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THE IMPACT OF INTER-ORGANISATIONAL NETWORK STRUCTURES ON RESEARCH OUTCOMES FOR ARTIFICIAL INTELLIGENCE TECHNOLOGIES

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Abstract:

The purpose of this study is to empirically explore the impact of inter-organizational network structures, such as alliances, on the research outcomes of artificial intelligence technologies during the adoption and diffusion phases of their lifecycle. The optimal inter-organizational network structure varies depending on the characteristics of the technology, industry and product. Artificial intelligence (AI) technology is rapidly being put to practical use, especially in the last few years, in a wide range of business domains, due to improvements in hardware performance and the increasing collection and use of big data. In collecting and using big data, collaboration among multiple organizations can be more advantageous than activities by a single organization, and the relationships among organizations are thought to have an impact on the expansion of research results. Nevertheless, the optimal structure of inter-organisational relations is thought to be influenced by the characteristics of the industry and products that use artificial intelligence technology, so we collected actual cases and carried out exploratory analysis. As a research method, we collected information about the cooperation between organizations related to artificial intelligence from press releases and newspaper articles, and analyzed the network structure between the organizations by supporting the method of social network analysis. The number of registered patents on artificial intelligence was used as an index of the research results. As a result of the statistical analysis, the research results of the organizations with weak network ties were large, mainly in the basic technology area. On the other hand, in the practical technology, there were some areas where the strong network of ties led to high research results.

Keywords:

Networks, Open Innovation, Management of Technological Innovation and R&D, IT Management, Firm Organization and Market Structure

JEL Classification: L14, O32, M15

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1 Introduction

The purpose of this study is to empirically explore the impact of the network structure of cooperation, such as inter-organisational alliances, on the innovation outcomes of technologies in the introduction phase of their lifecycle, such as artificial intelligence (AI). In the early 1990s, the development of AI technologies such as expert systems and knowledge bases flourished. However, due to the limitations of the performance of extant hardware and similar issues, the development of these technologies was impaired. Then, from the middle of the 2010s, the R&D of machine learning and deep learning technologies, including mainly neural networks, rapidly became popular. The reason for this rapid growth is the progress of basic research on machine learning, as well as the practical application of AI-related theories. For example, the idea of multi-layered neural nets, which are the key to deep learning, has existed for several decades, but the huge computational cost was a problem and research had not progressed to a suitable level. However, the improvement of the performance of the computer and the increase of the amount of data distribution, such as so-called big data, have made it possible to put it into practical use. In addition, in a wide variety of business areas, attention has been paid to the possibility of dramatically evolving the conventional business model, and has come to be called the digital transformation (DX) boom.

Thus, today's business applications of AI technology are closely related to the proliferation of big data. In other words, the ability to collect, analyse and use large amounts of high-quality data for business purposes is a key success factor in AI-related businesses, and the ability to collect data can be a source of competitive advantage in business. Big data can come from a variety of sources, such as company activities and consumer behaviour, but in order to collect and use more data, it may be more advantageous for multiple companies to collaborate than for a single company to collect and use data alone. By working together, companies have access to more sources of data and can accumulate more as a result. In addition, the more information resources are used, the more they can be analysed and utilised, the more economies of scale and network effects can be expected. Therefore, in AI-related businesses, inter-organisational collaboration is a key success factor, and what kind of collaboration network should be established can be an important strategic decision-making issue.

Nevertheless, inter-organisational relationships are influenced not only by economies of scale and network effects, but also by a variety of other factors. Consequently, it cannot be simply said that an increase in the number of inter-organisational collaborators will necessarily lead to an increase in technological development, profits, etc. For example, while it is thought that an increase in the number of inter-organisational collaborators enables the collection and use of new data, it also has negative aspects, such as a decrease in efficiency due to the dispersion of research resources and the incurrence of various transaction costs in order to collaborate.

In the first place, the optimal inter-organisational relationship is not uniform because it is affected by the characteristics of the industry in question and the structure of the product involved. For example, in the automotive industry, cohesive, closed, vertically integrated inter-organisational relationships among a relatively small number of firms have traditionally enhanced their performance, as typified by the so-called keiretsu transactions of Japanese firms. In the automobile industry, in order to differentiate products, many parts and materials are specially designed and developed for each car model. This is based on the trust that has been built up over a long period of time between the manufacturers of finished vehicles and a limited number of parts and materials manufacturers, who exchange information closely with each other and invest in technologies that cannot be used elsewhere. Subsequently, increasing the number of business partners can make it more difficult for R&D to proceed and reduce competitive advantage. On the other hand, in the IT industry, for example, relationships between organisations are generally open and ad hoc, with a horizontal division of labour. Computers and the Internet are composed of hardware and software based on standardised interface specifications. A typical example is the platform leader (Gawer and Cusumano, 2002), which provides a platform for interoperability and allows a myriad of firms to enter the market, which is a source of innovation. As mentioned previously, AI technology, the subject of this study, is used in a variety of industries, and inter-organisational relationships may have different characteristics depending on the characteristics of each industry. Therefore, in this study, we decided to conduct an exploratory analysis based on several competing hypotheses.

