, bringing confusion to the organization, and thus does not contribute much to follow-on technological innovation performance (Ahuja & Katila, 2001; Cloodt et al., 2006; Makri et al., 2010; Sears & Hoetker, 2014). Meanwhile, when the similarity of the technological knowledge bases is too low, it is difficult to deliver knowledge since it hinders absorptive capacity as there is a difference in R&D methods or innovation routines (Kogut & Zander, 1992). It also becomes difficult to absorb and exploit new knowledge obtained through M&A (Cohen & Levinthal, 1990; Mowery et al., 1998). Therefore, technological similarity that is too high or low has a negative effect on exploitative innovation performance. Accordingly, the following hypothesis can be proposed.

Hypothesis 2. In technological M&As, there is a curvilinear (inverted u-shape) relationship between technological similarity and post-M&A exploitative innovation performance.

The similarity of technological knowledge bases improves the acquirer's absorptive capacity, while also generating a considerable amount of path dependence (Makri et al., 2010). Common technology, language, and cognitive structure promote the exchange and combination of existing knowledge, reducing the possibility to contribute to a radical invention that is fundamentally different (Fleming, 2001; Orsi et al., 2015), while also deteriorating the motivation to learn new knowledge and technology and increasing the structural inertia (Benner & Tushman, 2003; Hannan & Freeman, 1984; Nonaka et al., 1996). Higher technological similarity promotes the understanding of resources and knowledge available between the two firms and strengthens exploitative learning and innovation, whereas it is resource-intensive to discover and exploit knowledge that is far away, thereby reducing exploratory learning (Orsi et al., 2015).

In other words, knowledge similarity reduces the chance to create new and radical knowledge that is different from existing knowledge and involves less exploratory learning while emphasizing exploitative learning (Makri et al., 2010). Moreover, a higher similarity of technological knowledge bases leads to the assimilation of related knowledge between the two firms, which may have a negative effect on the acquirer's exploratory learning (Cohen & Levinthal, 1989; Schildt et al., 2005). Accordingly, the following hypothesis can be set up.

Hypothesis 3. Technological similarity has a more positive effect on the exploitative innovation performance ratio than exploratory innovation performance ratio.

2.5. Technological Complementarity and Post M&A Innovation Performance, The Relationship between Explorative Innovation and Exploitative Innovation

Complementarity is a concept distinguished from similarity and indicates that resources are independent and complementary although not the same (Tanriverdi & Venkatraman, 2005). Complementarity occurs when the combination of complementary resources generates greater benefits than the sum of individual resources and creates new values that were not possible with individual resources (Helfat & Peteraf, 2003; Milgrom & Roberts, 1995). Complementarity is a key factor in estimating M&A synergies, and firms can share and combine complementary resources and activities through M&A, thereby creating new values and achieving innovation (Harrison et al., 1991; Hitt & Jeffrey S, 2001; Shimizu et al., 2004).

The complementarity of technological knowledge bases between the target and the acquirer affects qualitative and new inventions of firms (Makri et al., 2010). Cohen & Levinthal (1990) argued that innovative performance is maximized when technological knowledge bases have enough similarity to promote learning while also providing heterogeneity to give new opportunities and incentives for exploration. According to Makri et al. (2010), complementary knowledge integration expands the scope of the invention search, enables new and unique knowledge combinations, and has complementarity while also having a broadly defined common knowledge area, which promotes an understanding of the value of unique and complementary knowledge of the other firm after M&A and facilitates communication and mediation. This improves the firm's ability to effectively use new information, thereby having a positive effect on improving the quality of post-M&A inventions as well as innovative inventions (Makri et al., 2010). In other words, if the target and the acquirer have complementary technologies, this facilitates the integration of technological knowledge bases, which increases inventive productivity (Cassiman et al., 2005). Sharing similar and complementary knowledge bases allows the acquirer to improve operations by eliminating redundant efforts and reducing R&D costs and risks, thereby generating economies of scale and scope in the R&D process (Cefis et al., 2020; Cloodt et al., 2006; Hagedoorn & Duysters, 2002; Makri et al., 2010). Currently, by increasing the depth of knowledge about technologies and markets (Wang & Lam, 2019), it is possible to increase the potential for integration between the target and the acquirer and achieve incremental innovation by improving the existing technologies, competencies, products, and processes (Quintana-García & Benavides-Velasco, 2008). In other words, higher complementarity leads the acquirer to create a synergy by increasing efficiency in the innovation process and increases R&D activities between the two firms after M&A, which results in excellent corporate performance (Harrison et al., 1991).

On the other hand, according to the definition of complementarity by Makri et al. (2010), low complementarity of technological knowledge bases between firms indicates that the two firms have too much non-overlapping knowledge since they belong to different industries or have too much overlapping knowledge within the same industry, thereby not creating a synergy. When there is too much non-overlapping knowledge, the acquirer feels a lack of absorptive capacity and needs more time and resources to absorb obtained knowledge (Lane & Lubatkin, 1998). The inflow of too much new knowledge causes an information overload, which rather hinders the learning process through knowledge delivery (Ahuja & Lampert, 2001; Phene et al., 2006) and delays knowledge creation and transmission, making it difficult to absorb and integrate information in post-merger integration (PMI) promptly (Hagedoorn & Duysters, 2002; Koput, 1997). Moreover, this is more complicated and difficult than the integration of technological knowledge bases with an adequate level of complementarity, thereby requiring considerable effort in research and communication between the target and the acquirer (Grant, 1996) and requiring high costs in knowledge transfers and increasing inefficiency (Ahuja & Katila, 2001; Sears & Hoetker, 2014). If there is a substantial difference in the fields of technology between firms, the research method and innovation routine will also vary substantially (Kogut & Zander, 1992). Therefore, excessive non-overlapping knowledge may hinder the existing innovation activities and make the invention process complicated, thus having a negative effect on post-M&A innovation performance (Capron et al., 1998; Chakrabarti et al., 1994; Cloodt et al., 2006).

On the other hand, when there is more overlapping knowledge within the same industry, the acquirer will be unable to receive new knowledge necessary for innovation, which hinders the mutual learning effect among group members (Sapienza et al., 2004; Shenkar & Li, 1999). Moreover, technological innovation may also be hindered due to insufficient basic foundations to absorb various stimulations and information from the external environment (Ahuja & Katila, 2001; Jo et al., 2016). In other words, low complementarity of the acquirer and the target may have a negative effect on follow-on innovation performance. In sum, the following hypothesis can be set up.

Hypothesis 4. In technological M&As, there is a curvilinear (inverted u-shape) relationship between technological complementarity and post-M&A quantitative innovation performance.

M&A of two firms with complementary technologies increases the possibility of post-M&A technology recombination that contributes to product diversification (Rothaermel et al., 2006). Recombination of non-overlapping knowledge produces more valued inventions (Yayavaram & Chen, 2015). Moreover, it expands the scope of the search, enables new and unique knowledge combinations, and helps understand and effectively communicate the value of complementary knowledge, thereby having a positive effect on innovation performance (Makri et al., 2010). In other words, high complementarity of technological knowledge bases between firms has a positive effect on exploratory innovation performance by providing various combinations of possibilities while also sharing the same elements that promote learning and interaction.

Meanwhile, low complementarity of technological knowledge bases between firms indicates that the two firms have too much non-overlapping knowledge since they belong to different industries or have too much overlapping knowledge within the same industry, thereby not creating a synergy (Makri et al., 2010). New, completely different knowledge from existing industries hinders knowledge transfer within the organization; even if it is new knowledge with high value, organizations face problems in absorbing the newly acquired knowledge (Mowery et al., 1998). Excessive new knowledge may hinder the existing innovation activities and complicate the knowledge creation process, and this would have a negative effect on the follow-on innovation performance of the firm (Capron et al., 1998; Chakrabarti et al., 1994; Cloodt et al., 2006), while also generating costs and delays so that it is difficult to concentrate on developing specific technologies, thereby causing an adverse effect on innovation (Koput, 1997). On the other hand, when there is more overlapping knowledge within the same industry, there is little benefit to gain from combining knowledge bases, which hinders the mutual learning effect among group members and thus does not contribute much to innovation (Ahuja & Katila, 2001; Sapienza et al., 2004; Shenkar & Li, 1999). In sum, the following hypothesis can be put forward.

Hypothesis 5. In technological M&As, there is a curvilinear (inverted u-shape) relationship between technological complementarity and post-M&A exploratory innovation performance.

Technological complementarity can create synergies through the following mechanism and contribute to post-M&A innovation performance. Connection of knowledge that is not similar and has technological distance fulfills both aspects of the motivation to learn and the ability to learn, which helps recombine existing technologies with different external technologies and exploit new knowledge, thereby increasing the possibility to create original technologies (Fleming, 2001; Song & Shin, 2008). These new connections will increase potentially available innovation combinations and contribute to product diversification (Rothaermel et al., 2006). The newly acquired knowledge, processes, and routines will generate more recombination that can be diversified into new areas of technology (Ahuja & Lampert, 2001; Graebner et al., 2010; Karim & Mitchell, 2000; Larsson & Finkelstein, 1999). Furthermore, as the amount of non-overlapping complementary knowledge increases, the possibility of entering a new area of technology also increases (Phene et al., 2010), and firms can find new solutions and achieve radical innovation by learning different inference methods and causal relations through an open and flexible exploration process (Orsi et al., 2015). As such, the M&A of two firms with complementary technologies is likely to produce a creative synergy and can contribute to exploratory innovation. Accordingly, the following hypothesis can be set up.

