



Novelty Score and Technological Relatedness Measurement Using Patent Information in Mergers and Acquisitions: Case Study in the Japanese Electric Motor Industry

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Abstract Technological mergers and acquisitions (M&A) have been major strategic options for firm growth. However, it is not a rudimentary task to build a long list of target firms among a vast number of candidates. Technological relatedness measurement based on patent information is expected to support such a task. Although different measurement indicators have been proposed, there is still room to explore their functionality in regards to M&A. Therefore, we aim to quantify the technological relatedness between acquirers and acquired firms by investigating the cases in the Japanese electric motor industry. Our results showed that the common-IPC mode can efficiently eliminate the effects of irrelevant elements and effectively focus on the novelty level of the technologies in M&A. The measure is expected to help extract potential acquired firms for acquiring firms, construct exit strategies for startups, and monitor the dynamic capability of the focal firm.

Keywords Electric motor industry · M&A · Patent classification · Startup · Technological distance · Technological relatedness

JEL Classification C18 · D22 · D83 · L63 · O32 · O34

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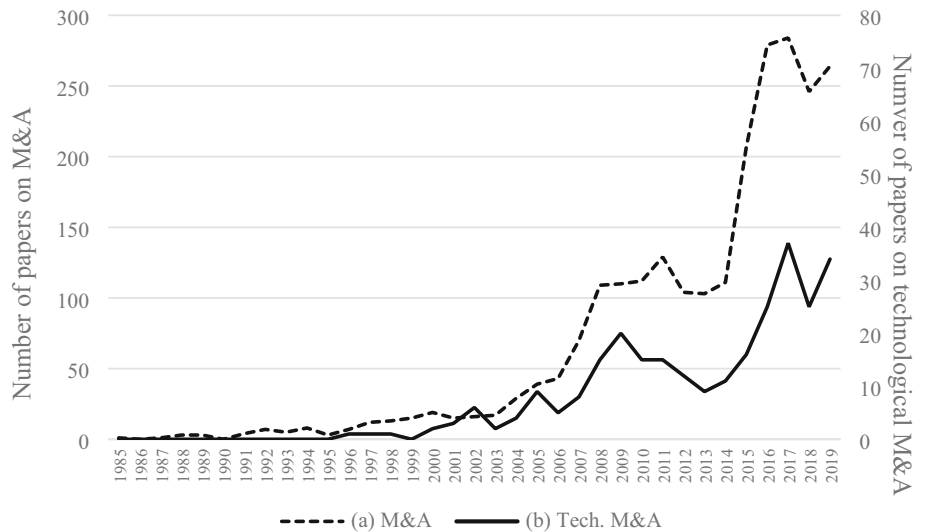
Introduction

Rapid societal and environmental changes elevate the importance of several competences such as the dynamic capabilities (Awwad et al., 2022; Petricevic & Teece, 2019) and the strategic flexibility (Abbott & Banerji, 2003; Dhar et al., 2022; Roberts & Stockport, 2009; Tan, 2021). To survive under these circumstances, firms need to strengthen their dynamic capabilities to prepare and adopt turbulent conditions. Deepening and diversifying technological capabilities are essential ways for capability building. Mergers and acquisitions (M&A) are one of the essential tools for it. Reflecting its importance, the number of papers related to M&As has been increasing, especially in the last decade (Fig. 1). The performance of M&A is not determined only by the technological relatedness between two firms. In fact, the synergic outcomes of M&A rely on financial characteristics (Melicher & Hempel, 1971; Settembre-Blundo et al., 2021) and relatedness among firms, including business, culture, size, and technological related factors, and combination of those (Homberg et al., 2009). However, among various factors, technological M&A has been still one of the important issues. Although a diversification of research topics lead to decreasing share of technological M&A studies, the number of technological M&A studies is still increasing and its composition has maintained a certain percentage of studies as shown in Fig. 1.

For successful M&A, the technological relatedness between the acquiring and merged firms plays an essential role. Technological relatedness can be also represented by using the concept of technological distance, where the longer distance means the lower relatedness, and has gained a research concern in the literature. For example, as theoretically (Nooteboom, 1999) and empirically (Gilsing



Fig. 1 Number of previous studies on M&A in social science from 1985 to 2019
a Dashed line, left axis: the number of papers on M&A
b Solid line, right axis: the number of papers on technology M&A



et al., 2008) shown in the previous literature, the relationship between technological distance, an indicator of the difference in technological positions between the two entities expressed by length, and innovative performance shows an inverted U-curve. This implies that candidate firms whose technological distance is too long or too short for acquirers cannot provide expected synergies after M&A.

However, how can we measure technological relatedness and design relevant target of acquisition based on the measurement? Relevant measures are necessary not only in the context of M&A, but also open innovation. Dezi et al. pointed out that although there are insufficient prior literatures on concepts between M&A and open innovation, those between M&A and innovation are established (Dezi et al., 2018). Innovation is expressed as the new combination of old ideas by Schumpeter (Olsson & Frey, 2002), and open innovation process is described as the combination of internal and external ideas by Chesbrough (Chesbrough, 2012). Among innovations, open innovation especially focuses on the importance of grasping and understanding external idea. We believe that the paucity of research on the concept of M&A and open innovation, as pointed by Dezi et al., could indicate the demand for a more precise method to capture the relationship between a firm and its potential external M&A targets. Therefore, the technological distance needs to be quantified to find and choose the appropriate targets. In addition, as innovation can be described as search and recombination process of external knowledges (Malaviya & Wadhwa, 2005; Savino et al., 2017), the advance in approach to find more suitable knowledges by quantifying them for firms' innovation can be crucial issue. In this context, developing quantitative methods to measure technological relatedness is

necessary to support the exploration of candidate firms and assess plausible M&A synergies.