As a method of quantitative analysis of inter-organisational relations, the method of social network analysis was applied in this study. By using a quantitative analysis, we expect to obtain more generalisable analysis results. Social network theory applies various theories on the properties of complex networks in the natural sciences (e.g., small-world, scale-free, cluster property, etc.) to social relations. By considering people and organisations as nodes and analysing the structure of the networks in which they are connected to other nodes, it is possible to identify the effects of embedded relationships between people and organisations on their thinking, behaviour, or performance. Additionally, the methods of social network theory facilitate the collection of various quantitative indicators to evaluate the network structure.

As data for analysis, we collected information about the cooperation between organisations related to AI from press releases and newspaper articles, and analysed the network structure between the organisations by supporting the method of social network analysis. The number of registered patents on AI was used as an index of the research results. Then, based on the patent information, we classified the areas of technology and statistically analysed the relationship between inter-organisational relations and the research results in each area.

2 Previous studies on inter-organisational relations

Prior to the analysis, we reviewed a number of previous studies on the impact of inter-organisational relationships on research performance.

2.1 Network size

According to a series of discussions on open innovation since Chesbrough (2003), it is assumed that the breadth of partners increases opportunities for new combinations of knowledge and promotes innovation. Adapting the dynamic capability argument proposed by Teece, Pisano, and Shuen (1997), when the technology is immature and uncertain, it is more desirable to select more types of technologies competitively, both internally and externally, by expanding the inter-organisational network. Furthermore, by collaborating with various partners, it is easier to disseminate their technical specifications and achieve standard status.

2.2 Horizontal specialisation

Several previous studies have argued that horizontal specialisation promotes technological innovation in interorganisational networks. The theoretical premise for horizontal specialisation is that the structure of a product or industry is becoming more modular (Ulrich, 1995). For example, in the case of computers and IT products, modularity facilitates horizontal specialisation and allows individual firms to concentrate their management resources on their own specialised business areas, thereby promoting efficient R&D. New entrants are encouraged to enter the market, and new products and services are created successively through the heavy production and high failure rate of innovation by many firms, with cost performance enhanced through competition.

2.3 Platform

The foundation of such horizontal specialisation-type innovation is the platform. One of the earliest and best studies on platforms is a platform leadership study by Gawer and Cusumano (2002), which analysed Intel's strategy for personal computers, along with follow-up studies. They defined a platform as a product or service that serves as the foundation on which multiple complementary firms can make products or provide services. Regarding the relationship between platforms and innovation, Gawer and Cusumano (2014) defined an industrial platform as the basis on which more firms can build innovations that complement a particular product, related service, or component technology. Industry platforms tend to accelerate the innovation of complementary products and services. The greater the complementary innovation, the greater the value created for the platform and its users through network effects, thus generating a cumulative advantage for existing platforms. These complementary elements become barriers to entry, as it becomes more difficult for rivals and new entrants to remove them.

2.4 Complementor

According to Iansiti and Levien (2004), in business ecosystems, it is vital to increase the innovation of complementary niche companies, rather than allowing only centre (keystone) organisations to grow and monopolise profits, in order to promote the healthy growth of the entire ecosystem. Niche firms with products and technologies that are difficult to imitate are indispensable to centre organisations, and niche firms that are sought-after by many centre organisations can also grow and become more profitable. Furthermore, complementary firms' ability to connect to a centre organisation not only allows the complementary innovator to create complementary innovations, but also to access the centre organisation's customers directly or indirectly, thereby facilitating firm growth (Ceccagnoli, Forman, Huang and Wu, 2012; Cennamo and Santaló, 2013).

2.5 Organisational capacity

On the other hand, certain previous studies have pointed out that the expansion of collaboration with external organisations may somewhat reduce the performance of research. For example, in extant research on organisational learning, based on a series of studies on the search for and evolution of knowledge, starting with March (1991), if a company disperses its limited research and development (R&D) resources and becomes more active in collaborating with outside parties, it is likely to lead to a decline in its own R&D capacity. In addition, according to a series of studies on absorptive capacity since Cohen and Levinthal (1990), in research on organisational capacity, if the company's own R&D capacity declines, its ability to understand and utilise external knowledge may also decline. Moreover, even if the company diversifies its partners, the probability of success is likely to be low if the company forms an alliance with a partner that diverges significantly from its own R&D content (Lane and Lubatkin, 1998).

2.6 Integral architecture

It has been highlighted that it is preferable to internalise R&D activities in one organisation or in a limited number of closely related organisations rather than divide the work among organisations, especially when the product structure is integral (Ulrich, 1995; Clark and Fujimoto, (Clark and Fujimoto, 1991). Here, integral means that there is a high degree of interdependence between the components of a product, for example, an automobile. When multiple components need to coordinate their specifications, the division of labour among organisations increases the coordination cost and reduces the efficiency of R&D.