Hypothesis 6. Technological complementarity has a more positive effect on the exploratory innovation performance ratio than the exploitative innovation performance ratio.

2.6. Heterogeneous Learning Capabilities and Post M&A Innovation Performance in Technological M&A

Many previous studies have focused on the relatedness of technological knowledge bases in examining their effect on post-M&A innovation performance (Ahuja & Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006; Kapoor & Lim, 2007; Colombo & Rabbiosi, 2014; Sears & Hoetker, 2014; Orsi et al., 2015; Miozzo et al., 2016;). However, these studies have limitations since they only consider the static element of "relatedness of technological knowledge bases" between the target and the acquirer with a focus on the context of technology acquisition. When M&A is actually implemented and the post-acquisition integration (PMI) proceeds, there is a dynamic process in which the target and the acquirer interact with each other. There are several case of failure even if M&A is executed with the expectation of acquiring new knowledge and synergy by choosing a suitable firm, which is because firms face difficulties in PMI—the post-M&A implementation and management stage (Deutsch et al, 2010; Song and Kim, 2010;). Firms can obtain new external knowledge from the target but may face difficulties in successfully converting and exploiting that knowledge (Jo et al., 2016). In other words, technological relatedness only defines the potential benefits that the acquirer may obtain from external knowledge acquisition, while the actual benefits depend on the acquirer's ability to support the production of new knowledge through absorptive capacity (Deng, 2010; Ganzaroli et al., 2016).

The acquisition includes the process of "active learning (learning by search)" and "passive learning by direct experience" that occurs in accumulating new knowledge from various internal and external sources (Levitt & March, 2003; Zollo & Winter, 2002). To apply knowledge to innovation, there must be a process of acquisition, assimilation, transformation, and exploitation (Zahra & George, 2002). Learning capability is the key factor affecting this process, defined as “the capability of an organization to process knowledge—in other words, to create, acquire, transfer, and integrate knowledge, and to modify its behavior to reflect the new cognitive situation, with a view to improving its performance” (Jerez-Gómez et al., 2005). Firms with more learning capabilities can benefit more from certain resources and transform them into excellent innovation performance, thereby improving post-M&A innovation performance (Zollo and Singh, 2004; Prabhu, Chandy and Ellis, 2018; Cefis, Marsili and Rigamonti, 2020).

Learning capabilities are affected by the level of internal investment in R&D (Winter & Nelson, 1982) as well as the level of expertise accumulated by the repeated M&A experience (Levitt & March, 2003). Accordingly, Cefis et al. (2020) explained M&A-related learning capabilities in two types: “active learning (or learning by search)” as in-house R&D outcomes and “passive learning (or learning by doing)” as M&A experience outcomes. Since these two types of learning capabilities refer to different areas, they are combined and referred to as heterogeneous learning capabilities.

In sum, the acquirer’s learning capabilities affect post-M&A innovation performance by transforming certain resources into excellent innovation performance (Zollo and Singh, 2004; Prabhu, Chandy and Ellis, 2018; Cefis, Marsili and Rigamonti, 2020). In this context, even for M&As with the same level of relatedness of technological knowledge bases, higher learning capabilities of the acquirer lead to more technology transfers and integrations as well as higher post-M&A innovation performance.

Active learning capabilities through R&D investment

Active learning capabilities through in-house R&D investment serve as a key factor that affects post-M&A innovation performance (Cefis et al., 2020). Firms that invest more in R&D can provide and exploit knowledge bases that are necessary for active learning and can encounter all kinds of knowledge and diverse areas of expertise both internally and externally, thereby creating opportunities for organizational innovation (Cefis et al., 2020; Levitt & March, 2003; Winter & Nelson, 1982).

A firm's R&D investment improves its absorptive capacity to perceive external knowledge values and effectively assimilate and apply them, through which the firm can develop existing knowledge and obtain problem-solving skills, thereby increasing profits in the internal/external knowledge exploration process as well as the possibility of integration (Cassiman & Veugelers, 2006; Cohen & Levinthal, 1989). Firms enthusiastic about R&D promote the efficiency of inventions by repeatedly learning through experiments as well as trial and error (Ng, 2007). They can improve innovation performance as they have a developed capacity to discover new resources, combine complementary resources, and create synergy (Cassiman & Veugelers, 2006). Moreover, by also efficiently dispersing R&D costs in various extensive areas through the accumulated technologies, knowledge, know-how, and experience, the benefits of internal/external knowledge exploration and development of new technologies are increased, positively affecting innovation (Cassiman & Veugelers, 2006; Cefis et al., 2020).

In this context, the acquirer's follow-on innovation performance may be affected by active learning capabilities through the acquirer's R&D investment, and firms with more R&D investments are expected to have a positive effect on follow-on innovation performance. Accordingly, the following hypothesis can be proposed.

Hypothesis 7. R&D investment has a positive effect on both exploratory and exploitative innovation performance.

Passive learning capabilities through M&A experience

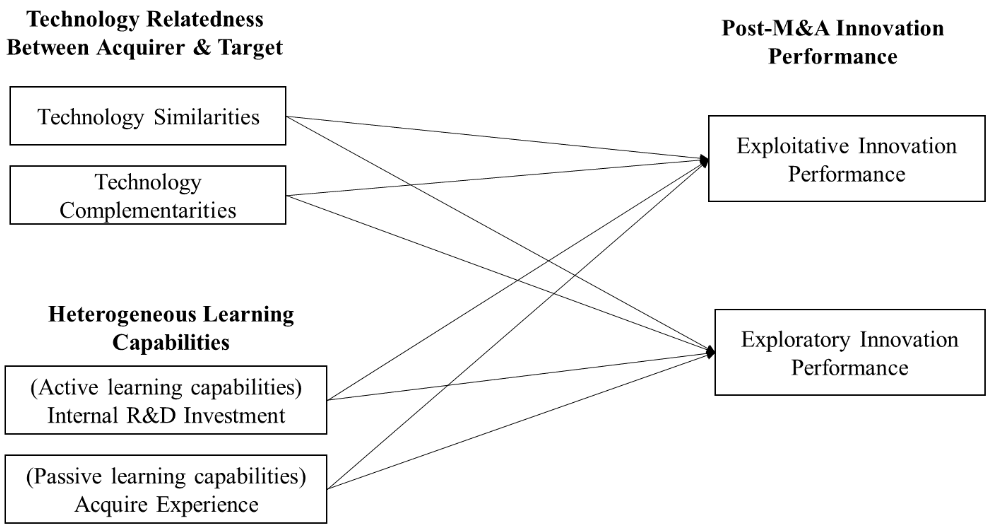
Post-M&A innovation performance is also affected by passive learning capabilities through M&A experience (Cefis et al., 2020). Firms with more M&A experience tend to have a positive attitude toward integration as well as a greater ability to evaluate and select external resources and transform them into innovation (Orsi et al., 2015). The more M&A experience the acquirer has, the more knowledge it can obtain to improve M&A performance and through M&A experience, firms develop the learning mechanism to effectively capture, absorb, and integrate knowledge, thereby contributing positively to innovation (Harrison et al., 2001; Hayward, 2002; Jo et al., 2016; Laamanen & Keil, 2008; Trichterborn et al., 2016).

Firms undergo the incremental learning pathway and at the beginning of the learning curve, experience promotes learning in areas with high relatedness. As time passes and continuous M&A experiences are accumulated, firms build big and diverse pools of experiences that enable effective learning even in areas with low relatedness (Barkema & Schijven, 2008; Cefis et al., 2020; Haleblian & Finkelstein, 1999). By learning through M&A, firms improve problem-solving skills in various fields and learn how to effectively use resources and perform tasks in repeated experiences (Cefis et al., 2020; Ng, 2007).

Furthermore, firms with more M&A experience tend to better resolve conflicts and effectively manage the organization in the merger of the two firms, and the acquisition of know-how obtained from M&A experience facilities interactions between the two organizations and promotes knowledge transfer and integration (Jo et al., 2016; Prahalad & Bettis, 1986). Moreover, firms with much experience in absorbing and managing external knowledge tend to have insight into adequate levels of collaboration and integration, thereby improving innovation performance afterward (Belussi & Orsi, 2015).

In sum, post-M&A innovation performance may be affected by passive learning capabilities through the acquirer's M&A experience, and more M&A experience will positively affect follow-on innovation performance. Accordingly, the following hypothesis can be stated.

Hypothesis 8. The acquirer's M&A experience has a positive effect on both exploratory and exploitative innovation performance.



[Figure 2] Research Model

III. Methodology

3.1. Data and sample

This study examines M&A in the semiconductor, biotechnology, and ICT industries to analyze technological M&A. These industries are knowledge-intensive industries where R&D is key, which is why they involve active M&A to secure new advanced technologies and strategic knowledge bases (Hagedoorn & Duysters, 2002). Moreover, patent activities are valued to protect the acquired technologies, and thus the firm's technological level and innovation performance can be evaluated more accurately (Puranam & Srikanth, 2007).

For empirical analysis, this study collected M&A transaction details in the semiconductor, biopharmaceutical, and ICT industries executed in various countries such as the United States (U.S.), Japan, Germany, and South Korea from 1980 to 2021. Subjects were limited to the case in which acquirers were American firms because the U.S. is the world's biggest market for technology, and firms worldwide apply for U.S. patents to protect their technologies (Albert et al., 1991; Jo et al., 2016), which facilitates the measurement of innovation performance based on patents (Ahuja, 2000; Hall et al., 2001; Mayes et al., 1990; Rothaermel & Hess, 2007; Sørensen & Stuart, 2000). M&A data was collected from the SDC Platinum M&A database of Thomson Reuters and the following criteria are applied for sample collection to select reliable data.

