Articles

日本大学生産工学部研究報告A
2022年12月 第55巻 第2号

A New Measure of Schumpeterian Competition in Assessing Research Competence : An Authorship Analysis Using Academic Literature Databases

*Yuji MIZUKAMI**

(Received April 18, 2022)

Abstract

This study focuses on the specialized fields of academic papers and attempts to classify them by comparing innovation strategies in research activities by country/region. In the analysis, the paper takes big data technology papers as its subject matter and develops a discussion by showing the fields of application and application of big data technology by country/region. Innovation in business administration can be viewed as an exploration of synergy effects through new combinations of existing knowledge and existing knowledge. In this paper, we apply the new framework of "management of both effects" as a classification method for the combination of existing knowledge. The "ambidexterity management" consists of two strategies: "exploration of knowledge," which seeks to combine new knowledge with different fields, and "exploitation of knowledge," which utilizes knowledge within a field or with a high affinity for it. The analysis in this paper consists of two steps. First, individual innovation capabilities are extracted based on the concept of "intrapersonal diversity" in the innovation strategy of Schumpeterian competition. Then, by building up those individual capabilities by region and country, the innovation capabilities by region, country, and other organizations are extracted. The analysis data is based on a three-year database of academic papers (2016-2018) from the top 10 countries in terms of the number of papers on big data technologies. The data are processed using the co-authorship analysis method proposed by the authors and the newly presented cross-disciplinary collaboration display method. The analysis results allow us to classify the styles of cross-disciplinary fusion in big data research into three patterns.

Keywords: Innovation, Knowledge Exploration, Intrapersonal Diversity, Research Capacity Assessment, Authorship Analysis

1. Introduction

This study examines and discusses each country's research promotion strategies from the perspective of inducing innovation by integrating different fields.

March (1991) defined "Exploration of knowledge" as the process of recognizing distant knowledge (new knowledge) and linking it with existing knowledge. It is the process of accumulating seeds of innovation (already known) for future consideration by the organization. From our perspective, analyzing "interdisciplinary collaborations" helps measure the "exploration of knowledge" of innovation strategies.[1)]

This study analyzes the "intrapersonal diversity" of Schumpeterian competition, which is an innovation strategy in three major types of interorganizational competition by Barney (1986)[2)]. Intrapersonal diversity is evaluated as an organization's competitiveness by accumulating an individual's intrapersonal diversity. This study is aimed at researchers, as they are considered to have high intrapersonal

*Department of Industrial Engineering and Management, College of Industrial Technology, Nihon University

diversity.

In this analysis, we first objectively define the fields of specialization and application of related authors from the perspective of co-authorship information using the analytical framework of Mizukami et al (2018)[3]. We then superimpose author information by country to show the connection of research fields by country. Specifically, the intrapersonal diversity of each researcher is grasped, accumulated, and evaluated as the organization's competitiveness. In this study, the analytical framework and its position in interorganizational competition are not yet clearly defined. It is defined as measuring the "intrapersonal diversity" of Schumpeterian competition, which is an innovation strategy. Next, the analytical framework of Mizukami and Nakano (2020) is used to quantitatively compare the research field connections[4]. In this analytical framework, hierarchical clustering and principal component analyses are used. Subsequently, the method for displaying cross-disciplinary collaboration is used, which is newly defined in this study, to show the connection patterns of research fields in a network graph. We apply these analyses to Big Data technologies, respectively.

For the study data, 3-year bibliographic data (2016–2018) from the top 10 countries in terms of the number of papers in big data technologies were included in the analysis.

2. Review of Related Areas

2.1 Types of Interorganizational Competition in Business Strategy

Barney (1986) stated that there are three types of interorganizational competition: industrial organization (IO), Chamberlainian, and Schumpeterian[2]. The analytical approach in this study provides a measurable framework for the concept of intrapersonal diversity in Schumpeterian competition. It also provides an extended framework for evaluating organizations' competitiveness by gathering information on intrapersonal diversity. In addition, the position of the analytical method in interorganizational competition was defined for the first time in this study. The following sections describe the characteristics of the Schumpeterian interorganizational competition to illustrate the position of the analytical method used in this study.