3 Analysis method and research hypotheses

Next, we describe the method of social network analysis, which is the method used to analyse inter-organisational relations in this study, and the hypotheses based on it. There are two main types of networks that can be analysed in social network theory: socio centric networks and ego centric networks. The former takes the whole network as the object of analysis. For example, it represents the overall character of the relationship between all organisations regarding AI business. The ego centric network, on the other hand, is a self-centred network structure. Organisations are connected to each other in a broad network structure, but each organisation is connected to the surrounding organisations in different ways. The main interest of ego centric network research is the difference in organisational performance due to the network structure surrounding the organisation. As a result, the subject of this study is the ego centric network in individual organisations.

Using social network analysis, various indicators that show the characteristics of the network's structure can be calculated (Borgatti, Everett and Freeman, 2002). In this study, we use centrality and density indices, which are the most commonly used indicators.

There are various ideas and calculation methods for centrality indices. First, we consider the most basic centrality, which is called degree centrality. One of the most prominent studies in social network analysis examined the weak-ties hypothesis proposed by Granovetter (1973), which empirically demonstrated the strength of weak ties. According to Granovetter (2005), interpersonal ties generally come in three varieties: strong, weak, or absent. The weak-ties hypothesis can be related to the management of innovation, in which a weak but wide network can promote innovation better than a strong but narrow network. In other words, in promoting innovation, it is necessary to search for knowledge that overcomes the limited rationality of people and organisations, and weak-but-wide networks are useful, as they allow for various forms of information to flow quickly and efficiently from a distance. However, a strong-but-narrow network tends to circulate only similar information, hindering the emergence of innovation, thereby preventing the organisation from expanding and improving its performance.

The advantage of a wide network can be related to network size and horizontal specialisation in the aforementioned previous studies on inter-organisational relations. The practical applications of AI technology are expanding rapidly in a variety of business domains, and various organisations are developing a wide range of technologies. Many commercialisation attempts are still in the early stages of their lifecycle, and it is not clear what businesses will be realised or what technologies will be effective. In the face of high technological uncertainty, it will be easier to realise good new technologies by further experimentation. To this end, it may be useful to collaborate with more external organisations rather than using only the company's own internal research resources. In particular, since big data is important for the practical application of AI technology, as mentioned previously, collaborating with more external organisations will facilitate the collection and use of big data and promote R&D. Furthermore, from the viewpoint of expertise, it is difficult for one company to be familiar with all the various technologies used in the practical application of AI. Rather, it would be more efficient for the company to concentrate its research resources on the technologies in which it excels, while collaborating with organisations outside the company that have their own strengths in other technologies. In addition, such cooperation would make it easier to standardise the company's technology in the industry, since the company's technology would be used by many other organisations. For this purpose, it is also expected that patent applications will be actively pursued. The following hypotheses are derived from this discussion.

Hypothesis 1: Organisations that collaborate with more external organisations in the practical application of AI technology will increase their R&D results.

Next, we consider centrality, such as that called between-centrality, and a related idea called structural hole. In social network analysis, it has been demonstrated that a network's performance and behaviour is affected by not only the number of connections it possesses, but also the way in which an organisation is connected to the networks around it. For example, the study of ego-centric network structures focuses on the question of triadic closure, i.e., whether the nodes to which the ego node is directly connected are also connected to each other. When there is no direct connection between those who are connected to the actor (ego), a structural hole is said to exist between them (Burt, 1992). On the other hand, if two people who are connected to the actor (the ego) are themselves connected, the three people (the triad) are described as closed. The high network density of the ego represents the degree to which the ego network triad is closed (Phelps et al., 2012).

Burt (2004) classifies ties into Bridging Ties and Cohesive Ties, and states that Bridging Ties, which can be widely deployed even with weak connections, are effective in searching for information. Bridging Ties are defined as ties that connect separated individuals and groups; their structural features include many bridge ties and a wide range of connectivity. These can be analysed by indexes such as the number of intervening ties and structural holes. The strength of Bridging Ties lies in the widespread dissemination of new, formal, and heterogeneous knowledge, and it is easily linked to radical innovation.

Such a mediated network structure can be associated with a platform in the aforementioned previous studies on inter-organisational relations. Since platform leaders connect various firms, they are likely to be the nodes that mediate many other nodes in the network structure. In the practical application of AI technology, we may see the emergence of platforms as being similar to those in the IT industry. For example, platform companies in the IT industry are expanding horizontally by creating new collaborative relationships with a large number of external companies beyond existing corporate affiliations and industries. In AI-related businesses, in order to collect and use big data extensively, it is useful to collaborate beyond the traditional industry boundaries, and it is assumed that each company is working to become a platformer. The following hypothesis is derived from this discussion.

