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EMPIRICAL STUDY OF CHANGES IN THE NETWORK STRUCTURE OF ORGANISATIONAL COOPERATION ON ARTIFICIAL INTELLIGENCE

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Abstract:

The aim of this study is to empirically clarify the changes in the network structure of organisational cooperation on artificial intelligence. The research questions are: 1) what kind of network structure of organisational cooperation is expanding, and 2) whether the so-called big techs are becoming more oligopolistic or decentralised as the central organisation of the network. As a research method, data for Japan as a whole for the past five-plus years, when the business use of machine learning technology has been expanding, were analysed using the method of social network analysis. The results of the analysis of each network indicator and the case studies show that the more open and mediated the network structure, the greater the scale of collaboration. The results also showed a tendency towards decentralisation, although big tech accounted for a large proportion of the total.

Keywords:

Organisational cooperation, Social network analysis, Artificial intelligence

JEL Classification: M15, M21, O32

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1 Introduction

The aim of this study is to empirically clarify the changes in the network structure of organisational cooperation on artificial intelligence.

Previous studies have pointed out that technological advances bring about changes in the structure of products and processes, which in turn bring about changes in the relationships between organisations. For example, advances in information and communication technology tend to promote modularisation of products and business processes, and horizontal division of labour as a suitable inter-organisational relationship (Fine, 1998, etc.). Advances in artificial intelligence-related technologies are also expected to bring about changes in the business processes of individual organisations (Iansiti and Lakhani, 2020) and to change the division of labour structures between different organisations (Jacobides, et al., 2021, etc.).

One of the main factors that could change products and business processes and influence inter-organisational relations as a result of developments in artificial intelligence-related technologies is the nature of data as an important resource. Artificial intelligence relies on data (Economist, 2017) and good quality data is a scarce resource. In addition, the good of data in artificial intelligence does not decrease with use, but rather a positive feedback loop tends to work, with quality improving through use (Jacobides, et al., 2021). Therefore, the success or failure of the development and use of artificial intelligence depends on how much good quality data can be collected for learning and how widely the results can be used. There are various sources of data on artificial intelligence, including information on the Internet, information devices such as smartphones, and various IoT devices. In order to expand opportunities to collect and utilise more data, it is considered more advantageous for more organisations to collaborate than for a single organisation. Therefore, in the development and use of artificial intelligence, good networking with other organisations could be a source of competitive advantage.

However, views are not necessarily uniform as to who should be at the centre and what structure is suitable for an inter-organisational network for the development and use of artificial intelligence. One view is that, based on the current situation to date, many in the media have argued that so-called big techs are central. Big techs, such as GAFAM in the US and BAT in China, are leading the development and use of artificial intelligence, with US companies in particular expanding their activities globally. Their abundant financial resources have enabled them to advance developments such as big data learning, which requires huge resources, and to expand its use horizontally across various sectors and industries, with the revenues generated further expanding development (Jacobides, et al., 2021). It is also expanding into various peripheral areas, investing in and acquiring venture companies and expanding vertically. In this way, big techs appear to be trying to fully integrate artificial intelligence in various application areas, from development to use. And it is predicted that the big techs will continue to be a central part of the AI ecosystem in the future.

On the other hand, there are many views, mainly in academic papers, that the proportion of non-BigTechs will rather expand (Jacobides, et al., 2021; Davenport, 2022, etc.). It has been pointed out that even in the current AI ecosystem, there is significant space for "speciation" (Saviotti, 2005) and that the future could see a differentiation into a very large number of industry-specific, vertically integrated ecosystems of traditional firms. For example, in the competition between traditional IT platforms, there are many cases where the platform leader, which seemed dominant, declines without becoming a winner-take-all situation, as explained by various theories such as multi-homing (Cennamo and Santalo, 2013; Negoro and Kato, 2010, etc.). The facts show that the US is the main source of the decline in the US. In reality, while the business areas of BigTechs are expanding, mainly in the US, different situations can be seen in China, Europe and Japan. In Europe and Japan, due in part to regulations, relatively closed industry-specific networks are being formed, centred on existing companies in the automotive and medical sectors. There are a wide range of application areas for artificial intelligence technology, and various collaboration structures may be generated in the future, each suited to a different area.

For this reason, the following research questions were set for this study. The research questions are 1) what kind of network structure of organisational cooperation is expanding, and 2) whether the so-called big techs are becoming more oligopolistic or decentralised as the central organisation of the network.

This study attempts to provide empirical and quantitative clarification of the aforementioned research questions. To this end, we collect actual information on cooperation networks regarding the development and use of artificial intelligence, analyse changes in these networks over time and examine causal relationships.