2.2 Exploration and Exploitation of Knowledge in Schumpeterian competition

In Schumpeterian competition, March (1991) defined ambidexterity as the importance of a considerably high balance between the activities of "exploration of knowledge" and "exploitation of knowledge" for an organization's long-term growth[1]. However, the organization is often biased toward "Exploitation of knowledge" activities and not "Exploration of knowledge" activities, resulting in the exhaustion of ideas. This phenomenon is defined as a "Competency trap." The difference in the characteristics of "Exploration of knowledge" and "Exploitation of knowledge" is cited as a factor that leads to an organization falling in to a state of competency trap. As "Exploration of knowledge" is an activity to recognize distant knowledge (new knowledge), acquiring these values systematically is challenging and involves risks. However, "Exploitation of knowledge" is an activity to combine existing knowledge, so the prospect is more certain and it is easier to plan the activity. When organizations seek short-term efficiency, they can benefit from proactively working on "Exploitation of knowledge." However, from a medium-to long-term perspective, March (1991) stated that without "exploration of knowledge," ideas will eventually dry up and innovation-type growth will slow down[1].

Organizations try to avoid falling into a competency trap by activating "exploration of knowledge." First, there is Chesbrough's (2003) Open Innovation, which seeks the source of knowledge from outside[5], and Rothaermel and Alexandre (2009) as an empirical study, who conducted a questionnaire survey on 4195 employees of 41 business units of 10 multinational companies[6]. The survey investigated whether they outsourced (procured externally) or produced internally using existing technologies while acquiring new technologies. The survey results showed that companies that used a balanced both in-house production and outsourcing when acquiring new technologies had higher ex-post return on equity (ROE) and the number of patents acquired.

2.3 Interdisciplinary Integration in Research Capabilities

Leydesdorff and Ivanova (2021) argued that policymakers often explore the effects of "synergy" when they seek "cross-disciplinary fusion," because crossing disciplinary boundaries is often needed to address problems[7]. This study discusses recent advances in the application and measurement of "cross-disciplinary fusion" and proposes an information theory-based method for measuring "synergy."

Such interdisciplinary approach in the field of academic studies include "joint research between different organizations," "joint research between different research fields," and "joint research through industry—academia—government collaboration."

Related studies on "joint research between different organizations" can be found in Mizukami et al. (2016)[8], who proposed a method for measuring these collaborations based on paper co-authorship, assuming that joint research within and outside the organization plays an important role in generating innovation to enhance its research capability. This method extends the concept of mediation centrality index of network theory to apply to organization theory, which allows for an aggregation of the connections within, outside, and inside the firm separately and the management of ease of information flow within and outside the organization, aiming at firms that innovate easily. This is an analytical framework for the "boundary spanner" presented by Leifer and Delbecq (1978)[9] and Ancona and Caldwell (1992)[10], and elaborated by Friedman and Podolny (1992)[11] using social network theory.

3. Analytical Methods

3.1 Visualization of the Organization's Research Capacity and Degree of Interdisciplinary Integration

Table 1 shows how the research areas in this study are classified based on the Essential Science Indicators Subject Areas (Clarivate Analytics, n.d.) in the Web of Science (WoS) Core Collection.

Mizukami et al. (2018) proposed deriving the field of expertise from authorship information for an objective definition[3]. Fig. 1(a) shows researcher A's field of expertise and its applications. If researcher A published two papers in mathematics (12), one in clinical medicine (4), one in economics and business (6), and one in general fields (15), his/her field of specialization is mathematics, with a 40% degree of concentration. If the degree of concentration is high, a researcher is considered to focus on research in his/her specialization field. Conversely, if the degree of concentration is low, a researcher is considered to apply research results in the specialized field to other fields.