This study aimed to investigate the relevance of measures of technological relatedness using patent classifications. Patents are useful information for measuring the technological portfolios of firms. Using patent information, it is possible to grasp the information of firms from outside, as they are obliged to disclose it by law. Technological relatedness has been used to measure relatedness among patents, technological fields, firms, industries, and regions. In this study, we focus only on the relatedness between firms. We conducted a case study in Japanese firms. The next section illustrates previous literature on relatedness using patents.

Previous Literature

Methods used to calculate technological relatedness comprise of mainly three key components: data type, data group, and formula (Fig. 2). Regarding data type,

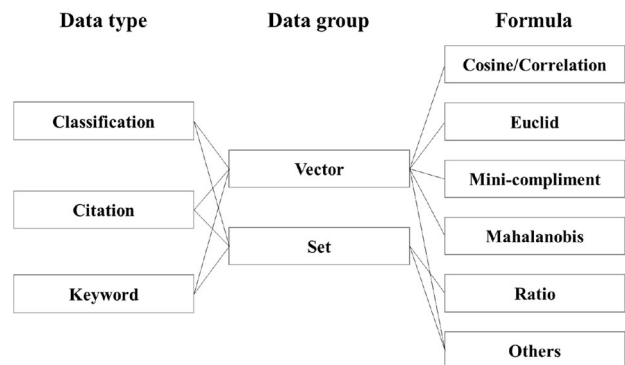


Fig. 2 Key components for calculating technological relatedness



keywords, citations, and classifications of patents were employed. For example, Arts et al. proposed the use of text matching with unique keywords to measure the similarity between two patents (Arts et al., 2018). Mowery et al. analyzed interfirm knowledge transfers in alliances from citation patterns, that is, the cross-citation rate between two firms (Mowery et al., 1996). Stuart and Podolny studied strategic partnership and changes in the technological positions of firms in Japanese semiconductor manufacturers by observing the citation overlap data of patents with Euclidian distance (Stuart & Podolny, 1996). Ahuja and Katila employed sets of citing patents to investigate how M&As affect the innovation performance of acquiring firms (Ahuja & Katila, 2001).

Among these data types, patent classifications such as the US Patent Classification (USPC) and International Patent Classification (IPC) have been widely researched and applied in many studies as shown in Table 1. IPC in particular is a well-established schema that can avoid home advantage biases and cultural influences on patenting behavior by national patent offices (Engelsman & Vanraan, 1994). The IPC comprises of hierarchical structures starting with section, which is the highest level in the classification hierarchy, followed by class, subclass, group, and subgroup. More than 100 countries use IPC to classify patent documents, and other important classifications, namely the Cooperative Patent Classification (CPC) in Europe and in the USA and the File Index (FI) in Japan, which are based on the IPC (WIPO, 2020). As IPC has been adopted in more countries and regions among these classifications (Degroote & Held, 2018), it can be considered suitable as patent data for use in studies on firms around the world.

Despite the wide dissemination of IPC, there seems to be no consensus on the granularity of the classification for the measurement of technological relatedness. For example, in a study on cross-industry collaborations, vom Stein et al., used the 1- and 3-digit IPC for their studies (vom Stein et al., 2015). Angue et al. pointed out that previous studies use a level of patent classifications, despite the difference in the granularities in the classification, which can facilitate the analysis. They proposed a systematic method for quantifying technological proximities from the viewpoints of basic and specific knowledge using multiple layers of IPC to find potential R&D partners (Angue et al., 2014). Simon and Sick discussed the appropriate granularities of patent classification based on the effects of the number of patents in irrelevant patent classes. They found that the group level of IPC seems valid for assessing technological relatedness in their study (Simon & Sick, 2016). Thus, suitable granularities of patent classification for measuring technological relatedness appear to vary, depending on previous studies. Therefore, we need to explore the relevant hierarchical granularities for measuring relatedness in M&As.

There are two types of data groups: a set and a vector. When sets are employed as data groups for measuring relatedness, the overlap or co-occurrence of elements in the two sets is focused. The Jaccard indices (Jaccard, 1912), Dice score (Dice, 1945), and Simpson indices (Simpson, 1960) are the basic and well-applied methods used to measure the similarity between two sets. Regarding studies on technological relatedness, the co-classification analysis of patents is used as the basis for constructing macro-level technology maps (Breschi et al., 2003; Engelsman & Vanraan, 1994) and quantifying the relatedness between technologies (Cantwell & Noonan, 2001) and industries (Teece et al., 1994).

The commonality of patent classification is also applied in M&A studies to ascertain the technological relatedness between acquirers and acquired firms (Ganzaroli et al., 2016; Hagedoorn & Duysters, 2002; Huang et al., 2016; Makri et al., 2010). Podolny et al. proposed a method to measure the competitive effect of one organization on another by comparing the magnitude of the ratio calculated by the number of common inventions between the two organizations to that of all the inventions of each organization (Podolny et al., 1996). Thus, the commonality of elements is focused on the data group of sets used to quantify relatedness (Aharonson & Schilling, 2016).