2 Previous research

Jacobides, a prominent researcher on business ecosystems, analyses the industry structure of AI development and use, the relationship between major organisations and other organisational groups, and their evolutionary processes, based on several case studies on AI (Jacobides, et al., 2021). Davenport, a prominent researcher on the business use of advanced information and communication technologies, discusses the facilitation of the formation of AI platforms by ordinary companies (Davenport, 2022). Burstrom, et al. (2021) discuss the linkage between business model innovation and ecosystem innovation through AI. In addition to the above, there are a number of excellent previous studies on the changes in industrial structures and inter-organisational relations due to artificial intelligence. However, most of them adopt case studies (including questionnaire surveys of specific companies) as their research method, and the results of the analysis include problems such as generalisability. Previous studies that analysed inter-organisational relationships using the same method of social network analysis as this study include a study analysing collaborative networks in the field of AI in the Yangtze River Delta, China (Xu, et al., 2022) and a study analysing AI research networks in Quebec, Canada (Colleret and Gingras, 2020), and other region-specific studies.

In Isada (2022), information on collaboration between organisations in artificial intelligence up to 2020 was collected from newspaper articles in four major Nikkei newspapers and press releases from companies, and the network structure between organisations was analysed using the method of social network analysis. The number of registered patents related to artificial intelligence was used as an indicator of research results, and the relationships were analysed. The results of the analysis showed that the research results were significant for organisations with weak networks, mainly in basic technical areas. This study is a follow-up to this study and attempts to provide quantitative evidence of changes over time.

3 Research hypothesis

This study assumes that the impact of artificial intelligence on inter-organisational relations is basically based on the view of "speciation" evolution as pointed out in the aforementioned academic papers. It is also assumed that there are various forms, such as big-tech types, industry-specific types and combinations of these types, depending on the industry and type of business, etc. It is assumed that various factors are involved in the development and use of artificial intelligence, such as the characteristics of products and business processes in each industry, the quality of knowledge such as industry-specific tacit knowledge, and national and regional legal systems. As mentioned above, many excellent previous studies have been published on the impact of the development and use of artificial intelligence on inter-organisational relations. However, most of them are either philosophical studies or studies based on cases of specific organisations, etc., and quantitative empirical studies have been scarce so far. As a background, artificial intelligence technology has only just begun to be used in earnest in real businesses, etc., and many cases were still only in the empirical research stage. However, the number of actual business cases in general companies has been increasing rapidly in recent years, and quantitative hypothesis testing has become possible. The aim of this research is to empirically and quantitatively clarify the relationship between the structure and growth of collaborative networks in artificial intelligence and changes in the network structure in response to research queries. Here, the method of social network analysis is used as a method to quantitatively clarify the structure of networks.

The theoretical basis for social network analysis is embedded theory. Embedded theory was first presented in Granovetter (1985), published in the American Journal of Sociology, and has developed significantly since that article. Its basic claim is that people are embedded in a network of connections with others, doing business within the scope of that network, and are therefore influenced by their relationships. Based on embedded theories, various theories have been proposed on the impact of network performance (Polidoro, et al., 2011).

Using social network analysis, various indicators that show the characteristics of the network's structure can be calculated (Borgatti, Everett and Freeman, 2002). One of the typical network indicators is centrality, and there are various types of centrality indicators. Centrality, in short, expresses the degree of social interaction. One of the earliest representative empirical studies of centrality indicators was the weak-ties hypothesis by Granovetter (1973). 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.

Among the various centrality indicators, betweenness centrality is a particularly strong indicator of centrality. Because betweenness centrality is a measure of centrality in a graph based on shortest paths. For every pair of vertices in a connected graph, there exists at least one shortest path between the vertices such that the number of edges that the path passes through is minimized. The betweenness centrality for each vertex is the number of these shortest paths that pass through the vertex. Freeman (1977) gave the first formal definition of betweenness centrality.

Therefore, in this study, we adopt betweenness centrality as a proxy variable for the level of centrality in the network. Therefore, the following hypothesis is derived.

H1. the higher the betweenness centrality in an organisation's cooperation network, the more the organisation's cooperation network grows.

Secondly, another prominent indicator in social network analysis is structural holes (Burt, 1995). This indicator can be said to represent something similar to the aforementioned betweenness centrality, although the method of calculation is different. Most social structures tend to be characterized by dense clusters of strong connections, also known as network closure. The theory relies on a fundamental idea that the homogeneity of information, new ideas, and behaviour is generally higher within any group of people as compared to that in between two groups of people （Burt, 2004）. The term ‘structural holes’ is used for the separation between non-redundant contacts. An individual who acts as a mediator between two or more closely connected groups of people could gain important comparative advantages. In particular, the position of a bridge between distinct groups allows him or her to transfer or gatekeep valuable information from one group to another (Burt, 1995). In addition, the individual can combine all the ideas he or she receives from different sources and come up with the most innovative idea among all (Burt, 2004). However, it is also noted that bridges can be fragile and unstable, as resources are required to maintain and expand links with a large number of heterogeneous groups. Therefore, the following hypothesis is derived.