First, since the transactions selected must not share technology between the two firms in the past to measure innovation performance through M&A, this study excluded acquirers that had held even a few shares of the targets before M&A. Thus, the transactions selected were ones with 100% acquisition of the target's shares through M&A, that have at least $1 million in M&A transaction value, and where the acquisition is ultimately completed.

Second, to limit the subjects only to firms where objective data can be tracked during the sampling period, this study considered only public listed firms with open transactions as the subjects of analysis.

Third, it considered only the cases that specified the goal of technological M&A which is securing technology or creating a synergy. Firms execute M&A for various purposes such as business diversification or market share increase, and non-technological M&A does not have a significant effect on post-M&A innovation performance (Ahuja & Katila, 2001). Therefore, this study considered only transactions where the purpose of the acquisition is indicated as technological M&A.

Fourth, this study selected only transactions in which the target or the acquirer is not reacquired by another firm during the sampling period and the acquirer does not execute technological M&A at least twice during the sampling period. These cases are excluded because other M&A transactions may affect follow-on innovation performance. As a result, 106 cases in the semiconductor industry, 247 cases in the biotechnology industry, and 268 cases in the ICT industry were revealed.

Next, to identify M&A transactions where technological relatedness and innovation performance can be measured, this study examined whether the target and the acquirer have U.S. patents. Patent data was collected from the United States Patent and Trademark Office (USPTO) and the cases in which the target and the acquirer have never applied for a patent to the USPTO were excluded from the samples. After selecting firms where both the target and the acquirer have patents applied for at the USPTO as the samples, this study considered only M&A transactions in which both the target and the acquirer have applied for at least one patent at the USTPO three years before and after M&A. The target and the acquirer had not applied for patents three years before and after M&A in many transactions, and thus the sample size decreased due to the absence of patents. Therefore, the final samples were 38 cases of transactions in the semiconductor industry, 52 in the biotechnology industry, and 21 in the ICT industry.

The financial data of firms from 1980 to 2021 were collected from Wharton Research Data Services (WRDS) with the Compustat database provided by Standard and Poor's, and the data collected was on the R&D investments of acquirers as well as the increase and decrease of annual R&D costs. The final datasets used in the empirical analysis included 111 cases of technology M&A transactions executed from 1980 to 2021.

3.2. Measure

3.2.1. Dependent Variables

Post-M&A Innovation Performance

To analyze how technological M&A affects post-M&A innovation performance, this study measured the patent activities of firms before and after M&A. Patents are a key indicator used to measure the innovation performance of firms and many studies prove that "innovation performance is directly related to the number of patents a firm has" (Ahuja, 2000; Hall et al., 2001; Rothaermel & Hess, 2007; Sørensen & Stuart, 2000).

Furthermore, to analyze how M&A affects a firm's innovation activities, it is important to set the period of analysis before and after M&A. The fastest a firm can apply for a patent with the technology acquired from M&A is one year on average after the transaction is complete (Ganzaroli et al., 2016; Makri et al., 2010). Moreover, technological knowledge depreciates significantly over time, and patent technology in high-tech sectors loses the majority of its value within five years (Griliches, 1979; Ahuja & Katila, 2001; van de Vrande et al., 2009). Since it is difficult to detect the effect of the target's knowledge five years after M&A, previous studies mostly measured innovation performance based on patents the acquirer applied for 1–3 years after M&A (Jo et al., 2016; Makri et al., 2010). Meanwhile, a patent application for 1–3 years after M&A may include studies conducted before M&A considering the R&D time for the patent, which is why it is necessary to extend the period of analysis. Therefore, considering that the effectiveness of advanced technology is five years, this study set the time frame for the dependent variables at 1–4 years after M&A and measured innovation performance based on the number of patents applied for at the USPTO.

Exploratory / Explorative Innovation Performance

New patents after M&A were used to measure exploratory and exploitative innovation performance based on patents possessed by acquirers before M&A. Exploratory innovation performance was measured by the number of new patents applied for after M&A from the patent class that had not been applied for before M&A and exploitative innovation performance was measured by the number of new patents applied for after M&A from the same patent class as before M&A (Ganzaroli et al., 2016; Gilsing et al., 2008; Nooteboom et al., 2007). To exclude the deviation in the number of patents per sample firm in analysis, the exploratory innovation performance ratio was estimated by dividing total innovation performance by exploratory innovation performance. The exploitative performance ratio was also obtained using the same method. This helped analyze how much post-M&A exploratory and exploitative innovation performance was achieved by acquirers.

3.2.2. Independent Variables

Technological Similarities

This study measured technological similarity and technological complementarity based on Makri et al. (2010) and the patent category and class were based on the International Patent Classification (IPC) with a hierarchical structure. Technological similarity represents "the extent to which two firms received patents from the same patent class" (Makri et al., 2010). This study observed and measured the number of patents submitted by the target and the acquirer to the same four-digit subclass 1–3 years before M&A (Orsi et al., 2015). The technological similarity is calculated by multiplying the ratio of the same patent class among total patents of the acquirer and the target by the ratio of the same patent class within the acquirer among all patents of the acquirer, and it is calculated as follows (Makri et al., 2010).

$$\begin{aligned} &Technological\ Similarity \\ &= \frac{Overlap\ all\ patent\ subclasses}{Total\ patents\ Acquirer\ \&\ Target} \\ &\times \frac{Total\ acquirer\ patents\ in\ common\ subclasses}{Total\ acquirer\ patents} \end{aligned}$$

Technological Complementarities

Technological complementarity is when the patents of the two firms belong to the same industry section but have different patent classes. It is measured by observing the number of patents applied for in other subclasses within the same industry section 1–3 years before M&A and it is calculated as follows (Makri et al., 2010).

$$
\begin{aligned}
&\mathit{Technological\ Complementarities} \\
&\quad = \frac{\mathit{Overlap\ all\ patent\ sections}}{\mathit{Total\ patents\ A\&T}} \\
&\quad - \frac{\mathit{Overlap\ all\ patent\ subclasses}}{\mathit{Total\ patents\ A\&T}} \\
&\quad \times \frac{\mathit{Total\ acquirer\ patents\ in\ common\ section}}{\mathit{Total\ acquirer\ patents}}
\end{aligned}
$$

Internal R&D Investments

High R&D investments of acquirers have a positive effect on the quantity and quality of post-M&A patents (Makri et al., 2010). Acquirers' R&D investments are represented by internal R&D expenditures, which are the sum of all costs related to R&D activities spent by the firm, including market research for new technologies and market entry, hardware and software purchasing costs, and R&D personnel training (Cefis et al., 2020). R&D investments are measured by the average of R&D costs for 3 years before M&A.

Acquisition Experiences

Acquirers with more M&A experiences can achieve PMI (Post-Merger Integration) more successfully due to the learning effect and have positive effects on follow-on performance (Ernst & Vitt, 2000). Acquirers' M&A experiences were measured by the number of total M&A transactions completed by acquirers from the founding date to the date of M&A transactions (Diestre & Rajagopalan, 2012).

3.2.3. Control Variables

Post-M&A innovation performance of firms may be affected by several variables. This study used the following control variables to control the alternative explanation. The relative size of the knowledge bases of the acquirer and the target may affect post-M&A innovation performance (Ahuja & Katila, 2001) and thus was selected as a control variable in this study. The relative size of the knowledge bases represents the size of technology and knowledge bases owned by the target compared to the acquirer. Here, relatively bigger knowledge bases make integration difficult for the acquirer, resulting in a negative effect on post-M&A innovation performance (Ahuja & Katila, 2001; Hagedoorn & Duysters, 2002). Therefore, to control this effect, the relative size of knowledge bases was calculated as follows and included in the empirical model. The size of the target's knowledge base was divided by the size of the acquirer's knowledge base, and the log of this number was taken (Ahuja & Katila, 2001). The variable representing the relative size must be smaller than one, and thus if the target's size was bigger, the acquirer's size was divided by the target's instead (Cloodt et al., 2006).

The size of the acquirer's knowledge base before M&A also serves as a factor affecting post-M&A innovation performance and, thus, was used as a control variable. The bigger size of the acquirer's knowledge base increases the firm's capacity to absorb and exploit new knowledge assets, which affects innovation performance (Cloodt et al., 2006; Cohen & Levinthal, 1990; Nooteboom et al., 2007). The size of the acquirer's knowledge base before M&A was calculated by the number of patents possessed before M&A, through which the effect of the number of patents before M&A on post-M&A innovation performance was controlled.