However, the information of each researcher shown in **Fig. 1**(a) does not show the connection between each research field unless it passes through the researcher located at the center of the Fig., and the linkage is unclear. Therefore, in this method, we used a simplified indication method for reconstructing the information about each researcher into the information between the fields. Fig. 1(b) shows an example of the simplified indication methods and the connection between each field is clarified.

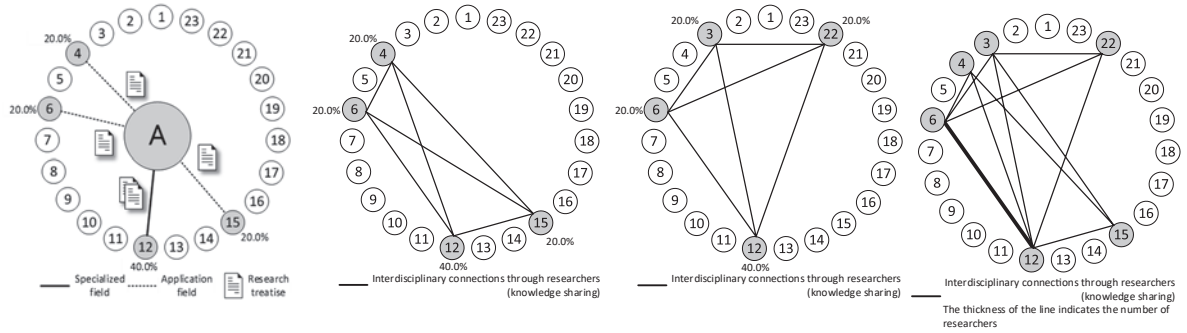
Fig. 1(b) shows the simplified field display method for researcher A. For example, clinical medicine (4) and mathematics (12) are connected through researcher A, and knowledge is shared. Thus, Fig. 1(b) shows how each field is linked through researcher A.

Next, Fig. 1(d) superimposes researcher A in Fig. 1(b) and researcher B in Fig. 1(c) to show the organization's research capabilities and cross-disciplinary integration. The thick line between business (6) and mathematics (12) in Fig. 1(d) represents the link between researchers A and B, while the thin line between the other fields are links through either researcher A or researcher B. Thus, the connections between

Table 1 Classification of Research Fields

#	Subject Area	#	Subject Area
1	Agricultural Sciences	13	Microbiology
2	Biology & Biochemistry	14	Molecular Biology & Genetics
3	Chemistry	15	Multidisciplinary
4	Clinical Medicine	16	Neuroscience & Behavior
5	Computer Science	17	Pharmacology & Toxicology
6	Economics & Business	18	Physics
7	Engineering	19	Plant & Animal Science
8	Environment/Ecology	20	Psychology/Psychiatry
9	Geosciences	21	Social Sciences, general
10	Immunology	22	Space Science
11	Materials Sciences	23	Arts & Humanities
12	Mathematics		

Note. Essential Science Indicators Subject Areas in the Web of Science Core Collection



a. Field indication of researcher A. b. Simplified field indication of researcher A. c. Simplified field indication of researcher B. d. Field display of organization (A + B).

Note. We used the bibliographic data of Web of science Core collection.

Fig. 1 Researchers' and an Organization's Fields of View

the disciplines via researcher A in Fig. 1(b) and researcher B in Fig. 1(c) are clearly shown. In the method for visualizing organizational research power and interdisciplinary integration, the connecting lines are thicker because of the understanding that knowledge sharing between disciplines is enhanced based on the number or ratio of mediating researchers. This chart of the organization's research capabilities and cross-disciplinary integration can be used for comparison between organizations.

3.2 Classification based on similarities in the interdisciplinary connections of organizations

Hierarchical cluster analysis method is commonly used for finding subgroups of multivariate data. This method creates a dendrogram based on the similarity of the items analyzed. The researcher can choose where to cut the dendrogram to create clusters. This method does not have a generally accepted stopping rule for researchers to find the best set of clusters (Zupic & Cater, 2015)[12]. Procedures for hierarchical cluster analysis include single, complete, average linkages, as well as Ward's method. Of these, Ward's method is the most frequently used for bibliometric analysis; McCain (1990) stated that both complete linkage and Ward's method produce similar interpretable results[13].