H2. the larger the structural holes in the co-operation network of an organisation, the more the co-operation network of that organisation grows.

Next, among the centrality indicators, eigenvector centrality is also taken up as another indicator apart from the aforementioned betweenness centrality. Bonacich (1972) provides a definition and calculation method for eigenvector centrality and argues for its superiority as a centrality indicator in social network analysis. In network theory, it is pointed out that the magnitude of a node's influence in a network is not only determined by the number of nodes to which it is directly connected, but also by the kind of nodes to which it is connected. Eigenvector centrality is then a centrality index that reflects the centrality of the nodes to which it is connected to its neighbours, and compared to other centrality indexes, it is an index that considers the structure of the entire network.

In calculating Eigenvector centrality, relative scores are assigned to all nodes in the network based on the concept that connections to high-scoring nodes contributes more to the score of the node in question than equal connections to low-scoring nodes. A high eigenvector score means that a node is connected to many nodes who themselves have high scores （Newman, 2006）.

In cooperation networks, even if an organisation is not directly connected to a large number of organisations, if it is connected to a highly centralised organisation, it will be indirectly connected to the network as a whole, facilitating the collection and use of information. Therefore, the following hypothesis is derived.

H3. the higher the eigenvector centrality in an organisation's cooperation network, the more the organisation's cooperation network grows.

On the other hand, there are also theories that conflict with the above-mentioned utility of network breadth. Coleman (1988) argued for the efficacy of dense networks, which are networks of multiple relationships with each other, and proposed the concept of social capital. Because it is a closed network, mechanisms such as mutual trust, norms, mutual monitoring and sanctions are more likely to work. Krackhardt (1992) argued for the effective character of strong ties and claimed that strong ties are very important in severe changes and uncertainty. For example, weak ties are useful for collecting a wide range of information, but only standardised formal knowledge can be transmitted through superficially weak links. On the other hand, tacit information, which is useful in research and development, is unlikely to be transmitted without strong mutual trust. Therefore, the following hypothesis is derived.

H4. the higher the density in the co-operation network of an organisation, the more the co-operation network of that organisation grows.,

4 Research methods

In order to empirically test the aforementioned research hypotheses, the following data and analysis methods were used in this study.

4.1 Data

In this study, it is necessary to collect and analyse real data on the development and use of artificial intelligence in a comprehensive and as timely manner as possible. 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 under analysis was set at just over five years from 2018 onwards. However, for 2023, data up to April were included. This is because, although artificial intelligence technologies have been studied over the past few decades, it was only from around 2018 that the practical application of artificial intelligence technologies, mainly machine learning and deep learning, attracted attention and actual commercialisation by companies became active.

4.2 Method of analysis

As an analytical method, the characteristics of the co-operation network structure between organisations were analysed by quantifying them using the method of social network analysis, as described above. The steps of the analysis were carried out in the following order.

First, as the aim of this study was to analyse changes in the structure of the cooperation network, the database for analysis was divided into two parts, with data from 2018 to 2020 in the first half and data from 2021 onwards in the second half, to be compared. Incidentally, the period analysed in the first half, from 2018 to 2020, is the same as that of the author's previous study, Isada (2022).

Then, for each period, the characteristics of the structure of the co-operation network of each organisation were calculated using the network indicators described below, and the relationship with the size of each co-operation network was analysed statistically. The reason for analysing the size of the networks is that, as mentioned above, this study assumes that one of the success factors in the development and use of artificial intelligence is the expansion of the co-operation network. Therefore, the research goal is to clarify under what circumstances the size of the cooperation network increases.

Next, the differences in the network indicators of each organisation between the first half, 2018-2020, and the second half, 2021 onwards, were analysed statistically. The purpose is to clarify how the structure of the cooperation network is changing. As some organisations are only included in either the first or the second half of the period, the results of the analysis are considered to be affected by the differences in the distribution of the groups of organisations included in each period if the analysis of differences is carried out as it is. Therefore, in analysing the differences, only those organisations that existed in both the first and second half of the period were extracted for analysis.