Hypothesis 2: Organisations that mediate between more external organisations in the practical application of AI technology will increase their R&D results.

Next, we consider the kind of centrality that is called eigenvector centrality. The aforementioned degree centrality directly expresses the number of connections of other nodes. Eigenvector centrality is not a simple centrality, but is instead loaded based on collaborations with highly centric firms. Even if the number of direct external connections is not necessarily large, the eigenvector centrality is larger if there are many connections to the central organisation. This advantage of eigenvector centrality can be related to Complementor in previous studies on inter-organisational relations. In the practical application of AI technology, in addition to the central analytical technology, various technologies such as software, devices, and networks are integrally related, and collaboration among organisations takes place. For an organisation with a specific technology, it is expected that collaboration with a central organisation will provide opportunities to apply their technology to more businesses and to collect big data, which will promote R&D. From these assumptions, the following hypothesis is proposed:

Hypothesis 3: Organisations that collaborate with more central organisations in the practical application of AI technology will see their R&D output grow.

Next, we examine the density of the network, which is one of the theories in social network analysis, including a centrality index called closeness centrality. These focus on the mutual cohesion and proximity of connected nodes in social network analysis. According to Krackhardt (1992), there are a number of problems in the Granovetter definition. There are subjective criteria in the definition of the strength of a tie such as emotional intensity and intimacy. Strong ties are crucial in severe changes and uncertainty. According to Coleman (1988), In a high-density, closed network, it is easier for players to develop trust in each other. Players are more likely to trust each other because they are more closely and strongly connected and interact more frequently. They are also more likely to form collective norms and to engage in mutual monitoring.

In the sparse and open network structure, it is easy to obtain various kinds of information and knowledge, but it is difficult to develop trust, and it is challenging to exchange private information and tacit knowledge. On the other hand, the structure of a dense and closed network allows for transactions that are not possible in normal business transactions. For example, in R&D, a wide open inter-organisational relationship is useful in the information collection phase, but in the research realisation phase, a dense closed inter-organisational relationship is more desirable, where especially confidential information can be shared and exchanged in a secure and close manner.

To quantify the characteristics of the network, its density is the degree to which other nodes connected to a node are also connected. If the nodes are closely connected to each other, we can determine that they are likely to form a strong and cohesive group. Additionally, in network analysis, if node A is connected to node B, and node B is connected to node C, we evaluate that A and C are connected even if not directly so. This is because node A may obtain information from node C via node B, and may be affected by it. However, in this case, the strength of the relationship between node A and node B may differ from the strength of the relationship between node A and node C. Closeness centrality in network analysis methods evaluates the number of close relationships, rather than the simple number of connections, by giving greater weight to more direct connections. It can be said that network density and closeness centrality evaluate relationships as opposed to the weak ties, mediation, or structural holes mentioned previously.

Furthermore, these can be related to organisational capacity and integral architecture among previous studies on inter-organisational relationships, as mentioned in prior sections. According to various studies on organisational capabilities, wide and weak interorganisational networks may not necessarily promote R&D. Achieving tangible results in R&D often requires a long period of trial and error, which can only be achieved in collaboration with external organisations through close communication and strong relationships of trust. For this reason, it may be inefficient to expand the number of external partners and to collaborate with unfamiliar partners. In particular, according to the discussion of the integral architecture, whether it is better to expand or to narrow the inter-organisational relationship depends on the characteristics of the product and the industry in question. For example, a small number of fixed organisational members may be more likely to produce results for special one-off products that are not mass-produced, or for products that require customisation and integration among a large number of hardware, software, and other components. From these assumptions, the following hypotheses are proposed:

Hypothesis 4a: In the practical application of AI technology, organisations with a higher density of inter-organisational collaboration will achieve more R&D results.

Hypothesis 4b: In the practical application of AI technology, organisations with closer inter-organisational collaboration will achieve greater R&D results.

4. Research methodology

4.1 Research data

Next, we discuss the methodology used to empirically verify each of the aforementioned research hypotheses. First, there are two types of data used in the analysis: data on inter-organisational relations and data on research results. Regarding data on inter-organisational relations, this study used data from newspaper articles and corporate press releases, through which it is possible to collect comprehensive and timely data on the relationships among many firms. Specifically, we collected data from Nikkei Telecom, a database operated by Nikkei Inc. In addition to the information on all the articles in the major newspapers published by Nikkei Inc., a full-text search of investor relations (IR) information and press releases published by companies is possible in Nikkei Telecom. Of course, there is a limit to the information that can be covered in newspapers, but Nikkei Inc. is the most widely sold newspaper in Japan and is characterised as an economic newspaper, so it is possible to comprehensively collect the latest information on companies and businesses. In addition, by adding IR information and press releases of companies to the article information, it is possible to collect information on individual companies that were not published in the newspaper.