Research papers with high similarity in interdisciplinary connections of organizations are gathered and grouped. In the classification process, we conducted a hierarchical cluster analysis using interdisciplinary connections as a variable for each organization and visualized the results using a dendrogram. Ward's method was used to determine the distance between clusters (Fig. 3). This process is considered effective in simplifying the characteristics of each group when interpreting the results.

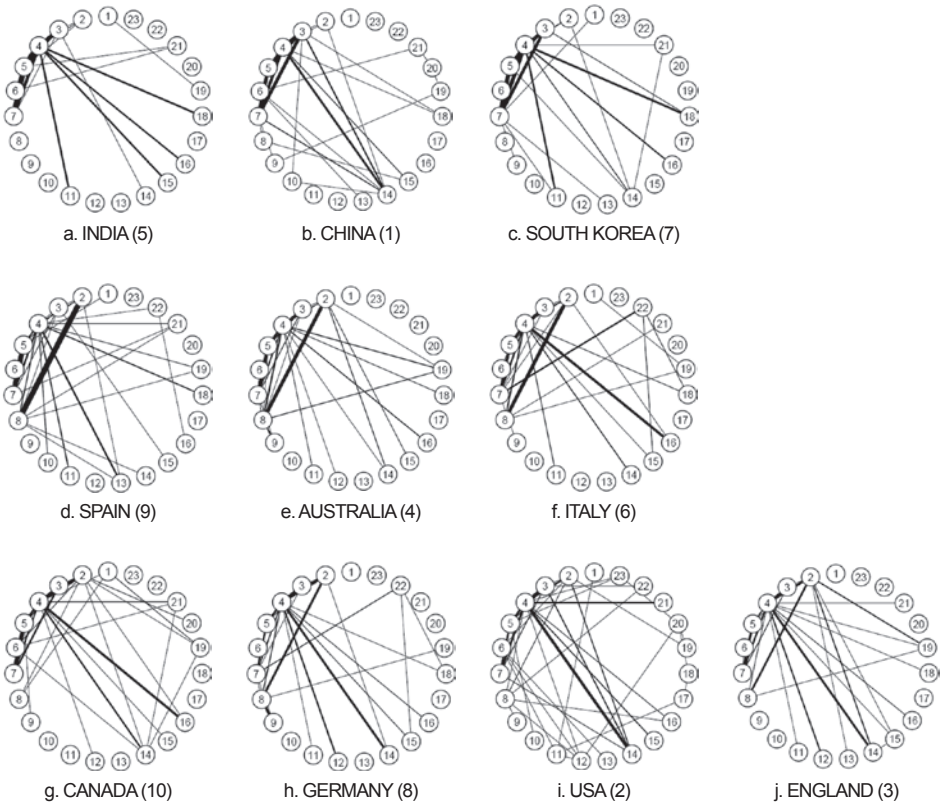
4. Analysis

4.1 Collected Data

The number of studies on big data continuously increased in 2018, to reach 6,054 respectively. We used the bibliographic data of Web of Science (WoS) core collection, which is the one of the biggest bibliographic databases. We have permission to use the Web of Science (WoS) Core Collection, a subset of which Clarivate Analytical Inc. provided to the Institute of Statistical Mathematics. This database has been optimized for bibliometric data analysis; using them, some unavailable items on the regular WoS site are accessible for analysis. However, due to contractual regulations, this database only contains data up to 2018 that we have used in our research.