Network indicators for characterising the structure of the cooperation network were selected based on each of the aforementioned hypotheses. Hypothesis 1 is the hypothesis on betweenness centrality, which was calculated based on Freeman (1977). Note that if the betweenness centrality is calculated as it is, it is simply affected by the size of the network, and as the size of the network increases, the value of the betweenness centrality tends to increase as well. Here, the values of the betweenness centrality were normalised in order to understand the characteristics of the network structure, so that they can be compared without being affected by the size of the network. Hypothesis 2 is a hypothesis about structural holes. In various studies after Burt (1992), structural holes were statistically analysed using log-transformed values of the degree of constraint, which was also followed in this study. The relationship is that the higher the degree of constraint, the smaller the structural holes. Hypothesis 3 is a hypothesis on eigenvector centrality, calculated in accordance with Bonacich (1972) and later studies. Hypothesis 4 is a hypothesis on the density of networks, and the density of the ego-network of each organisation was calculated according to the calculation method in graph theory. UCINet 6.7 was used to calculate the network indices, and IBM SPSS 29 was used for other multivariate analyses.

5 Analysis results

5.1 Number of data

Following the aforementioned extraction method, data were extracted for the first half, from 2018 to 2020, and the second half, from 2021 onwards, as shown in Table 1. First, the number of original newspaper articles and press releases totalled 1,804 for the first half and 2,126 for the second half. From these, the total number of inter-organisational cooperation combinations extracted was 1,921 for the first half and 2,272 for the second half. From these data, 1,713 and 2,097 were extracted as the number of organisations that had some kind of co-operation partner in the first half and the second half, respectively.

Table 1 Number of data extracted

	First half	Second half

Original article	1,804	2,126
Number of combinations	1,921	2,272
Number of organisations	1,713	2,097

5.2 Network indicators and network size

Next, network indicators were calculated for each of the first and second halves, considering each organisation as a node in the network. The network indicators calculated were nEgoBetween, Ln(Constraint), Eigenvector and Density, in the order of the aforementioned hypotheses.

Next, a regression analysis was conducted with network size as the objective variable and network indicators as explanatory variables. However, as there was a possibility of a strong correlation between each network indicator, a principal component analysis was conducted and the principal component scores were calculated prior to the regression analysis. As a result of the principal component analysis, two principal components with eigenvalues of 1 or more were extracted for the first and second halves, respectively. The component matrix of each principal component is shown in Table 2. Note that if each network indicator had a missing value, it was replaced by the mean value.

Table2 Principal component matrices of network indicators

	First half		Second half	
	First principal component	Second principal component	First principal component	Second principal component
nEgoBetween	-.948	-.262	-.966	-.091
Ln(Constraint)	.793	-.325	.802	-.073
Eigenvector	-.252	.926	-.119	.989
Density	.950	.256	.966	.091

As shown in Table 2, in both the first and second periods, the first principal component consisted mainly of the three indicators nEgoBetween, Ln(Constraint) and Density, and the second principal component consisted mainly of Eigenvector. Here, as mentioned above, nEgoBetween and Ln(Constraint) are based on similar theories of betweenness centrality and structural holes, respectively. Ln(Constraint) is an indicator of fewer structural holes and is considered to be more correlated with betweenness centrality. Density also expresses the degree to which the surrounding nodes are interconnected as a whole, and is considered to be highly correlated with the other two indicators.

Next, a multiple regression analysis was conducted using each of the principal component scores of the network indicators as explanatory variables and the network size as the objective variable. The results of the analysis are shown in Table 3.

Table 3 Regression analysis between network indicators and size

	First half	Second half
Regression coefficient of the first principal component	-1.024**	-.781**
Regression coefficient of the second principal component	2.263**	.829**
R-squared	.676	.200
F value	1783.794***	262.057***

(***: probability of significance <0.001, **: probability of significance <0.01)

5.3 Difference in network indicators

Next, a significant difference test was conducted between the network indicators of the first half and the second half. Note that 510 organisations were extracted that were included in both the first half and the second half, and They were included in the analysis and the corresponding sample t-tests were conducted. The results of the analysis are shown in Table 4, where significant differences were detected for all four indicators.

Table 4 Differences between network indicators in the first and second period

	Period	Mean	t-value (two-tailed test)
nEgoBetween	First half Second half	90.621 64.488	9.481***
Ln(Constraint)	First half Second half	1.064 -.891	4.293***
Eigenvector	First half Second half	.011 .005	2.725**
Density	First half Second half	9.22 5.60	2.009*

(***: probability of significance <0.001, **: probability of significance <0.01, *: probability of significance <0.05)

6 Discussion

Next, the aforementioned research queries are discussed based on the results of each analysis.