Another data group is vectors, where the formulas of cosine similarity and Euclidean distance have been extensively employed. For example, Jaffe employed the distribution of the patents of firms over patent classes as vectors and calculated the technological relatedness using cosine similarity (Jaffe, 1986). Following Jaffe's proposition, vector types have been employed as a dataset for evaluating technological relatedness (Aldieri et al., 2020; Angue et al., 2014; Bar & Leiponen, 2012; Benner & Waldfogel, 2008; Bloom et al., 2013; Simon & Sick, 2016;). Different formulas including cosine, Euclid, min-complement, Mahalanobis, etc., have been employed as similarity measures, as summarized in Table 1 (Aldieri & Cincera, 2009; Cincera, 2005; Dushnitsky & Lenox, 2005; Gaschet et al., 2017; Hjaltadóttir et al., 2020; Hussinger, 2010; McNamee, 2013; Ornaghi, 2009; Paruchuri et al., 2006; Rosenkopf & Almeida, 2003; Xiang & Huang, 2019). This table shows that quantified technological relatedness is used for various research purposes.

However, there is no standard for determining the relevant data type, group, and formula. Therefore, we compare the well-applied calculation methods of Jaccard, Dice, and Simpson as set data, and Cosine, Euclid, and min-complement as vector data methods for appropriately quantifying technological relatedness using two grades of classification: 4- and 6-digit granularities in the globally coordinated IPC.



Table 1 Summary of previous literature on the technological relatedness using patent classifications

Year	Author	Classification*	Mainly used Digit	Mainly investigated or applied formula					Aim of study	
				Vector						Set
				Cosine/Correlation	Euclid	Min-compliment	Mahalanobis	Others		Co-occurrence Overlap
1986	Jaffe	USPC	Main Class	+					“To quantify the effects on the productivity of firms’ R&D of exogenous variations in the state of technology (technological opportunity) and of the R&D of other firms (spillovers of R&D)”	
1994	Engelsman	IPC base	–					+	“To develop a cartography of technology by using in particular patent-based methods and techniques in order not only to reformat the data into a specific graphical representation, but also to accomplish data reduction while retaining the essential information”	
2001	Cantwell	USPC base	Main Class					+	“To document received wisdom which suggests that seemingly unrelated technologies become more related during the second half of the twentieth century by using quantitative measures of the relationship between technologies”	
2002	Hagedoorn	IPC	3-digit					+	“To study the effect of M&As on innovation in a high-tech sector”	
2003	Breschi	IPC base	–					+	“To proposes an original measure of knowledge-relatedness, using co-classification codes contained in patent documents, and examines the patterns of technological diversification of firms”	
2003	Rosenkopf	USPC	Main Class		+				“To explore if the formation of alliances and mobility of active inventors facilitate interfirm knowledge flows across geographical and technological contexts through demonstrating both the geographic and technological localization of knowledge”	
2005	Cincera	IPC base	–	+					“To assess the impact of R&D spillovers on firms’ economic performance as measured by productivity growth”	
2005	Dushnitsky	USPC base	–	+					“To explore the conditions under which firms are likely to pursue equity investment in new ventures as a way to source innovative ideas”	
2006	Paruchuri	USPC	Main Class		+				“To investigate the hypothesis that the productivity of corporate scientists of acquired companies is generally impaired by integration, but that some scientists experience more disruption than others”	
2008	Benner	USPC	Main Class etc	+	+				“To guide future research using patent data by outlining the conditions under which bias and precision issues might emerge”	
2009	Aldieri	USPC base	–	+					“To assess the magnitude of R&D spillover effects on large international R&D companies’ productivity growth”	
2009	Ornaghi	USPC	Subclass	+					“To study the effects of mergers on the R&D activity of consolidated firms and to explore the relationship between ex-ante relatedness of merging parties and their ex-post performances”	

Table 1 continued

Year	Author	Classification*	Mainly used Digit	Mainly investigated or applied formula					Set	Aim of study
				Vector						
				Cosine/Correlation	Euclid	Min-compliment	Mahalanobis	Others		
2010	Makri	USPC	Main Class						+	“To develop a model of relatedness and invention performance of high-technology M&As that considers science and technology similarity and complementarity as important drivers of invention”
2010	Hussinger	IPC	1-digit	+						“To analyze the importance of a related technology portfolio in the decision to acquire a particular firm, with the sample of a large share of small and medium-sized enterprises in addition to exclusively large firms”
2012	Bar	Not specified	–	+	+	+				“To construct an intuitive measure of technological distance that satisfies a desirable independence axiom other commonly used measures fail to satisfy”
2013	McNamee	USPC	Subclass	+						“To introduce modifications for current measures of technological distance or similarity, modifications which enable various common management research methods to fully make use of hierarchical classification data”
2013	Bloom	USPC	Main Class				+			“To develop a general framework incorporating technology and product market spillovers and implement this model using measures of a firm’s position in technology space and product market space”
2014	Angue	IPC	from 1 to 6-digit	+						“To show how the information contained in patent documents can be used to identify basic and specific technological proximities between firms and therefore a potential research and development (R&D) partner”
2015	vom Stein	IPC	1 and 3-digit		+	+				“To compare well established measuring methods based on Euclidian distances with method of the min-complement distance for investigating cross-industry collaboration”
2016	Huang	IPC	8-digit						+	“To develop a model of target selection of Technology M&A from the perspective of technology relatedness and R&D capability”
2016	Aharonson	USPC	Subclass	+				Algorithm	+	“To develop and apply a set of measures that enable a fine-grained characterization of technological capabilities based on the USPTO database”
2016	Simon	IPC	from 1 to 6-digit	+	+	+				“To identify factors that influence the results of technological distance calculation using simulation and investigate cross-industry collaboration”
2016	Ganzaroli	IPC	3-digit						+	“To investigate the combined effect of M&A partners’ technological relatedness and the acquirer’s effective utilization of the target’s knowledge on explorative and exploitative invention performance post-M&A”