Industry relatedness is a key factor for M&A that represents the extent to which the target and the acquirer are engaging in the related market (Ahuja & Katila, 2001; Boschma & Elwanger, 2012). This shows how related the resources associated with the target's industrial activities are to the acquirer's industry. In the industry where the acquirer and the target are involved, it is possible to achieve the economy of scale by integrating knowledge, combining operating methods, reducing overlapping parts, and increasing efficiency (Ahuja & Katila, 2001; Elena Cefis & Damiana Rigamonti, 2013; Laurence Capron, 1999; Nesta & Saviotti, 2005). Moreover, higher industry relatedness enables the acquirer to more easily understand the target's technology, which helps the acquirer absolve the target's capabilities and results in better PMI performance (Cohen & Levinthal, 1990; Duysters & Hagedoorn, 2000; Elena Cefis & Damiana Rigamonti, 2013; Mowery et al., 1998). On the other hand, lower industry relatedness makes it more difficult to create a post-M&A synergy and requires more effort in integration, which results in lower benefits compared to high costs (Elena Cefis & Damiana Rigamonti, 2013). In M&A, industry relatedness and post-M&A innovation performance have an inverted-U relationship (Cefis et al., 2015). To control this effect, the industry relatedness was measured as follows and included in the empirical model. Accordingly, the relatedness between the target and the acquirer is coded by giving the values 0, 0.25, 0.333, 0.5, or 1 depending on the first-digit number that matches the Standard Industrial Classification (SIC) codes (Schildt et al., 2005)

Meanwhile, the tendency in patents is determined partially by the firm's nationality and industry (Nooteboom et al., 2007). Even if the target and the acquirer have different nationalities, there may be an effect on post-M&A innovation performance, which is why heterogeneity between nations was used as a control variable. National heterogeneity was coded as 1 if the target is the same U.S. firm and 0 if it is another country's firm, using dummy variables since it is a categorical variable. The samples of this study include three industries such as semiconductor, biotechnology, and ICT. To control industrial differences within the samples, biotechnology is used as the reference group, and semiconductor and biotechnology were converted to dummy variables.

Finally, the unknown impact of the annual period may lead to different macro-economic conditions that affect innovation in each period (Nooteboom et al., 2007). For example, in the biotechnology industry, R&D costs increased around 2000 while clinical trial success rates decreased, resulting in a rapid decline in R&D productivity (Jo et al., 2016). As such, the industrial paradigm changes depending on the period, which serves as a factor affecting post-M&A innovation performance. Therefore, the period dummy variable was added to control the effect of certain periods on the firm's decision-making. With 1991~2000 as the reference period, M&A transactions in 2001~2010 and in 2011~2020 were coded.

3. 4. Empirical Method

This study conducted different regression modeling based on the characteristics of the dependent variables in each hypothesis. When the dependent variables represent the number of patents after M&A (hypotheses 1, 2, 4, 5, 7 and 8), the negative binomial regression model was used; when they represent the ratio of post-M&A innovation performance (hypotheses 3, and 6), the Tobit regression model was applied for empirical analysis.

First, if count variables such as the number of times a certain event has occurred are used as dependent variables, they do not have negative values and, thus, it is difficult to apply the general OLS regression model. Traditional statistical methodologies to analyze count variables include the Poisson regression model and the negative binomial regression model (Hausman et al., 1984; Henderson & Cockburn, 1993). The Poisson regression model is used when count variables that are presumed to follow the Poisson distribution are used as dependent variables, while the negative binomial regression model is used when there is overdispersion due to unequal mean and variance of variables in applying the Poisson regression model (Rothaermel & Boeker, 2008). Table 1 shows that the mean and variance of the dependent variables are different, and accordingly, this study selected the negative binomial regression model instead of the Poisson regression model. Negative binomial regression is a combination of the Poisson distribution and gamma distribution, expressed as follows (P. McCullagh & J.A. Nelder, 1983).

$$P = (Y_i = y_i;\ X_1, X_2, \cdots, X_k) = \frac{\gamma(y_i + \alpha^{-1})}{\gamma(\alpha^{-1})\gamma(y_i + 1)}(1 + \alpha\mu_i)^{-\alpha^{-1}}(1 + \alpha^{-1}\mu^{-1})^{-y_i}$$

$$= \frac{\gamma(y_i + \alpha^{-1})}{\gamma(\alpha^{-1})\gamma(y_i + 1)}\left(\frac{1}{1 + \alpha\mu_i}\right)^{-\alpha^{-1}}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}$$

$(= 0,1,2,\cdots)$

μ_i represents expectation, and α is the parameter that represents overdispersion measured from data. Based on the concept of negative binomial regression, this study applied the following equation.

$$E[Y_i] = \lambda_i = \exp(y_i = \mu + \beta x_i + \alpha_i + \varepsilon_i)$$

$\exp(\varepsilon_i) \sim \Gamma[1, \alpha]$ assumes the γ distribution, and the value of mediating variable λ may vary depending on the value of i (Ganzaroli et al., 2016).

Meanwhile, if dependent variables have a percentage between 0 and 100, they do not follow the normal distribution. Thus, applying the Ordinary Least Squares regression

(OLS) may create a bias in the results by underestimating the effect of the independent variables (Greene, 2000). The Tobit model that considered the structure of the limited dependent variables can be used to solve this problem (Maddala, 1991; McDonald & Moffitt, 1980). The Tobit regression model is used when censored variables with the upper and lower limit values are used as dependent variables, and it is also referred to as the censored regression model that estimates the dependent variables within the given range. This is set as follows in this study.

$$y_i * = \beta x_i + u_i, \qquad u_i \sim N(0, \sigma^2)$$

$$y_i = \begin{cases} y_i * & if\ y_i * > 0 \\ 0 & if\ y_i * \leq 0 \end{cases}$$

Here, x_i is the explanatory variable, β is the parameter vector that must be estimated representing the linear relationship between x_i and y_i, and u_i is the error term in the form of normal distribution. y_i* is the latent variable and the observed variable y_i in this study represents the exploitative or exploratory innovation performance ratio, defined as 0 when it is 0 or negative, and as its proper value when positive. In this study, x_1 indicates R&D investment, x_2 indicates M&A experience, and x_k is applied as a control variable. The maximum likelihood method is used to estimate the coefficients considering the latent values lower than 0 and 1 or higher that are not observed in estimating parameters (Tobin, 1958).

Based on the two statistical models above, this study came up with results to use in the empirical analysis.

Table 1. Descriptive statistics and correlation matrix

Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Technological similarity	0.45	0.37	0.00	1.00	1																
Technological complementarity	0.27	0.26	0.00	1.00	-.69**	1															
R&D Investment	64.65	81.58	0.01	391.00	-0.09	-0.03	1														
M&A experience	5.75	7.97	0.00	36.00	-.23*	.21*	0.18	1													
Post M&A Innovation Performance (1~4year)	59.23	76.88	1.00	382.00	-0.03	0.10	.44**	.41**	1												
Exploitative Innovation Performance (1~4year)	53.60	71.67	0.00	316.00	-0.01	0.10	.44**	.42**	.99**	1											
Explorative Innovation Performance (1~4year)	13.60	19.38	0.00	101.00	-0.14	0.10	.32**	.43**	.78**	.73**	1										
Exploitative Innovation Performance ratio (1~4year)	83.80	25.34	0.00	100.00	.45**	-0.18	0.16	-0.01	.21*	.26*	-0.03	1									
Explorative Innovation Performance	32.02	28.30	0.00	100.00	-.41**	.22*	-0.17	-0.04	-.25*	-.29**	0.10	-.67**	1								

ratio (1~4year)																					
Relative patent portfolio size	1.27	1.55	-2.85	5.05	-.28**	.30**	.29**	.19*	.26*	.29**	0.10	.24*	-.23*	1							
No. of patents pre-M&A	3.07	1.42	0.00	6.18	0.07	0.07	.50**	.32**	.58**	.61**	.31**	.52**	-.55**	.65**	1						
Industry (Semiconductor)	0.19	0.39	0.00	1.00	0.01	0.02	0.01	0.08	.25*	.23*	.21*	-0.08	-0.02	0.10	.19*	1					
Industry (IT)	0.34	0.48	0.00	1.00	-0.16	0.09	0.04	.19*	0.01	0.01	-0.01	-0.03	-0.10	.20*	.19*	-.35**	1				
Period (2001~2010)	0.48	0.50	0.00	1.00	-0.01	0.07	-0.13	-.28**	-0.09	-0.10	-0.16	-0.20	0.04	-0.12	-.29*	-0.02	-0.15	1			
Period (2011~2020)	0.46	0.50	0.00	1.00	0.03	-0.08	0.17	.32**	0.12	0.13	0.18	.23*	-0.11	0.11	.32**	0.05	0.15	-.89**	1		
Industry Relatedness	0.58	0.39	0.00	1.00	.23*	-0.11	-0.03	0.09	0.04	0.05	-0.02	.37**	-.21*	0.05	0.14	-.24*	0.17	-0.19	.197*	1	
Nation (nonUS=1)	0.68	0.47	0.00	1.00	-0.02	-0.02	0.15	0.06	.21*	.22*	0.08	-0.09	-0.13	0.05	0.11	.21*	-0.03	0.06	0.04	-.27**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

IV. Results

Table 1 analyzes the descriptive statistics of variables included in the model and the correlation among variables. The bivariate correlation between the independent variables and control variables was below the threshold of 0.7, which represents the effectiveness of acceptable discrimination and has been widely considered to indicate the validity of acceptable discrimination in research (Cohen et al., 2003; Ganzaroli et al., 2016). A lower correlation among variables indicates less possibility that the model has multicollinearity. As a result of diagnosing multicollinearity among variables through the variance inflation factor (VIF) test, the VIF of variables in Table 2 shows that all variables except the period dummy were lower than the threshold 10. VIF higher than 10 or allowable error higher than 1 or lower than 0.1 indicates that the multicollinearity is high (Myers, 1990). In this variable, independent and dependent variables were all lower than 10, which eliminates the possibility of multicollinearity. The period dummy that is the only variable with a value greater than 10 is used only as a control variable in this study, and is a categorical dummy that categorizes the period and has no collinear relationship with independent and dependent variables of the model. Thus, it does not affect the regression variables of the model and does not damage the control power of the control variables. Therefore, multicollinearity was not a problem in this study and the statistical analysis of the model was conducted as follows.

Table 2. Results of the VIF test.