Concerning the search criteria, we selected articles on AI from the chosen database and extracted information on cooperation between organisations, such as strategic alliances and joint development. The period covered by the analysis was three years, from 2018 to 2020. This is because, as mentioned earlier, AI technology itself has been researched for decades, but it was only in the latter half of the 2010s that attention began to focus on the practical application of AI technology, particularly machine learning and deep learning, and it is only in the last three years that actual commercialisation by companies has become active.

Next, we used patent information for the data on research outcomes. Although there are many ways to measure research outcomes, patent information is useful for collecting objective, comprehensive, and quantitative data, and has been used in many previous studies. As with the data on inter-organisational relations, the period of analysis was set to cover 2018 to 2020. The period of time between research activities and research results varies in previous studies; for example, some set a long period, such as research on drug development, while others set a shorter period, such as in IT-related research. In the case of drug development, there is usually a period of several years for demonstration, called a clinical trial, before the results of the research can be put to practical use, whereas in the case of IT, the results are put to practical use almost immediately. In the case of AI technologies, we assumed that they would be similar to IT-related technologies and that they would fall within the three-year measurement period.

The patent information was collected from J-PlatPat, which is a database of patent information operated by the Japanese Patent Office. Therefore, the survey covers domestic applications and international applications based on the Patent Cooperation Treaty (PCT), which have been transferred to Japan. In addition, the patents to be collected are registered, not patent applications. This is because, while application patents are a mixed bag, registered patents are limited to those that have been found to be novel through patent examination.

For the selection of AI-related patents, numerous definitions are possible, and in this study we set them with reference to previous research by the Japanese Patent Office (Japanese Patent Office, 2020). AI-related inventions can be classified into two categories: AI core inventions and AI-applied inventions. AI core inventions are, so to speak, inventions related to AI technology itself. Specifically, these are characterised by mathematical or statistical information processing techniques that form the basis of AI, such as various machine learning techniques including neural networks, deep learning, support vector machines, and reinforcement learning, as well as knowledge-based models and fuzzy logic. By contrast, AI-applied inventions are inventions in the application domain in which the AI core inventions are applied. Specifically, the AI core inventions are applied to various technologies such as image processing, speech processing, natural language processing, equipment control and robotics, and diagnosis, detection, prediction, and optimisation systems. It is assumed that there is a difference in the style of research between the core inventions and the applied inventions; indeed, the former may be more research-oriented, basic, and exploratory, while the latter may be more development-oriented and practical. Therefore, the appropriate inter-organisational relationship for each may be different, and we decided to analyse them after classification.

The Japanese Patent Office uses its own classification system called File Index (hereinafter referred to as "FI"), which has been intricately developed based on the International Patent Classification (IPC). The FI assigned to the former AI core inventions is mainly G06N. There are many FIs which are expected to be granted to the latter AI-applied inventions. The Japanese Patent Office (2020) selects FIs based on the classification used in the Methodology of WIPO Technology Trends; AI so that AI-related inventions can be properly extracted from domestic patent documents. The FIs corresponding to AI-applied inventions are shown in Table 1. The right-hand column of Table 1 reveals the classification symbols according to the FI of the patents corresponding to AI-applied inventions. The "Classification" in the left column of Table 1 is the classification code of the higher level FI of each and its description. In this study, when analysing each application area of AI technology, the patents in the same area are grouped together using the classification in the left column of Table 1.

Table 1 Patents for AI-applied inventions (FI)

Classification	FI
A61B: Diagnosis; surgery; personal identification	A61B1/045,614
B23Q: Details of machine tools; components or auxiliary equipment	B23Q15/00,301@C
B60T: Braking control systems or parts thereof for vehicles; braking control systems or parts thereof in general; configuration of braking elements in vehicles in general; portable devices for preventing the vehicle from moving unexpectedly; modifications to vehicles to facilitate cooling of braking systems	B60T8/174
F02D: Control of combustion engines	F02D41/14,310@H
F24H: Fluid heaters with heat-generating means, e.g., water or air heaters Water heaters or air heaters, general	F24H1/10,302@N
G05B: Control or regulating systems in general; functional elements of such systems; monitoring or testing devices for such systems or elements	G05B13/02@L G05B13/02@M G05B13/02@N G05B19/4155@V