Table 1 continued

Year	Author	Classification*	Mainly used Digit	Mainly investigated or applied formula					Aim of study	
				Vector						Set
				Cosine/Correlation	Euclid	Min-compliment	Mahalanobis	Others		Co-occurrence Overlap
2017	Gaschet	IPC	6-digit			+			“To assess the role of the relatedness of knowledge bases used by different sectors within a region, as a major driver of clusters’ development”	
2019	Xiang	USPC	Main Class etc	+	+	+			“To assess the contribution of nonlocal manufacturing subsidiaries and nonlocal R&D subsidiaries on cluster firms’ innovation performance respectively and ascertain the moderating effect of geographical distance and social distance”	
2020	Hjaltadottir	IPC	2-digit			+			“To assess whether structural heterogeneity in the context of the “urban–rural dichotomy” and international borders can explain differences in the regions’ engagement in inter-regional innovation cooperation”	
2020	Aldieri	IPC	4-digit				+		“To explore the relationship between a firm’s knowledge sourcing strategy and green innovation”	

*“base” means that the classification is modified for research by authors or prior studies based on the IPC or USPC

Data and Methods

Case Selection

We investigate methods and conditions used to measure technological relatedness more suitably by observing M&A cases in the Japanese electric motor industry. We selected the industry as the target of this study for the following reasons. First, Nidec, which is a well-known Japanese electric motor company developed using a series of over 60 M&As during the growth period (Kosaka & Nie, 2019), belongs to this industry. Despite being in the traditional industry, it is the fastest growing company in Japan, with a market capitalization that has increased about 70-fold in this past 30 years by applying M&A (Nippon Keizai Shinbun, 2019). According to De-man and Duysters, the success rate of M&A, measured by stock market reaction, is around 30%, and it is expected that valuable suggestions can be drawn by analyzing the case in which this company grew through M&A (De-man & Duyster, 2005). Moreover, by focusing on this company which has survived under long harsh economic conditions in Japan, it can also be expected to gain useful insights from the strategic flexible perspectives (Roberts & Stockport, 2009). Second, the electric motor industry is more conventional than ICT or digital industries. Furthermore, the analysis of the industry is expected to provide implications for acquiring dynamic capability in the mature industrial sector. Third, the

industry is technology-oriented, with sufficient patent activities. Patent data are one of the essential factors for quantifying technology distance in this study. Finally, there are few previous studies on Japanese firms in the industry. Thus, focusing on them can be expected to have unknown implications.

The steps of the M&A case selection are as follows. First, we selected the major electric motor manufacturers in Japan as acquirers; their M&A cases were extracted from their disclosure information, such as corporate histories, securities reports, and contents of investor relations, including business results and financial information. Consequently, we extracted 17 electric motor manufacturers in Japan and found 106 M&A cases before 2019. Among the 106 cases, we eliminated the following:

- *Internal M&A*: This is a type of merger with a company that already belongs to an acquirer’s group. In this type, the knowledge bases of an acquired firm can be considered as already being shared among group firms. Furthermore, the technologies of the acquired firm have already become a part of those of the acquirers.
- *Merger of only divisions from an external firm*: Patent documents provide information on companies, inventors, and assignees, rather than on divisions to which applicants or assignees belong. Therefore, it is difficult to identify the parts of patented technologies that are transferred to acquirers through division mergers.

- *A small portion of investment*: Like cross-shareholdings, acquiring a small percentage of the stock of external firms will not yield new external technologies or knowledge.
- *Acquired firms with less than three patent families applied in one year before M&A or even during the extended three-year period before M&A*: It will be difficult to observe the technology and knowledge bases of such companies on an objective scale without patent information. Furthermore, acquired firms that are inactive in patent applications might insignificantly contribute to acquirers as a technological M&A. We also investigated each case where name disambiguation cannot be resolved in patent search, for example, M&A of Nidec with Copal, and with Copal Electric.

After the above investigation, we are left with 28 cases by four acquiring companies namely Nidec, Minebea-Mitsumi, Yaskawa, and Mitsuba, where Nidec overwhelmingly had 24 cases.

Data

We used the patent database, Derwent Innovation, provided by Clarivate to measure technological relatedness based on patents. For acquirers, we extract patent family information applied one year before M&A; for acquired firms, we extract patent information applied one to three years before M&A using the criteria mentioned in the section of Case Selection. All the 4- and 6-digit IPCs were excerpted and their numbers counted. The data of the family unit of patents are suitable for the purpose of this study, as we can prevent duplicate counting of the same technologies. This will also help us to focus on only the number of unique technologies in acquirers and acquired firms. After extracting those data, we eliminate data noise and confirm that the patent families of acquirers include only those of acquired firms. This is in accordance with the chronological order of M&A. In some data, the patent families of the acquired firms are included as noise data before the M&A. We manually corrected these errors as much as possible to calculate technological relatedness.

Methods

Technological relatedness contains a wide range of concepts, such as proximity, similarity, commonality, dissimilarity, or distance of technologies. In this study, we use the term “technological relatedness.” To measure technological relatedness between acquirers and acquired firms, we compared the Euclid, Cosine, min-complement, Jaccard, Dice, and Simpson coefficients, which are defined as:

- *Euclid*: $\sqrt{\sum_{k=1}^n (p_{ik} - p_{jk})^2}$
- *Cosine*: $\frac{p_{i1}p_{j1} + \dots + p_{in}p_{jn}}{\sqrt{p_{i1}^2 + \dots + p_{in}^2} \sqrt{p_{j1}^2 + \dots + p_{jn}^2}}$
- *Min-complement*: $1 - \sum_{k=1}^n \min\{p_{ik}, p_{jk}\},$
 $\sum_{k=1}^n p_{ik} = \sum_{k=1}^n p_{jk} = 1$

where the p_{ik} and p_{jk} represent the element of vector P_i and P_j , respectively. Namely, vector P_i and P_j are denoted as $P_i = (p_{i1}, p_{i2}, \dots, p_{in})$ and $P_j = (p_{j1}, p_{j2}, \dots, p_{jn})$.