Variable	VIF	1/VIF
Technological similarity	2.85	0.35
Technological complementarity	2.55	0.39

R&D Investment	1.61	0.62
M&A experience	1.30	0.77
Relative patent portfolio size	2.40	0.42
No. of patents pre-M&A	3.47	0.29
Industry (Semiconductor)	1.38	0.73
Industry (IT)	1.38	0.73
Period dummy (2001~2010)	10.36	0.10
Period dummy (2011~2020)	10.75	0.09
Industry Relatedness	1.37	0.73
Nation (nonUS=1)	1.21	0.83
Mean VIF	3.39	

Table 3.1, 3.2, and 3.3 show the results of negative binomial regression on the number of patents after M&A to analyze post-M&A quantitative, exploitative, and exploratory innovation performance. Table 3.1 presents the results of negative binomial regression predicting the determinants of post-M&A quantitative innovation performance. In the same method, Table 3.2 presents the results of analyzing the determinants of exploitative innovation performance and Table 3.3 presents the results of analyzing the determinants of exploratory performance. In each table, Model 1 shows the effect of control variables on post-M&A quantitative, exploitative, and exploratory performance. Model 2 shows the effect of technological similarity, which is an independent variable, as well as of control variables on post-M&A exploitative and exploratory innovation performance. Lastly, Model 3 shows the effect of technological complementarity, which is an independent variable, as well as of control

variables on post-M&A exploitative and exploratory innovation performance.

Table 3.1. Negative binomial regression results for analyzing the determinants of Post-M&A quantitative innovation performance (111 obs.)

Variables	Model 1 Control Variables Post M&A Innovative performance (1~4year)	Model 2 Technological similarity Post M&A Innovative performance (1~4year)	Model 3 Technological complementarity Post M&A Innovative performance (1~4year)
Intercept	3.47***(0.72)	3.08***(0.62)	2.93***(0.62)
Technological similarity		2.18 † (1.31)	2.24(1.48)
Technological similarity^2		-2.26(1.38)	-2.47(1.80)
Technological complementarity			
Technological complementarity^2			
Industry dummy (Semiconductor)	0.16(0.27)	0.39(0.26)	0.26(0.25)
Industry dummy (IT)	0.63(0.40)	1.03***(0.31)	1.05***(0.31)
Period dummy (2001~2010)	0.28(0.75)	0.24(0.61)	0.37(0.62)
Period dummy (2011~2020)	0.59(0.74)	0.59(0.62)	0.73(0.62)
Likelihood Ratio Chi-Square	4.97	18.08	17.65
Likelihood Ratio Chi-Square (sig.)	0.29	0.01	0.01
Log likelihood	-338.02	-456.10	1.56
Pearson Chi-Square (Value/df)	1.59	1.53	-456.32
AIC	686.04	926.21	926.64
BIC	697.06	943.79	944.22

† p<.10, *p<.05, **p<.01, ***p<.001

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Table 3.2. Negative binomial regression results for analyzing the determinants of exploitative innovation performance after M&A (111 obs.)

Variables	Model 1 Control Variables Exploitative Innovative performance (1~4year)	Model 2 Technological similarity Exploitative Innovative performance (1~4year)	Model 3 Technological complementarity Exploitative Innovative performance (1~4year)
Intercept	3.46***(0.72)	2.77***(0.64)	2.78***(0.62)
Technological similarity	0.56(0.74)	2.48*(1.31)	
Technological similarity^2	0.21(0.75)	-2.45 † (1.38)	
Technological complementarity			2.29(1.52)
Technological complementarity^2			-2.62(1.87)
Industry dummy (Semiconductor)	0.14(0.27)	0.42(0.26)	0.26(0.25)
Industry dummy (IT)	0.61(0.40)	1.01***(0.31)	1.02***(0.31)
Period dummy (2001~2010)	0.21(0.74)	0.37(0.62)	0.44(0.62)
Period dummy (2011~2020)	0.56(0.74)	0.75(0.62)	0.82(0.62)
Likelihood Ratio Chi-Square	5.14	18.54	17.23
Likelihood Ratio Chi-Square (sig.)	0.27	0.01	0.01
Log likelihood	-333.42	-447.36	-448.02
Pearson Chi-Square (Value/df)	1.71	1.68	1.69
AIC	676.84	908.73	910.04
BIC	687.86	926.30	927.61

† $p<.10$, * $p<.05$, ** $p<.01$, *** $p<.001$

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Table 3.3. Negative binomial regression results for analyzing the determinants of exploratory innovation performance after M&A (111 obs.)

Variables	Model 1 : control variables Explorative invention performance (1~4year)	Model 2 : Technological similarity Explorative invention performance (1~4year)	Model 3 : Technological complementarity Explorative invention performance (1~4year)
Intercept	1.93**(0.77)	2.34***(0.62)	1.56*(0.66)
Technological similarity		1.25(1.43)	
Technological similarity^2		-2.12(1.54)	
Technological complementarity			3.05*(1.38)
Technological complementarity^2			-2.79 † (1.61)
Industry dummy (Semiconductor)	0.14(0.28)	0.12(0.26)	0.18(0.25)
Industry dummy (IT)	0.49(0.41)	1.00**(0.32)	1.06***(0.32)
Period dummy (2001~2010)	0.16(0.78)	-0.12(0.64)	-0.06(0.64)
Period dummy (2011~2020)	0.68(0.78)	0.36(0.65)	0.53(0.63)
Likelihood Ratio Chi-Square	6.16	22.57	23.06
Likelihood Ratio Chi-Square (sig.)	0.19	0.00	0.00
Log likelihood	-234.63	-320.67	-320.42
Pearson Chi-Square (Value/df)	1.78	1.75	1.73
AIC	479.26	655.33	654.84
BIC	490.28	672.91	672.42

† p<.10, *p<.05, **p<.01, ***p<.001

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Table 4.1 and 4.2 show the results of Tobit regression on the ratio of patents after M&A to comparatively analyze the post-M&A exploitative and exploratory innovation performance ratios. Table 4.1 presents the results of Tobit regression predicting the determinants of the post-M&A exploitative innovation performance ratio. In the same method, Table 4.2 presents the results of analyzing the determinants of the exploratory innovation performance ratio. In each table, Model 1 shows the influence of control variables on the post-M&A exploitative and exploratory innovation performance ratio. Model 2 shows the effect of technological similarity, which is an independent variable, as well as of control variables on post-M&A exploitative and exploratory innovation performance ratio. Lastly, Model 3 shows the effect of technological complementarity, which is an independent variable, as well as of control variables on post-M&A exploitative and exploratory innovation performance ratio.

Table 4.1. Tobit regression results for analyzing the determinants of the post-M&A exploitative innovation performance ratio (111 obs.)

Variables	Model 4 Control Variables Exploitative invention performance ratio (1~4year)	Model 5 Technological Similarity Exploitative invention performance ratio (1~4year)	Model 6 Technological Complementarity Exploitative invention performance ratio (1~4year)
Intercept	45.37**(16.25)	41.94**(14.64)	54.66***(16.33)
Technological similarity		36.34***(8.08)	
Technological complementarity			-23.90*(10.71)
Relative patent portfolio size	-1.99(2.271)	2.71(2.28)	-0.30(2.33)
No. of patents pre-M&A	11.28***(2.77)	6.79**(2.66)	10.10***(2.73)
Industry dummy (Semiconductor)	-12.31*(6.3)	-7.63(5.72)	-11.76*(6.111)
Industry dummy (IT)	-17.44*(7.89)	-14.97*(7.05)	17.21*(7.66)
Period dummy (2001~2010)	5.83(15.18)	2.88(13.76)	6.36(14.75)
Period dummy (2011~2020)	12.11(15.53)	10.93(14.06)	11.42(15.10)
Industry Relatedness	20.14**(7.18)	12.75*(6.63)	18.32**(7.02)
Nation (nonUS=1)	-1.06(6.2)	-1.18(5.59)	-1.00(6.05)

Log likelihood:	-309.60	-299.86	-307.16
D.f.	10.00	11.00	11.00
Wald statistic	45.29	74.50	52.84

† p<.10, *p<.05, **p<.01, ***p<.001

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Table 4.2. Tobit regression results for analyzing the determinants of the post-M&A exploratory innovation performance ratio (111 obs.)

Variables	Model 4 Control Variables Explorative invention performance ratio (1~4year)	Model 5 Technological Similarity Explorative invention performance ratio (1~4year)	Model 6 Technological Complementarity Explorative invention performance ratio (1~4year)
Intercept	105.62*** (15.72)	109.12*** (14.55)	95.19*** (15.42)
Technological similarity		-28.50*** (7.73)	
Technological complementarity			28.06** (10.19)
Relative patent portfolio size	3.84 † (2.19)	0.09(2.26)	1.95(2.19)
No. of patents pre-M&A	-14.15***(2.63)	-10.61***(2.60)	-12.96***(2.53)
Industry dummy (Semiconductor)	-2.193(5.984)	-5.80(5.62)	-3.14(5.70)
Industry dummy (IT)	5.64(7.81)	3.58(7.24)	5.22(7.44)
Period dummy (2001~2010)	-27.09 † (14.67)	-25.22 † (13.55)	-27.57*(13.97)
Period dummy (2011~2020)	-20.29(14.95)	-19.92(13.81)	-19.33(14.24)
Industry Relatedness	-11.06(6.95)	-5.95(6.56)	-9.08(6.65)
Nation (nonUS=1)	-9.78 † (5.925)	-9.56 † (5.47)	-9.69 † (5.64)
Log likelihood:	-375.92	-369.59	-372.31
D.f.	10.00	11.00	11.00

Wald statistic	50.04	71.81	62.70

† p<.10, *p<.05, **p<.01, ***p<.001

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Table 5.1 and 5.2 show the results of negative binomial regression on the number of patents after M&A to analyze the effect of the acquirer's learning capabilities on post-M&A exploitative and exploratory innovation performance. Table 5.1 shows the results of negative binomial regression analyzing the determinants of the number of post-M&A patents in exploitative patent classes. In the same method, Table 5.2 shows the results of analyzing the determinants of the number of patents in exploratory patent classes. In each table, Model 1 presents the influence of control variables on post-M&A exploitative and exploratory performance. Model 2 shows the effect of R&D investment, which is an independent variable, as well as of control variables on post-M&A exploitative and exploratory innovation performance. Finally, Model 3 shows the effect of M&A experience, which is an independent variable, as well as of control variables on post-M&A exploitative and exploratory innovation performance. Model 4 shows the effect of all variables, such as the two independent variables as well as of control variables on post-M&A exploitative and exploratory innovation performance.