G06F: Electrical digital data processing	G06F7/02,630 G06F11/14,676 G06F11/22,657 G06F11/22,663 G06F16/36 G06F16/90,100 G06F17/22,682 G06F17/27,615 G06F17/28,618 G06F17/30,180@A G06F17/30,180@B G06F17/30,180@C G06F17/50,604@D
G06K: Recognition of data; display of data; recording carriers; handling of recording carriers	G06K7/14,082
G06T: Image data processing or generation in general	G06T1/40 G06T3/40,725 G06T7/00,350@B G06T7/00,350@C G06T7/00,350@D G06T7/143 G06T9/00,200
G08B: Signalling or calling devices; command transmitters; alarm devices	G08B31/00@A
G10L: Speech analysis or synthesis; Speech recognition; Speech processing; Speech or acoustic coding and decoding	G10L15/10,300@J G10L15/14 G10L15/16 G10L17/10 G10L17/16 G10L17/18 G10L25/30 G10L25/33 G10L25/36 G10L25/39
G16B: Bioinformatics, i.e., information and communication technology [ICT] specifically adapted to the processing of gene or protein-related data in computational molecular biology	G16B40/00
G16C: Computational chemistry; chemoinformatics; computational materials science	G16C20/70
G16H: Health care informatics, i.e., information and communication technologies [ICT] specifically adapted to the handling or processing of medical or health care data.	G16H50/20
H01M: Methods or means for the direct conversion of chemical energy into electrical energy, e.g., Battery	H01M8/04992

Sources – Prepared by the author based on Japanese Patent Office (2020), p.18-20

4.2 Analytical method

After constructing the database for the analysis as described, the analysis was conducted using the following steps to verify each hypothesis. First, prior to the analysis, the database for the analysis was cleaned. Next, the structure of each organisation's inter-organisational network was analysed using the network-analysis method. For each organisation, the number of registered patents for each of the aforementioned patent categories was calculated. Finally, the relationship between the inter-organisational network's structure and number of registered patents was examined. Each procedure's details are as follows.

Regarding data cleaning, the database for the social network analysis was based on newspaper articles and press releases, and the notation of organisation names is not consistent. For example, some organisation names are complete, while others include abbreviations, common names, or notation errors. The name of the organisation is the key item that links the information in each newspaper article, press release, and the patent information in the subsequent analysis, so the same organisation must have exactly the same name. Consequently, for all information, the name of the organisation was checked individually and standardised.

Next, each organisation's inter-organisational network structure was analysed according to each hypothesis based on the database for analysis after data cleaning. For the inter-organisational network structure analysis, each organisation was viewed as a node in the network, and the social network analysis method was applied. In this study, the following network indices were used among them:

As for Hypothesis 1, degree centrality, which represents the size of the ego network comprising nodes connected to the organisation in question, was calculated as an indicator of network size.

In Hypothesis 2, EgoBetweeness was calculated as network indicators for between centrality. EgoBetweeness is an index that indicates that the firm in question connects other firms that are not directly connected to each other. The aforementioned degree centrality does not take into account whether other nodes connected to the node in question are also connected. On the other hand, EgoBetweeness measures only the connections among other nodes that are connected only through its own node. Note that network size affects this index, e.g., if the ego network's size increases, the number of intermediaries may naturally increase, so nEgoBetweeness, which is an index showing the normalised ratio, was used. Through the normalisation process, we can determine the proportion of mediating nodes to all connections of a node. This allows us to determine the degree of mediation without being affected by the size of the nodes' connections.

As for Hypothesis 3, eigenvector centrality was calculated as an indicator of the size of the connection to nodes with large mediation centrality.

As for Hypothesis 4, ego network density and closeness centrality were calculated as indicators of interorganisational networks' cohesiveness and closeness. As mentioned previously, the ego network's density is the degree of connection between each node in the ego network, and the higher the density value, the more closely connected the nodes are. It is estimated that the value will increase as the grouping of companies progresses, such as in an affiliated group. Closeness centrality is a centrality that is loaded based on the relationship between nodes that are close in distance and is factored in to indicate the number of companies with close relationships. UCINet (Version 6) was used to calculate network indices.

Next, for AI-related patents, we extracted the registered patents under the extraction conditions described previously, and tabulated the number of patents by organisation according to the classification in Table 1. Then, by using the organisation name as a key, we correlated the data of the aforementioned network index of each organisation with the data of the number of patents, and conducted a correlation analysis. SPSS (Version 25) was used to conduct the analysis.

5 Survey results

5.1 Overview of the survey

The following is a summary of the survey carried out according to the methodology described. The total number of relationships between organisations related to AI technology extracted from newspaper articles and press releases was 635 in 2018, 641 in 2019, and 582 in 2020, comprising a total of 1,858 relationships over the three years. After data cleaning of the organisations' names, the number of organisations extracted was 1,675. We calculated the network indices of the relationships among these organisations using the social network analysis method. As for the number of patents related to AI technology, the total number of patents extracted was 3,801. We compared the database of inter-organisational relationships with the database of AI technology-related patents using the organisation name as a key item, and discovered that the total number of organisations in both databases was 145. Table 2 evidences the number of patents in each category and the number of organisations that could be matched by using the organisation name as a key item.