For the dataset data group, the calculation methods for sets A and B are as follows:

- *Jaccard indices*: $|A \cap B| / |A \cup B|$
- *Dice score*: $2|A \cap B| / (|A| + |B|)$
- *Simpson indices*: $|A \cap B| / \min\{|A|, |B|\}$, where A and B represent sets containing elements

Each coefficient is calculated with a 4- and 6-digit IPC by considering the effects of granularity in the classification. The dimension of vector n was defined as twofold. One is “all-IPC mode” and another is “common-IPC mode.” In the all-IPC mode, n is the total number of classifications in the 4-digit and 6-digit IPC. In the common-IPC mode, n is calculated by counting the number of common IPCs in both acquirers and acquired firms. After creating the above vector, we applied L1 and L2 normalization for all formulas except for min-complement, which is already defined with L1 normalization. For vector P_i , L1 normalization is defined by dividing each element p_{ik} by $\sum_{k=1}^n p_{ik}$, and L2 normalization is defined by dividing each element p_{ik} by $\sqrt{\sum_{k=1}^n p_{ik}^2}$.

“Technological relatedness” has a wider range of meanings. One possible reason for this is that this term contains both distance and similarity. In this study, we use the term, “technological distance” for calculation methods, which indicates that the larger the result values, the greater the distance between technologies in the two firms. This is the case for Euclid and min-complement. We refer other formulas, where the larger value means the shorter distance, to as “technological relatedness.” To evaluate the relevance of technological relatedness measurements, we compared those with novelty scores, which were manually annotated for each M&A. We labeled each M&A based on the novelty of acquired technology at four levels represented by N, Nc, Cn, and C. N, which is the first letter of the term “new,” shows the most unfamiliar technology level for acquirers. C, the first letter of the term “common,” shows that the technologies are already common for acquirers. Nc and Cn are between those of N and C, respectively. We collected information on the aim of M&A, the status of owned technologies both in acquirers and in acquired firms, and the business situations of both companies at the time of M&A. We mainly collect information from the disclosed materials of each company, and complement them with multiple articles in reliable



Japanese newspapers, such as Nihon Keizai Shimbun, NIKKEI BUSINESS DAILY, NIKKEI VERITAS, The Nikkan Kogyo Shimbun, Asahi Shimbun, Yomiuri Shimbun, and Sankei Shimbun. Newspaper articles were collected from the NIKKEI TELECOM database.

The criteria for the annotation are as follows:

- *N*: Technologies that acquirers have not already had, or that they have intended to develop by themselves but have not succeeded.
- *Nc*: Technologies that acquirers have not directly used in their products but contacted them from upstream or downstream of their supply chain. This includes cases in which acquirers already have related basic technologies, but have little experience in applying them to new uses for entering inexperienced markets. Alternatively, this could also be cases in which acquirers indirectly know the technologies of component parts or manufacturing processes in their current products.
- *Cn*: Technologies that are not identical, but they are close or similar enough to be recognized as a peripheral one. Therefore, it is not very difficult for acquirers to understand and adapt them.
- *C*: Technologies that are nearly identical to those of the acquirers and that the acquirers have directly experienced and can easily apply to their current businesses.

After categorizing all the M&A cases into *N*, *Nc*, *Cn*, and *C*, we assign each of the categories a score from zero to three, respectively. We further assign 0.5 to any case between the two adjacent categories. Therefore, the novelty scores are given in 0.5 increments. For instance, we assigned ‘*N*’ to the M&A between Nidec and Honda Elesys in 2013. In this case, the novelty level of the technologies is high for the acquires. This M&A aimed to shift from Nidec’s conventional motor business segment to a module business segment by combining Nidec’s motor technologies for electric power steering with the technologies of the electric control unit in the Honda Elesys. Around 2013, Nidec analyzed the market shift and expected that there would be a strong demand for motors integrated with electric control units in the automotive market for power steering. Nidec further decided to attain technologies on the electric control unit, for which Nidec had not had sufficient experience at that time (Nidec Corporation, 2013). Based on these situations and information in 2013, we assigned this case the “*N*.” As another example, we considered the case between Nidec and Shinano in 1989 as the novelty level “*C*.” This M&A aimed to solidify Nidec’s position in the electric motor market for storage devices such as the Floppy and Hard Disk Drives used in computers. In 1989, Nidec had the largest market share, followed by Shinano, which had the second largest market share. These two companies competed in the same market

(Nikkei Business Daily, 1989). Similar to these examples, we evaluated the novelty level of the technologies of the acquired firms for all the 28 M&A cases and counted their scores. We then compared the technological relatedness measures with novelty scores.

Results

Figure 3 shows a scatter plot between technological relatedness measures and novelty scores. Here, we used min-complement as an example of a technological relatedness measure. Based on the definition of min-complement, relatedness by this calculation method indicates the distance between the two firms in an M&A case. Accordingly, the value of technological relatedness is expected to become large when the technologies of the acquired firms are far from the level of those of the acquiring firms, that is, when the novelty score becomes large. By comparing Fig. 3a, b, c and d, the common-IPC mode (i.e., b and d) seems to have a larger correlation. In areas where the x-axis values are small, the values of the y-axis tend to be compressed closer to one in the all-IPC mode than in the common-IPC mode, regardless of the IPC digit. Similarly, when we compare Fig. 3a, b, c and d the 4-digit-IPC seems better than the 6-digit-IPC.