Table 5.1. Negative binomial regression results for analyzing the determinants of exploitative innovation performance after M&A (111 obs.)

Variables	Model 7 Control Variables Explorative invention performance (1~4year)	Model 8 R&D Investment Explorative invention performance (1~4year)	Model 9 M&A experience Explorative invention performance (1~4year)	Model 10 All variables Explorative invention performance (1~4year)
Intercept	3.462*** (0.7188)	3.358*** (0.720)	3.495*** (0.7192)	3.391*** (0.7198)

R&D Investment (3 year average)		0.007*** (0.0019)		0.005** (0.0017)
M&A experience			0.041**(0.0142)	0.034**(0.0146)
Industry dummy (Semiconductor)	0.139(0.2673)	0.079(0.268)	-0.128(0.2768)	-0.20(0.2711)
Industry dummy (IT)	0.614(0.3986)	0.616(0.402)	0.642(0.3995)	0.756 † (0.4080)
Period dummy (2001~2010)	0.211(0.7470)	-0.227(0.752)	0.026(0.7458)	-0.317(0.7497)
Period dummy (2011~2020)	0.562(0.7448)	0.107(0.750)	0.178(0.7541)	-0.202(0.7622)
Likelihood Ratio Chi-Square	5.14	22.39	15.30	28.74
Likelihood Ratio Chi-Square (sig.)	0.27	0.00	0.01	0.00
Log likelihood	-333.42	-324.79	-328.34	-321.62
Pearson Chi-Square (Value/df)	1.71	1.50	1.36	1.30
AIC	676.84	661.59	668.68	657.24
BIC	687.86	674.82	681.91	672.67

† p<.10, *p<.05, **p<.01, ***p<.001

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Table 5.2. Negative binomial regression results for analyzing the determinants of exploratory innovation performance after M&A (111 obs.)

Variables	Model 7 Control Variables Explorative invention performance (1~4year)	Model 8 R&D Investment Explorative invention performance (1~4year)	Model 9 M&A experience Explorative invention performance (1~4year)	Model 10 All variables Explorative invention performance (1~4year)
Intercept	1.933 † (0.7692)	1.875** (0.7696)	1.978** (0.7698)	1.880** (0.7699)
R&D Investment (3 year average)		0.005** (0.0016)		0.004** (0.0015)
M&A experience			0.038** (0.0139)	0.38** (0.0143)

Industry dummy (Semiconductor)	0.142 (0.2802)	0.147 (0.277)	0.025 (0.2801)	0.113 (0.2788)
Industry dummy (IT)	0.489 (0.4076)	0.681 † (0.412)	0.589(0.4112)	0.856* (0.4230)
Period dummy (2001~2010)	0.163 (0.7764)	-0.209 (0.784)	-0.119 (0.7803)	-0.432 (0.7851)
Period dummy (2011~2020)	0.678 (0.7794)	0.281 (0.785)	0.266 (0.7890)	-0.108 (0.7940)
Likelihood Ratio Chi-Square	6.16	17.49	15.41	26.21
Likelihood Ratio Chi-Square (sig.)	0.19	0.00	0.01	0.00
Log likelihood	-234.63	-228.96	-230.01	-224.61
Pearson Chi-Square (Value/df)	1.78	1.55	1.63	1.33
AIC	479.26	469.93	472.01	463.21
BIC	490.28	483.16	485.24	478.64

† p<.10, *p<.05, **p<.01, ***p<.001

Reference group: Industry (BIO), Period (1991~2000), Nation (US)

Standard errors are reported in parentheses.

Technological Similarity

Hypothesis 1 assumes that there is an inverted-U relationship between technological similarity and post-M&A quantitative innovation performance. The coefficient of technological similarity in Model 2 of Table 3.1 was not statistically significant, and thus Hypothesis 1 could not be tested. The results of Table 3.1 were not significant, but the results of the sensitivity test additionally performed in Section 5.1 showed empirical evidence that partially supports Hypothesis 1 depending on the observation period of post-M&A innovation performance.

Moreover, as shown in the results of Model 2 in Tables 3.2 and 3.3, technological similarity affects the number of patents in exploitative patent classes, but its effect on exploratory innovation performance is not significant. The number of patents in exploitative patent classes in Table 3.2 shows a significant positive effect with technological similarity, while the coefficient of the second-order term shows a significant negative effect. This supports Hypothesis 2 assuming that there is an inverted-U relationship between technological similarity and the number of patents in exploitative patent classes. Meanwhile, Table 4 shows how technological similarity contributes to the ratio of post-M&A exploitative and exploratory innovation. As shown in Table 4.1, technological similarity has a positive relationship with the post-M&A exploitative innovation performance ratio. This supports Hypothesis 3 by confirming the assumption that firms with higher technological similarity will show more exploitative than exploratory innovation performance.

Technological Complementarity

The results of Model 3 in Table 3.1 show the relationship between technological complementarity and quantitative innovation performance. The linear term of technological complementarity was positive and significant. Meanwhile, the second-order term of technological complementarity was negative and not significant. Hypothesis 4 assumes that there is an inverted-U relationship between technological complementarity and post-M&A quantitative innovation performance; but, as shown in Table 3.1, the second-order term did not show a statistically significant result, so Hypothesis 4 is not supported. This implies that there is an insignificant adverse effect on follow-on innovation performance when the technological complementarity between the target and the acquirer is extremely high or low in actual data. As shown in the results of Model 3 in Table 3.3, technological complementarity had a significant effect on post-M&A exploratory innovation performance. The linear term of technological complementarity showed a significant positive effect and the second-order term showed a significant negative effect. As assumed by Hypothesis 5, there is an inverted-U relationship between technological complementarity and exploratory innovation performance.

Table 4 shows how technological complementarity contributes to the ratios of post-M&A exploitative and exploratory innovation. As shown in the results of Model 6 in Table 4.1, technological complementarity has a significant negative effect on post-M&A exploitative innovation performance ratio. Meanwhile, in Table 4.2, there is a significant positive effect on exploratory innovation performance ratio. This supports Hypothesis 6 assuming that firms with technological complementarity will show more exploratory than exploitative innovation performance.

Heterogeneous Learning Capability

Table 5 shows the effect of the acquirer's heterogeneous learning capabilities on post-M&A exploitative and exploratory innovation performance. In Model 8 of Table 5.1, the relationship between exploitative innovation performance and R&D investment that represents active learning capabilities had a positive coefficient, which was statistically significant. Moreover, Model 8 in Table 5.2 also showed that there was a significant positive coefficient with exploratory innovation performance. This result supports Hypothesis 7 assuming that R&D investment has a positive effect on both post-M&A exploitative and exploratory innovation performance.

M&A experience representing passive learning capabilities also showed a significant positive relationship with exploitative innovation performance in Model 9 of Table 5.1, as well as with exploratory innovation performance in Model 9 of Table 5.2. This supports Hypothesis 8 assuming that firms with more M&A experience will positively affect post-M&A exploratory and exploitative innovation performance.

Meanwhile, Model 10 shows the effect of exploitative and exploratory innovation performance on all variables. The results showed that both R&D investment and M&A experience had a significant positive relationship and M&A experience had a higher positive coefficient than R&D investments. This indicates that, in terms of post-M&A

innovation performance, firms with more M&A experience will show better innovation performance than firms that merely make more R&D investments. All things considered, these results show that heterogeneous learning capabilities serve as factors positively affecting follow-on innovation performance in PMI.

Control Variables

Control variables did or did not have significant effects on post-M&A innovation performance depending on the model. Table 3 shows the effect of the industry dummy and period dummy as control variables on quantitative, exploitative, and exploratory innovation performance. As shown in Table 3, the industry dummy had a significant effect on quantitative, exploitative, and exploratory innovation performance. This implies that the industrial difference is a factor that affects the number of patents. Meanwhile, the period dummy affects the number of patents in exploitative patent classes as shown in Table 3.2 but does not affect the number of patents in quantitative and exploratory patent classes as shown in Tables 3.1 and 3.3. This suggests that the effect of a period on the number of patents is relatively insignificant.