First, the results of the analysis of the relationship between each network indicator for the cooperation network and the size of the cooperation network indicate that the size of the cooperation network may be related to the network structure. The positive or negative sign of the relationship was invariant regardless of time period. A significant negative correlation was observed for the first principal component with network size. Among the network indicators comprising the first principal component, density and constraint were positively related to the principal component score, which is an indicator of the strength of the connections between the nodes of the network. The betweenness centrality, which had a negative relationship with the principal component scores, is an indicator of the extent of the connections. A significant positive correlation was observed for the second principal component with network size. The second principal component is mainly composed of eigenvector centrality, which is also a network indicator of the extent of the network.

The results of these analyses suggest that in inter-organisational co-operation on artificial intelligence, weak co-operation relationships are more likely to expand the network than strong co-operation relationships. In other words, for example, in the development of artificial intelligence, open and decentralised inter-organisational relationships are considered to be more conducive to co-operation than closed and integrated relationships. As a design concept for AI systems, it can be imagined that a design concept in which mutual interfaces are standardised and openness and mutual interaction are reduced is more desirable than a design concept in which special development is carried out in closed inter-organisational relationships. This feature of co-operation relationships does not differ between the first and second halves of the period, so it can be assumed to be a relatively stable feature of co-operation relationships related to artificial intelligence.

Next, the results of the analysis of the temporal changes of each network indicator showed that significant differences were detected between the earlier and later periods for each network indicator. It was also shown that the values of each indicator changed uniformly towards smaller values. The results of this analysis indicate that the overall trend of the network structure may be more decentralised than integrated. In other words, it is assumed that various co-operation networks are emerging and differentiating, rather than that a particular co-operation network is expanding more and more over time. The research question for this study was whether the large artificial intelligence-related cooperation networks held by so-called big techs such as GAFAM would become increasingly expanded and integrated, or whether the cooperation networks would become more diversified and decentralised. It can be inferred that the results of the analysis of this study point towards the latter trend.

Next, a complementary analysis of the results of the quantitative analysis is attempted based on the case studies of individual organisations. First, in the collected database for analysis, organisations with particularly large co-operation networks were extracted. The US big techs such as Microsoft, Google and Amazon formed huge co-operation networks in Japan, as in the US. In addition, major Japanese information and telecommunications-related companies such as Nippon Telegraph and Telephone (NTT), NEC, Hitachi, Fujitsu, KDDI, Softbank and their affiliates, so to speak, Japanese big tech companies, also occupy the top positions, and this trend is common in the first and second semesters. Another feature of the artificial intelligence-related industry in Japan is that automobile manufacturers such as Toyota Motor Corporation, Nissan Motor Co. are among the top-ranking companies. They are working on the development of technologies such as automated driving and connected cars based on artificial intelligence, and their high ranking is also constant.

On the other hand, unlike previous trends, a number of cooperation networks are being expanded by companies that are not in the so-called information and communication industry. For example, companies in the financial sector were developing fintech products and expanding their cooperation networks. Companies that at first glance do not seem to have any relationship with the development of artificial intelligence technology, such as general trading companies, advertising agencies and publishing companies, are also working on new business development and business transformation, and expanding their cooperation networks. In addition, some venture companies are also rapidly expanding their co-operation networks and are working to change the business models of existing companies in various industries. Other trends include diversification in terms of artificial intelligence technologies, such as the expansion of edge computing-based ventures, whereas big techs are expanding their operations in a centralised and integrated manner, mainly cloud-based. Thus, it can be inferred from the case studies that, at present, the co-operation networks related to artificial intelligence are becoming more decentralised, with new central companies appearing one after another.

7 Conclusion

The aim of this study was to empirically clarify the changes in the network structure of co-operation relationships between organisations with regard to artificial intelligence technology, which is now rapidly entering the diffusion phase in real business. For this purpose, actual information on co-operation relations related to artificial intelligence was collected, an analytical database was constructed and analysed quantitatively using the method of social network analysis. The first research question concerned the relationship between the structure of the co-operation network and the expansion of co-operation. The results of the analysis showed that the scale of co-operation tended to expand more in co-operation relationships with open and decentralised network structures than in co-operation relationships with closed and integrated network structures. This trend was stable regardless of the time period. The second research question concerned changes in the central organisation of the co-operation network. The results of the analysis showed a trend towards decentralisation of the cooperation network, both from the quantitative analysis results and from the case studies. However, the use of artificial intelligence in real business is only just beginning to spread and is expected to change in the future. In addition, as the analysis was conducted in Japan, there is a possibility that the analysis results may be biased by industrial characteristics specific to Japan. Therefore, continuous research and international comparisons are issues for the future.

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