Table 2 summarizes the results of evaluating the values of the correlation coefficients. In all calculation conditions, we observed the same trend between the novelty score and the technological relatedness with the above case, which shows that the values of the correlation coefficient by the common-IPC mode are larger than those by the all-IPC mode.

Regarding the data group of set, there were slight differences in the values of the correlation coefficients among the three formulas, between the 4- and 6-digit, and between L1 and L2 normalizations for the all-IPC mode. However, there were significant differences in the common-IPC mode. In the dataset data group, the combination of the common-IPC mode, the 4-digit, and L1 normalization showed better results. There was however a slight difference among the three formulas for that combination. Regarding the data group of the vector, contrary to that of the set, the all-IPC mode does not provide stable results. While the overall performance of the vector data is better than that of the set data, the common-IPC mode is still better in the all-IPC mode. In the vector data, Euclid with the L1 normalization is lower than those by other formulas. This was however mitigated by either using the common-IPC mode or by applying the L2 normalization.

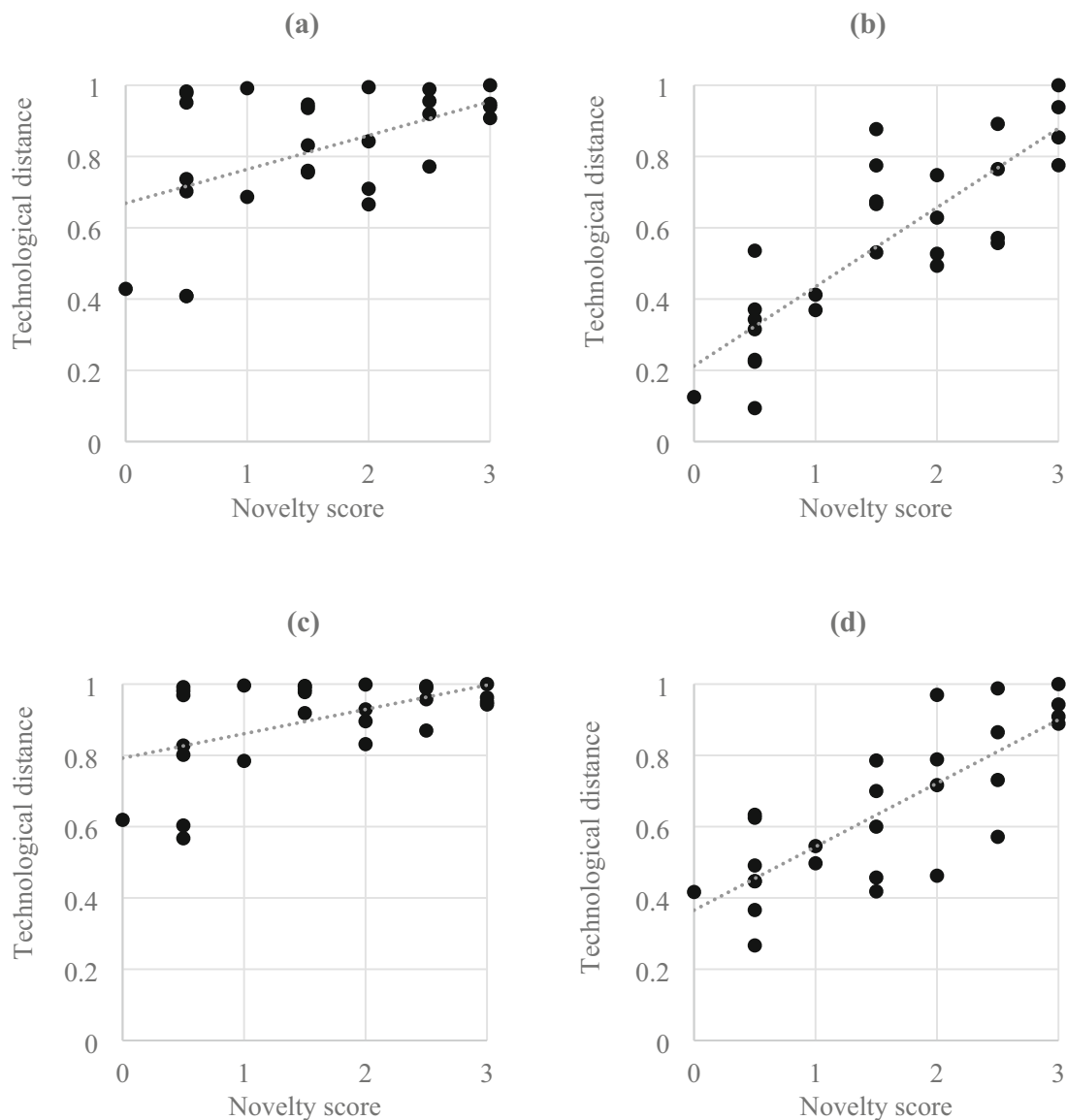


Fig. 3 Comparison of the scatter plots between the all-IPC mode and the common-IPC mode by min-complement **a** The all-IPC mode with the 4-digit IPC **b** The common-IPC mode with the 4-digit IPC **c** The

all-IPC mode with the 6-digit IPC **d** The common-IPC mode with the 6-digit IPC

Discussion

This study focuses on quantifying the novelty level of the technologies of acquired firms to those of acquirers as technological relatedness, and further compares different measures of technological relatedness based on patents. Through the investigation of Japanese electric motor industries, we found the advantage of the common-IPC mode in quantifying technological relatedness. One feature of technological M&A cases in this industry is the size difference in the number of IPCs between the acquiring and acquired firms. The common-IPC mode demonstrates its

superiority, especially in such cases, by effectively eliminating irrelevant IPC and has sensitivity in technological relatedness measurement during M&A. Therefore, the common-IPC mode can be applied to a wider range of M&A cases than in conventional conditions.