Table 4 shows how multiple control variables affect exploitative and exploratory innovation performance ratios. The results showed that the relative size of knowledge bases does not affect each ratio. On the other hand, the size of the acquirer's knowledge base before M&A has a significant effect on exploitative and exploratory innovation performance ratios. One thing to note is that it had a significant positive effect on the exploitative innovation performance ratio and a significant negative effect on the exploratory innovation performance ratio, providing that patents possessed before M&A had different effects depending on the type of innovation. Industry relatedness had a significant effect on the exploitative performance ratio but not on the exploratory performance ratio. As shown in Table 4.1, industry relatedness had a positive effect on exploitative innovation performance. This result supports previous studies claiming that more industry-relatedness between the acquirer and the target, tends to show R&D efficiency, which can achieve the economy of scale, and thus increases absorptive capacity and facilitates knowledge integration (Elena et al, 2013; Capron and Insead, 1999; Ahuja and Katila, 2001; Cohen and Levinthal, 1990; Mowery et al., 1996;). The industry dummy that represents the difference among industrial clusters within the samples did not have a significant effect on the exploratory innovation performance ratio, but it showed a significant negative effect on exploitative innovation performance. This implies that, compared to the semiconductor and IT industries, the biotechnology industry shows higher exploitative than exploratory innovation performance and that, in many cases, the type of post-M&A innovation in the biotechnology industry is exploitative innovation. Meanwhile, the nation and period dummies did not have much effect on exploratory and exploitative innovation performance ratios. This implies that the effect of the nation and period is relatively limited in determining the direction for post-M&A innovation.

Table 5 shows that when heterogeneous learning capabilities affect the number of patents in exploitative and exploratory patent classes, the industry and period dummies do not have a statistically significant effect. This indicates that the effect of the industry and period is limited in PMI and innovation performance is determined more by the acquirer’s R&D investment and M&A experience.

4.1. Sensitivity Analysis

To improve the robustness of this study’s test results, a sensitivity analysis was conducted with different time windows of the dependent variables. Previous studies tended to measure post-M&A innovation performance in 1–3 years after M&A (Jo et al., 2016; Makri et al., 2010). This might include many studies conducted before M&A considering the R&D time for patents. Accordingly, this study conducted the statistical analysis by setting the research period as 1–4 years after M&A. However, since the time windows of measurement for dependent variables is a key factor that may affect post-M&A innovation performance, the measurement period was extended to 1−3 years, 1−4 years, 1−5 years, 2−4 years, and 3−5 years for additional analysis.

As shown in Table 6, Hypotheses 4, 5, and 6 on exploratory and exploitative innovation performance and Hypotheses 7 and 8 on learning capabilities showed significance in all periods. Meanwhile, Hypothesis 1 on post-M&A quantitative innovation performance showed significance in 1−3 years after M&A but lacked significance after that. This may be due to the fact that the value of technological knowledge declines rapidly over time, and patent technology in knowledge-intensive high-tech industries loses most of its value within 5 years, which is in line with the results of previous studies (van de Vrande et al., 2009). Therefore, it is difficult to detect the effect on the target's knowledge 5 years after M&A and, thus, the effect of M&A declines over time after M&A. The effect of technological similarity on the number of patents in exploitative patent classes was significant in all periods, and the effect of technological complementarity on exploratory innovation performance was significant for 1~3 years and 1~4 years after M&A, although it lacked significance over time. This may also be due to the limited effect of M&A over time after M&A like quantitative performance.

In sum, the results of the empirical study show that technological similarity and complementarity affect post-M&A exploratory and exploitative innovation performance depending on the period after M&A. Moreover, learning capabilities had a positive effect on exploratory and exploitative innovation performance in all periods. Meanwhile, the effect on quantitative performance tended to lack significance over time. This may be because technology loses its value over time in high-tech industries, and thus the effect of the target's knowledge decreases as time passes after M&A, thereby reducing the effect on innovation performance. Nonetheless, technological similarity and complementarity had a significant effect on quantitative performance in 1−3 years after M&A, indicating that technological M&A had a significant effect on post-M&A quantitative innovation performance.

Table 6. Sensitivity Analysis Results

Type I (same as Table 3)	Dependent Variable	Quantitative Innovation Performance					Exploitative Innovation Performance					Explorative Innovation Performance				
		Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5	Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5	Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5
	Technological Similarity	**	†	x	x	x	**	*	**	*	*	**	x	x	x	x
	Technological Complementarity	**	x	x	x	x	**	x	x	x	x	**	*	x	x	x

Type II (same as Table 4)	Dependent Variable	Exploitative Innovation Performance					Explorative Innovation Performance				
		Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5	Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5
	Technological Similarity	***	***	***	***	***	**	***	***	***	**
	Technological Complementarity	***	*	**	**	**	***	**	**	**	*

Type III (same as Table 5)	Dependent Variable	Exploitative Innovation Performance					Explorative Innovation Performance				
		Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5	Year 1~3	Year 1~4	Year 1~5	Year 2~4	Year 3~5
	R&D Investment	***	***	***	***	**	**	**	**	**	*
	M&A experience	***	**	**	**	**	***	**	**	**	*
	All variables	**	**	*	*	x	**	**	**	**	x

V. Discussion

5.1. Conclusion

Studies on technological M&A and post-M&A innovation have been conducted continuously, but many factors and relationships that affect Post-M&A innovation performance have not been identified (Cefis et al., 2020). Many firms execute technological M&A to obtain technological knowledge bases from the target, but reported failure rates are still high (Ganzaroli et al., 2016; Orsi et al., 2015). More studies must be conducted on technological M&A to find what affects its performance. This study focused on technological similarity and technological complementarity between the acquirer and the target and examined how these affect technological post-M&A quantitative, exploitative, and exploratory innovation performance.

This study selected 111 cases of technological M&A executed from 1980 to 2021 in knowledge-intensive high-tech industries such as semiconductors, bio, and ICT for analysis and used negative binomial regression and Tobit regression to analyze how technological similarity, technological complementarity, and heterogeneous learning capabilities affect follow-on innovation performance in technological M&A. The following results were obtained based on empirical analysis.

First, technological similarity had an inverted-U relationship with quantitative innovation performance. In other words, the optimum quantitative innovation performance can be anticipated by acquiring a target firm that has an adequate level of technological similarity. Moreover, technological similarity had an inverted-U relationship with exploitative performance while technological complementarity had an inverted-U relationship with exploratory performance. Considering these results, firms could achieve both incremental and radical innovation through technological M&A.

Second, higher technological similarity led to a higher ratio of exploitative rather than exploratory innovation performance, whereas higher technological complementarity led to a higher ratio of exploratory rather than exploitative innovation performance. The results of the empirical analysis show which technology trajectory post-M&A innovation tends to follow regarding each technological relatedness. Third, this study presented heterogeneous learning capabilities as a factor that increases post-M&A innovation performance and investigated the relationship with post-M&A innovation performance. The acquirer's learning capabilities had a positive effect on post-M&A innovation performance. Firms with more R&D investment, which is a factor of active learning capabilities, and firms with more M&A experience, which is a factor of passive learning capabilities, tended to show more post-M&A innovation performance. This proved that learning capabilities serve as a factor affecting follow-on innovation performance in PMI. This study promoted an understanding of the difference in performance among technological M&A transactions by proving that a firm's heterogeneous learning capabilities have a positive effect on follow-on innovation performance.

5.2. Limitations and suggestions for further research

Despite the effort to investigate the factors and relationships affecting technological relatedness and post-M&A innovation performance, this study has a few limitations. First, this study evaluated post-M&A innovation performance based on the number of patent applications. However, not all innovations are patented and high-tech firms in particular may not apply for patents of their innovation performance due to concerns over imitation or breach of confidentiality (Miozzo et al., 2016). Thus, considering the characteristics of these high-tech firms, it may not be adequate to evaluate the innovation performance of firms based on patents. Moreover, while this study identified the number of innovations with the number of patents, the qualitative level of innovation such as influence or the importance of patents cannot be identified by using just a quantitative index (Zvi Griliches, 1990). For example, qualitative innovation performance can be considered high when a few patents were cited many times, even though the number of patents is small (Valentini, 2012). However, without considering the above, this study has limitations in that it has quantitatively evaluated innovation performance. Further studies must consider the qualitative aspects in measuring innovation performance for more advanced research.

Second, just as in the various previous studies that examined innovation performance and technological relatedness of M&A (Ahuja & Katila, 2001; Cloodt et al., 2006; Ganzaroli et al., 2016; Jo et al., 2016; Makri et al., 2010), the current study utilized patent data provided by the USPTO when measuring for independent and dependent variables. The limitation of this method is that the risk of common source bias may occur from using the same database for both independent and dependent variables (Campbell & Fiske, 1959). When collecting variables from a single source, it is difficult to explore the fundamental relationship between variables since it is impossible to partially eliminate commons source bias relations (Podsakoff & Organ, 2016). In addition, with respect to using patent data, when there is no patent data on target firm or acquirer before or after M&A despite having made significant technological M&A transaction, such transactions cannot be included in this study, and a significant number were actually omitted. Since not all innovation performance of firms are apparent in the form of patents (Makri et al., 2010), such omissions demonstrate a drawback of research that limits the scope of performance innovation to patent data. The academic world continues to study indicators that can accurately measure the innovation performance of firms, and these indicators range from patents, and new product announcements to R&D inputs. Hagedoorn et al. (2003) argued that rather than using a single indicator, a composite construct based on these indicators can better capture innovation performance. Progress in research on developing indicators to precisely measure firms' innovation performance is expected to resolve the fundamental problem of single source bias that this and many other studies face.