Table 2. Total number of patents by classification

Area	Classification	Number of patents	Number of organisations
AI core	G06N	1,456	107
AI application	A61B	28	5
	B23Q	22	4
	B60T	5	0
	F02D	11	3
	F24H	0	0
	G05B	174	15
	G06F	554	60
	G06K	1	0
	G06T	1,300	82
	G08B	6	2
	G10L	148	22
	G16B	26	4
	G16C	1	1
	G16H	63	11
	H01M	6	0

5.2. Results from correlation analysis

We subsequently conducted a correlation analysis between each network analysis indicator and the number of patents for each of the aforementioned categories of organisations whose names were present in the databases of both inter-organisational relations and patents. However, we decided to exclude the classification with a small sample size from the analysis in order to avoid the error of judging that there is no correlation even if there is actually a correlation due to the small sample size. Four categories were therefore selected for analysis: G06N, G06F, G06T, and G10L. The results of the correlation analysis are shown in Table 3.

Table 3: Correlation between network analysis indicators and the number of patents

Classification	Degree centrality (H1)	nEgoBetween (H2)	Eigenvector (H3)	ego density (H4)	Closeness centrality (H4)
G06N	.694**	-.071	.389**	.041	-.295**

G06F	.642**	-.082	.362**	.092	-.263*
G06T	.507**	-.107	.203	.086	-.300**
G10L	.443*	-.518*	.451*	.500*	-.132

*(**: 1% level of significance, *: 5% level of significance)*

6. Discussion

Based on the aforementioned survey results, each hypothesis was verified.

The first hypothesis concerned network size, i.e., the larger the size of the network, the greater the R&D output. In terms of network size, significant correlations with R&D performance were observed in all four classification areas investigated. The results of this analysis indicate that Hypothesis 1 is likely to be supported. In a new technological field such as AI technology, it is useful to explore and collaborate across a wide range of technologies and businesses, and the breadth of the network of collaboration among organisations is thought to contribute to the expansion of research results.

Among the organisations analysed, Nippon Telegraph and Telephone Corporation (NTT), NEC Corporation, Hitachi Ltd., and Fujitsu Ltd. are examples of organisations with particularly large networks and many research achievements. NTT is the largest telecommunications infrastructure operator in Japan. It is also one of the largest Japanese research organisations in areas such as the Internet and information technology, and is engaged in a wide range of research from basic to applied. In terms of AI technology, they have the largest number of inter-organisational collaborations and the largest number of patents. In addition, NEC, Hitachi, and Fujitsu are the three largest companies in the field of computer and information technology in Japan. AI technology has a wide range of research areas, from basic to applied, and its R&D requires a great deal of resources. One of the characteristics of R&D in Japan is that the research that requires such a large amount of research resources is mainly carried out by existing large companies as part of their diversification, rather than by universities or venture companies. This characteristic generally brings advantages such as having sufficient research resources like funds, being able to conduct long-term R&D, and being able to easily link research and business. On the other hand, large firms generally lack a challenging attitude and tend to conduct research at a slower pace. In addition, their research is limited to the individual circumstances of each company, and they try to enclose their research results in a closed system between themselves and a limited number of related companies, so that the range of applications of their research results is not broadened and platform-type growth is difficult to achieve.

Next, Hypothesis 3 will be discussed before Hypothesis 2. This is because the results of the statistical analysis of Hypotheses 2 and 4 are different and relatively contrasting across the four categories, suggesting that the results of Hypotheses 2 and 4 are influenced by the contrasting characteristics of each category, and will be discussed together later.

Eigenvector centrality, which is a network indicator of Hypothesis 3, was observed to have a significant relationship with the research results, with the exception of classification G06T. Eigenvector centrality is an indicator of the connection with organisations with high centrality, and Hypothesis 3 may be generally supported, although not in all areas. A variety of technologies are involved in the basic research and practical application of AI technology, and various organisations, large and small, are engaged in R&D. Some organisations are working on basic research, while others are trying to improve their own business by incorporating AI technology. In basic research, it is important to search for a wide range of technology seeds. In practical applications, various technologies are used in complex ways, and the quantity and quality of data for analysis and use are critical. As mentioned, in the case of Japan in particular, much research is carried out, and mainly by large companies. Therefore, it would be easier for other organisations to enhance and exploit their own technologies by collaborating with the central organisation of the network, which is likely to have a large number of technology, data, and commercialisation opportunities. In addition, it is desirable for the central organisation to be able to collaborate with external organisations that have technologies that are difficult to imitate or rare business opportunities, and it is thought that they mutually enhance each other's research results.

Among the extracted organisations, Toyota Motor Corporation, Yahoo Japan, and KDDI are examples of organisations with particularly large eigenvector centrality and many research results. Although Toyota is a large company, its main business is not telecommunications, and its AI technology is applied to its core business of automobiles, such as automated driving. For this reason, we believe that they are actively collaborating with centre companies such as NTT. Yahoo's core business is e-commerce, whilst KDDI is a telecommunications infrastructure company, but its research scale is not as large as that of NTT. They too seem to be mainly engaged in R&D to incorporate AI technology as a complement to their core business.