This study further implies that the common-IPC mode can provide analytical quantification more precisely. However, the methods based on the all-IPC mode have been widely used in previous studies. Furthermore, some of them consider the effects of such size differences or attempt to eliminate them. The average number of elements in the two sets is adopted as a denominator in Dice.



Table 2 Comparison of correlation coefficients between the all-IPC and the common-IPC

Conditions of calculation				Absolute value of correlation coefficient	
Data group	Granularity	Normalization	Formulas	All-IPC	Common-IPC
Set	4-digit	L1	Jaccard	0.51	0.83
			Dice	0.50	0.83
			Simpson	0.50	0.83
		L2	Jaccard	0.55	0.80
			Dice	0.54	0.80
			Simpson	0.57	0.73
	6-digit	L1	Jaccard	0.52	0.77
			Dice	0.51	0.79
			Simpson	0.51	0.79
		L2	Jaccard	0.55	0.73
			Dice	0.54	0.74
			Simpson	0.56	0.64
Vector	4-digit	L1	Cosine	0.54	0.76
			Euclid	0.30	0.74
			Min-Comp	0.50	0.83
		L2	Cosine	0.54	0.76
			Euclid	0.56	0.79
			Min-Comp	–	–
	6-digit	L1	Cosine	0.55	0.69
			Euclid	0.15	0.63
			Min-Comp	0.51	0.79
		L2	Cosine	0.55	0.69
			Euclid	0.55	0.65
			Min-Comp	–	–

Moreover, a smaller number of two elements is used in Simpson to consider the size difference. The min-complement is presented by focusing on the effect of irrelevant elements. Furthermore, for all the formulas in this study, L1 or L2 normalization is applied. Beyond these countermeasures for the size difference, the common-IPC mode shows that this mode is efficient for measuring technological relatedness, especially in such cases, judging from the values of correlation coefficients. However, this investigation is based on a limited number of cases.

Developing reliable measures has practical implications. Previous studies have shown inverted U-shaped relationship between technological distance and innovative performance (Gilsing et al., 2008; Nooteboom et al., 2007). This implies that acquirers can obtain an additive effect with low risks when the technology distance between acquirers and acquired firms is short. This is because the acquirer can easily understand and apply the technologies of acquired firms. However, the acquirers were not able to expect synergistic effects. Contrarily, acquirers can attain opportunities for synergy when they merge acquired firms

with a large technological distance. However, they can neither sufficiently absorb the technologies of acquired firms nor obtain enough returns through M&A investments.

Nidec, the number one firm in the Japanese electric industry, has conducted M&A cases with various novelty scores ranging from zero to three (Fig. 4). Only the top two firms in the industry have carried out M&A cases with a technology novelty score above 2.5. There are some possible explanations for this result. First, the higher ranked large companies can take risks of acquiring firms with large distances as they can make up for the failures. However, the lower-ranked companies do not have such corporate powers to endure risk taking for their growth or survival. Moreover, they might reluctantly adopt M&A as a strategic option. Second, the higher ranked companies are ranked highly following past success in achieving synergies by absorbing distant technologies. Middle-ranked firms need to be careful about failing to achieve the expected goals of M&A. Further, they may tend to harvest additive effects by acquiring familiar technologies rather than taking risks that could lead them to synergies. Although further studies are

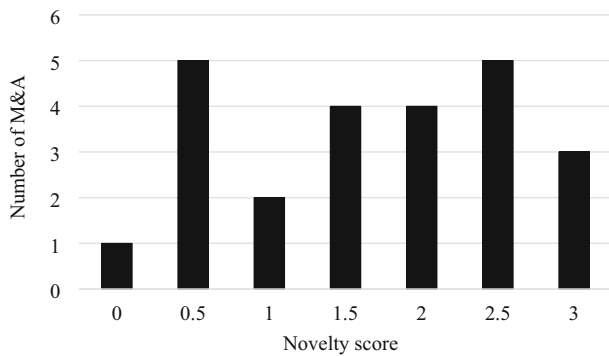


Fig. 4 Distribution of novelty scores of M&A by Nidec

needed to clarify the causal relationship, it is inferred that the correlation between the size of a company in sales and risk-taking attitude can be analyzed using the novelty score. Therefore, the common-IPC mode, which has a higher correlation with the novelty score, has the potential to be a beneficial tool for company management in designing M&A strategies.

Although past research shows an inverted u-shaped performance after M&A, the selection of target firms depends on the corporate strategy of acquiring firms and risk-taking behavior. In any case, it is important to measure technological relatedness and list and select target firms corresponding to strategy and risk levels. Furthermore, M&A involves a large investment and its success or failure significantly influences the survival or growth of the company. Therefore, it is essential to grasp the technological relatedness for selecting candidate target firms more appropriately. Our results show that patent analytics with the common-IPC mode have superior performance, which can be utilized to support relevant business partner searches. It can also be used to ascertain the competitors' strategies for technological acquisition.

Reliable technological relatedness measures will also contribute to academic research on dynamic capabilities. The measure can be used not only between two firms, but also within the focal firm between two consecutive years. Therefore, we apply the common-IPC mode to observe the time varying in the technological “self-relatedness” of Nidec. Self-relatedness is defined as the extent to which the technological relatedness of a company changes in the time interval observed. Figure 5 shows the change in technological self-relatedness in chronological order using the min-complement and 4-digit IPC. For instance, the change in technological self-relatedness between 2007 and 2008 was measured using the distribution of the IPC in 2007 that is common and used in 2008, as a reference point. Thus, the y-axis value shows the self-technological shift of Nidec during this one-year period. Nidec received a value of 0.19, from 2007 to 2008.