Third, this study employed SDC platinum data, which was widely used in previous studies to collect data on M&A transactions (Kapoor & Lim, 2017; Makri et al., 2010; Valentini & Dawson, 2010; Valentini & di Guardo, 2012). Although such data are frequently used in a number of studies, the database itself is lacking in completeness and accuracy in that excludes a significant amount of data (Barnes et al., 2014; Bollaert & Delanghe, 2015). This study also used 40 years' (1980-2021) worth of data to collect transaction information for statistical analysis. However, considering the length of the aforementioned period, the number of applicable data was quite low. Therefore, this study may face potential availability bias due to the shortcoming of the SDC Platinum Database (Schmidt & Hunter, 2016). Future studies may supplement this study by using other databases related to M&A in the place of SDC Platinum Database, such as Medtrack (Orsi et al., 2015), which includes transactions in the bio-pharmaceutical industry or Orbis (Ganzaroli et al., 2016) that provides data on unlisted firms.

Fourth, this study applied strict standards to sample selection by considering only technological M&A that specified the purpose, which is why the number of samples obtained was small. Therefore, this study may not fully represent the relationships between technological relatedness and post-M&A innovation performance. By obtaining more samples later, it would be possible to obtain analysis results that can supplement some relationships with low significance. Future studies can make up for the deficiencies of this study by tracking M&A that did not specify the purpose and increasing the number of samples that are identified as technological M&A.

Fifth, this study considered only the similar and complementary areas in the entire patent portfolios of the target and the acquirer, while not examining the effect of the area with non-overlapping portfolios. In other words, it did not consider the effect of the area that is represented as the unrelated area in Figure 1, in which the target's and the acquirer's patent classes belong to different industries and have different patent classes. However, there are cases in which exploratory innovation performance turns out to be significant even if technological similarity and complementarity both have a value of 0. This may have been affected by the non-overlapping area with novelty in the technological knowledge bases of the two firms. According to previous studies, the ratio of overlapping and non-overlapping areas of the target's and the acquirer's knowledge bases affects post-M&A performance (Sears & Hoetker, 2014). This study did not consider this factor, but the scope of this study can be extended by additionally considering the characteristics of not only similarity and complementarity but also non-overlapping areas when subdividing technological relatedness into future studies.

This study strived to find various factors affecting post-M&A innovation performance and investigate the relationship between independent and dependent variables. Further research can investigate the moderating variables that affect this relationship. This will add insight to existing studies and lead to a more significant study that provides suggestions that are necessary for actual management practices.

5.3. Contribution to literature

A major contribution of this study is that it classified innovation into two types, exploratory and exploitative innovation performance, based on patent portfolio and examined whether technological M&A serves as a strategy that supports both exploration and exploitation of firms. Technological M&A is considered to be a strategy that can induce both exploitative innovation and exploratory innovation (Belussi & Orsi, 2015), but in fact, its significance is barely known.

This study focused on technological relatedness, a key factor covered in numerous previous studies, to investigate factors that influence exploratory and exploitative innovation performance following M&A. Furthermore, This study subdivided "technological relatedness," which had been commonly studied before, into "technological similarity" and "technological complementarity". Technological similarity and technological complementarity are concepts clearly distinguished from technological relatedness, and each area can have different effects on post-M&A innovation performance. Previous studies had only analyzed technological relatedness as a single dimension when examining post-M&A innovation performance. Accordingly, when the acquirer and the target have complementary technological knowledge bases, they can create a synergy and show high innovation performance, but these cases were not considered in previous studies. To bridge this research gap, this study analyzed 111 cases of technological M&A and investigated how technological similarity and complementarity between firms affect follow-on innovation performance. This study has significance as it extends previous literature on technological M&A.

The results showed that higher technological similarity led to a higher ratio of exploitative than exploratory innovation performance, whereas higher technological complementarity led to a higher ratio of exploratory than exploitative innovation performance. Through this comparison, this study identified which technology trajectory post-M&A innovation tends to follow regarding each technological relatedness. Meanwhile, technological similarity had an inverted-U relationship with quantitative innovation performance. Moreover, technological similarity had an inverted-U relationship with exploitative performance, and technological complementarity had an inverted-U relationship with exploratory performance. When piecing together the aforementioned results, firms could achieve both incremental and radical innovation through technological M&A.

Moreover, this study also presented heterogeneous learning capabilities as a factor that can promote post-M&A innovation performance and investigated whether each of the learning capabilities promotes exploitative and exploratory innovation performance. The heterogeneous learning capabilities of acquirers had a positive effect on both exploitative and exploratory innovation performance. This proved that learning capabilities serve as a factor affecting follow-on innovation performance in PMI. An interesting aspect of the empirical analysis results is that M&A experience had a higher positive coefficient than R&D investments. This indicates that, in terms of post-M&A innovation performance, firms with more M&A experience will show better innovation performance than firms that merely make more R&D investments. This implies that learning more about the target's technological knowledge transfer and PMI can create a synergy between the acquirer and the target, emphasizing the importance of M&A experience as a crucial learning capability that affects post-M&A innovation performance. These results promoted an understanding of factors that increase innovation performance in PMI of technological M&A, thereby contributing to the literature.

5.4. Implications to managers

This study provides a few practical implications for managers looking for ways to promote post-M&A follow-on innovation performance or for firms looking for potential targets. First, depending on which type of innovation performance a firm's manager intends to obtain after technological M&A, the target with suitable technological similarity and complementarity can be selected, thereby improving the anticipated M&A innovation performance. As implied by the results of this study, a firm with an adequate level of technological similarity with the acquirer can be selected first to improve exploitative innovation performance, whereas a firm with an adequate level of technological complementarity with the acquirer can be selected first to improve exploratory innovation performance. Furthermore, The results of this study prove that technological complementarity has a significant effect on follow-on innovation performance as much as technological similarity. This implies that technological complementarity is an important factor that should be considered just as much as technological similarity of a target firm when selecting one for acquisition.

Second, it is possible to predict the possibility of knowledge recombination with the confirmed target as well as the type of post-M&A innovation and performance level to come up with adequate strategies. In particular, the target with high technological similarity will generally result in higher exploitative rather than exploratory innovation performance, whereas the target with high technological complementarity will generally result in higher exploratory rather than exploitative innovation performance. This prediction may contribute to establishing preemptive strategies to supplement the type of innovation that appears to be underperforming.

Third, managers can perceive "heterogeneous learning capabilities" as a factor that can increase post-M&A innovation performance and actually improve follow-on innovation performance by increasing the level of R&D investments that contribute to active learning capabilities. Moreover, they can be aware of the importance of M&A experience as a passive learning capability and hire talented human resources with expertise in PMI to make up for deficiencies, or organize a team of managers with M&A experience who can manage PMI, thereby enhancing relevant competencies.

In conclusion, this study implies that managers must evaluate not only the financial aspects but also the technological resources of the target firm when they execute technological M&A. The results contribute to predicting the type of post-M&A innovations and level of performance as well as establishing strategies to supplement them.

5.5. Summary

This study investigated whether the target's and the acquirer's technological similarity and complementarity and the acquirer's learning capabilities in technological M&A contribute to post-M&A innovation performance. The results imply that this hypothesis is supported. More specifically, technological similarity and complementarity had a significant effect on exploitative and exploratory innovation performance, and "heterogeneous learning capabilities" were emphasized as a key factor for improving follow-on innovation performance in PMI. Higher R&D investment that contributes to the acquirer's active learning capabilities leads to higher post-M&A innovation performance, and more M&A experience leads to higher passive learning capabilities, which may result in higher follow-on innovation performance.

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국문 초록

본 연구는 기술적 M&A가 기업의 혁신 성과에 미치는 영향을 조사하며, 주요 요인으로 인수기업과 피인수기업의 기술적 관련성과 인수기업의 학습 역량에 주목한다. 또한 혁신이 기존의 기술 궤적을 따라가는 점진적인 혁신인지, 새로운 기술 궤적으로의 이동을 수반하는 급진적인 혁신인지에 따라 혁신의 유형을 활용적 혁신과 탐색적 혁신으로 나누어 보고, 주요 요인들이 두 가지 유형의 혁신에 미치는 영향을 조사하였다.

가설의 검증을 위하여 지식집약적 산업인 반도체, 바이오, ICT 산업에서 일어난 기술적 M&A를 분석 대상으로 설정하고, 미국 특허 데이터 베이스를 이용하여 음이항 회귀분석(negative binomial regression)과 토빗 모형 분석(tobit regression)을 실행하였다. 그 결과, 기술 유사성과 기술 상호보완성은 인수 후 양적 혁신 성과와 역U자 관계를 가짐을 확인하였으며, 기술 유사성은 활용적 성과와, 기술 상호보완성은 탐색적 성과와 역U자 관계를 가지는 것으로 나타났다. 한편 기술 유사성이 높을수록 탐색적 혁신 성과에 비해 활용적 혁신 성과 비율이 높은 경향을 띄는 것을 확인하였으며, 반대로 기술 상호보완성이 높을수록 활용적 혁신 성과에 비해 탐색적 혁신 성과 비율이 높아지는 것으로 나타났다. 이러한 결과는 피인수기업과 인수기업의 기술적 관련성이 후속 혁신 성과에 미치는 영향에 대한 이해도를 높인다. 나아가 본 연구에서는 기술적 M&A 이후 통합 과정에 있어 혁신 성과를 높이는 요인으로써 '학습 역량'의 중요성을 밝힌다. R&D 투자를 통한 능동적 학습 역량과 인수 경험을 통한 수동적 학습 역량은 활용적, 탐색적 혁신 성과 모두에 긍정적인 영향을 주었으며,

이러한 결과를 통해 기업의 학습 역량이 기업의 경쟁 우위의 원천으로서 기능함을 확인할 수 있다.

주요어 : 기술적 M&A, M&A 이후 혁신 성과, 기술 관련성, 기술 유사성, 기술 상호보완성, 이질적인 학습 역량
학번 : 2016-20622