Next, we will consider Hypotheses 2 and 4 together. This is because the results of the statistical analysis of these two hypotheses ascertain that there is a difference in the presence or absence of significant correlations among the categories, which may indicate the influence of their characteristics. That is, among the four categories, G06N, G06F, and G10T show relatively similar trends for each network indicator of Hypotheses 2 and 4, while G10L shows a different trend from the other three categories.

For the network indicator of Hypothesis 2, betweenness centrality, G06N, G06F, and G10T did not show any significant relationship with the research results. On the other hand, a significant negative correlation was found for G10L. In terms of density, the network indicator of Hypothesis 4a, there was no significant relationship between G06N, G06F, and G10T and the research results. On the other hand, there was a significant positive correlation in G10L. Regarding the network index of Hypothesis 4b, proximity centrality, G06N, G06F, and G10T identified a significant negative correlation with the research results. By contrast, no significant correlation was found for G10L.

These results indicate that the research efficiency of the three areas of G06N, G06F, and G10T may be reduced if the collaborators have only relatively close relationships with each other. On the contrary, the results suggest that the higher the number of distant ties not directly connected, the more research results are likely to be obtained, which supports the weak ties hypothesis. The weak ties hypothesis suggests that it is easier to obtain new information if there is a wider range of ties, even if they are weak, than if there are only strong ties with similar people.

On the other hand, the G10T analysis shows a stark contrast to the three categories described, indicating that research is more likely to be successful when the density of inter-organisations is high, i.e., when all the organisations involved are closely linked to each other. By contrast, when the between centrality is strong, i.e., when only one particular organisation is connected to the other organisations and the other organisations are not directly connected, the research results are difficult to obtain. In this sense, the low correlation with between centrality and the high correlation with density are consistent with this result. To cite the previous studies, in cohesive organisations with strong relationships, mutual trust is fostered, and tacit intellectual information and highly confidential information are easily exchanged.

As for between centrality, we did not observe any relationship that would enhance the research results in any of the categories. This may imply that there is still no clear platform in the area of AI technology. Such a result may be due to the fact that mainstream AI technology is still difficult to identify, and new technologies are emerging one after another. Additionally, as mentioned, the existing firms at the centre of AI development in Japan may be more inclined to internalise the technology within their own groups.

Among the organisations to be analysed, NTT, NEC Corporation, Hitachi Ltd., and Fujitsu Ltd. were selected as examples of organisations with low degree centrality and many research achievements. These were also extracted as the organisations with large degree centrality. In other words, these inter-organisational relationships are characterised by many connections, albeit distant, and such organisations are considered to have achieved particularly good research results. It may be that companies that have broad and exploratory collaborations in AI technology and its commercialisation have achieved more research results. Toyota Motor Corporation also had similar characteristics of inter-organisational relationships. Although Toyota Motor Corporation is a traditional automobile manufacturer, today it faces dramatic changes in the industry environment, which is called CASE (Connected, Autonomous/Automated, Shared, Electric). In response to a new external environment, it is presumed that Toyota is expanding its R&D activities with a wide range of partners in areas such as those related to AI technology, far beyond the traditional affiliation in the automotive industry.

Among the organisations analysed, Mitsubishi Electric, Omron, and Toshiba were identified as examples of organisations with particularly high density and low betweenness centrality. The common characteristics of these firms are that they are electronics-based manufacturers, that they are mainly engaged in production goods for firms rather than consumer goods, and that they are strong in large-scale facilities. These are businesses where R&D takes a relatively long time. The patents in G10L are mainly in the area of research on the application of AI technology to speech recognition. These companies may not necessarily be researching or commercialising AI technology itself; they may be working on AI for applications in their own businesses, and are likely to be working closely with partners in their existing businesses. This style of R&D, in which a relatively limited number of organisations work closely together, is generally a traditional feature of the Japanese manufacturing industry, and has traditionally been a style that has enhanced competitiveness. Even in the case of new technological developments such as AI technology, it can be said that, depending on the application area, the inter-organisational relationship appropriate to that area facilitates R&D.

7. Conclusion

This study's purpose was to empirically examine the effect of the interorganisational relationships surrounding an organisation on R&D outcome. In particular, we explored the relationship between inter-organisational relationships and research results in the development of AI technology at a relatively early stage of its lifecycle, when practical applications are rapidly advancing. As a result of using the method of social network analysis concerning the inter-organisational relationship, the study demonstrated that the relationship could be explained by applying theories of social network analysis such as the weak ties hypothesis. In addition, we identified the possibility that the relationship differs depending on the area of research, such as basic research and applied research.

The significance of this study is that it quantitatively demonstrated the reality of research in AI technology, which is a relatively new technological field, using actual data. On the other hand, as a limitation of this study, the results may be affected by factors specific to Japan, because we used information on firms and patents in Japan. Therefore, regarding future research, it is desirable to expand the scope used and to conduct an international comparative study.

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