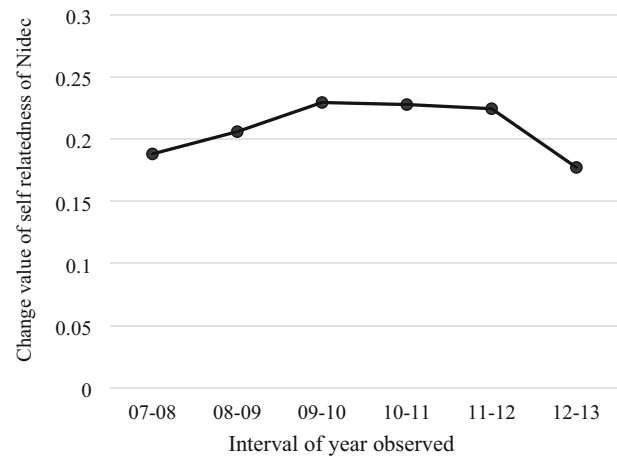


Fig. 5 Time course change in the value of self-relatedness using the min-complement with the 4-digit IPC

According to information officially announced by Nidec, this term was strategically positioned as a preparatory period for the transformation of its business portfolio for the future from 2008 to 2012 (Nidec Corporation, 2014). At the beginning of this period, the values of self-relatedness show a continuous increase. This implies that Nidec took in technologies that were different from its own and increased its dynamic capability. In the following interim period, Nidec kept assimilating different technologies and obtained a change value of over 0.2. After that, it decreased the value, as it would have achieved sufficient dynamic capability for the future. In the financial report of Nidec (Nidec Corporation, 2019), it was showed that the automotive, consumer electronics, and commercial industrial businesses, which were not the main component segments of sales around 2008, have grown to a scale on par with its core and conventional business of precision small motors. By the analysis with this secondary data from Nidec, the implication has been verified. Thus, the common-IPC mode can also be applied to track the self-technological change to observe the strategic activities of firms.

Additionally, it can also be used to investigate or monitor whether the behavior of firms follows their strategies properly. Strategic management in firms can apply this common-IPC mode not only to analyze their competitors, but also to monitor the consistency among their own strategies, tactics, and practices.

This method can also be adopted by potential acquired firms. M&A is one of the important means for technological startups as an exit strategy. Furthermore, the number of M&As involving them has been increasing significantly since 2010 (Mind the Bridge, 2018). There are several previous studies on exit strategies of startups, such as studies on the relationship between the performance of startups and exit options (Coad & Kato, 2020; Schary,

1991; Wennberg et al., 2010). However, Cotei et al. point out that previous studies insufficiently discuss decision-making on exit strategies in startups, despite the fact that these decisions influence the life of firms (Cotei & Farhat, 2018). Regarding technological startups, our study can present more practically beneficial means to find appropriate candidate acquirers as one of the exit options through a precise evaluation of the technological relatedness before the M&A is conducted. For both sides, more precise methods and conditions used to quantify technological relatedness can provide the basis for developing strategies to seek profitable candidate partners.

Conclusion

This study comparatively evaluates technological relatedness measures for 28 M&A cases in the Japanese electric motor industry. By investigating the publicly shared information, we classified these M&As into four categories, namely N, Nc, Cn, and C, and investigated the correlations between the technological relatedness measure and novelty score. We analyzed two quantification modes of technological relatedness: the all-IPC-mode and the common-IPC mode. The former is widely used and investigated in prior studies, and the latter is proposed in this study to focus more on the acquirers' viewpoints. By comparing these modes in typical measurement formulas using two sources of data, sets and vectors, we found that the common-IPC mode shows higher values of correlation coefficient with novelty scores. In other words, the common-IPC mode can quantify the relationship more accurately, especially in cases with such size differences. This is achieved by effectively and efficiently eliminating the influence of irrelevant IPCs in calculating technological relatedness. As an application of the common-IPC mode, with the understanding that correlation does not automatically imply causation, we observe the strategies of Nidec and show that this mode can effectively depict its corporate activities based on its strategies. Further, this enables firms to monitor the alignment between the strategies and the direction of practical activities, both for their own and for their competitors. In conclusion, the common-IPC mode has the potential to be widely applied regardless of the size difference in IPC, as well as to provide the basis for strategic planning for both acquirers and the acquired firms, such as designing an exit strategy for startups.

This study has several limitations. First, we excluded acquired firms with less than three patent families in one year before M&A. The beneficial analytical tools for investigating M&A with large size differences have the potential to become more essential. Therefore, the application potential of our approach to nascent start-ups is not

clear. Second, we conducted a case study on the Japanese electric motor industry. Therefore, the generality of the results is not validated. Third, the degree of the novelty of the technologies of target firms for acquirers is estimated based on publicly available information, such as securities reports, investor relations, news releases, or newspapers, and is scored with the same weight. However, if it is possible to give proper weighting among the novelty levels, N, Nc, Cn, and C, more precise conditions would be attained. Fourth, we used the data of patent families applied up to three years before each M&A. However, more findings may be gained by changing the period or using the data of granted patents. Finally, we can have room to reflect the relationships among the hierarchical structures of IPC, the relationships that are calculated using other data, such as citations (Kay et al., 2014).

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Declarations

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Key questions for further reflection

1. Can the proposed method to measure technological relatedness provide the M&A targets in an effective way for practical use?
2. Can we apply the method not only for M&A but also for open innovation in wider contexts?
3. Can we recommend research collaborators and business partners based on the measurements?
4. Can we sophisticate the proposed method by integrating the other data source such as business deals and financial data in addition to patent data?

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