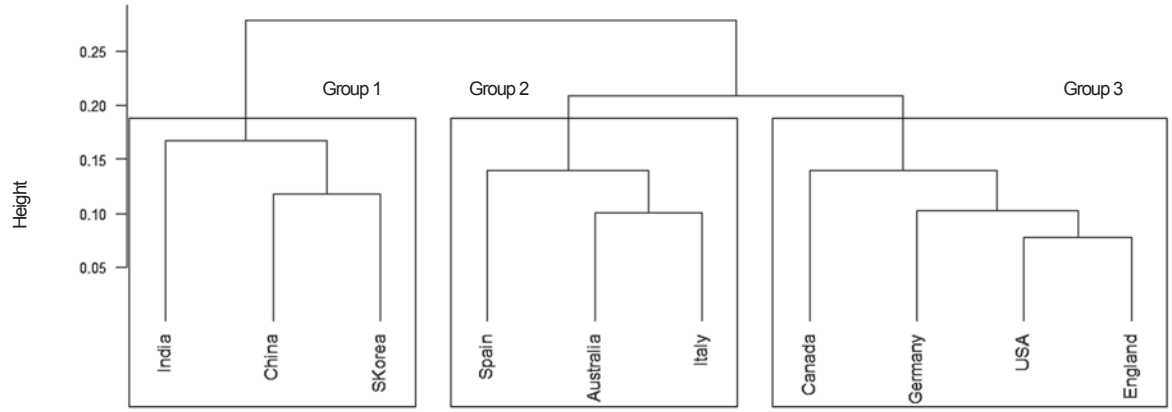
4.2 Analytical Methods and Results

Fig. 2 shows the connections between the research fields of the top 10 countries in terms of the number of big data papers, the top three being China, the United States, and England. China ranked first, with a complete network of chemistry, clinical medicine, and engineering (3–4–7); clinical medicine, computer science, and engineering (4–5–7); and chemistry, clinical medicine, and molecular biology and genetics (3–4–14). The United States ranked second, with clinical medicine, computer science, and engineering (4–5–7); chemistry, clinical medicine, and molecular biology and genetics (3–4–14); and biology, biochemistry, and chemistry (3–4–14). Biology and biochemistry, chemistry, and molecular biology and genetics (2–3–14) were complete networks. Clinical medicine and general social sciences (4–21) were also connected. The United States has a wide range of connections but none was strong. England, in the third place, has numerous connections, mainly in clinical medicine (4) and



Note: This indicates connections with a strength of 1% or more. We used the bibliographic data of Web of science Core collection.

Fig. 2 Connections between Author Research Fields in the Top 10 Big Data Countries (2018)



Note. Distance: hclust (*, "ward.D2"). We used the bibliographic data of Web of Science Core collection.

Fig. 3 Similarity Dendrogram by Country: Links between Author Research Areas in the Top 10 Big Data Countries

biology and biochemistry (2) and is considered to have many and wide connections with no exceptionally strong ones.

The interdisciplinary links of the top 10 countries were analyzed using hierarchical cluster, using countries as individuals and interdisciplinary links as variables and visualized using a dendrogram (Fig. 3).

In **Fig. 3**, the top 10 big data countries were classified into three groups for the ease of interpretation: Group 1 comprised India, China, and South Korea. Group 2 included Spain, Australia, and Italy. Group 3 consisted of Canada, Germany, the United States, and England.

5. Discussion and Conclusions

This study contributes to the Industrial development by identifying cross-disciplinary fusion patterns in big data based on Innovation theory.

Innovation is a thinking approach that creates new knowledge (value) from "a new combination of existing knowledge and existing knowledge," which Schumpeter called new combination in business administration. This study uses the definition of existing knowledge as an interdisciplinary field and considers new knowledge (value) created by fusion

of these disciplines as innovation. This study examines how each country is promoting research from the perspective of innovation. The analysis method includes measuring the "intrapersonal diversity" of Schumpeterian competition, which is an innovation strategy in Barney's three major types of interorganizational competition. Intrapersonal diversity is evaluated as an organization's competitiveness (in this study, a country/region) by accumulating intrapersonal diversity. For example, in Region A, if the disciplines of clinical medicine and computer science are strongly connected (many researchers are involved in research in both disciplines), the knowledge of these disciplines will be combined. In this case, it is likely that new value (knowledge) is created by fusing the knowledge of these disciplines.

The reader may wonder why this study did not focus on the development of each field instead of innovation-type development. These are the ideas of IO-type and Chamberlain-type competition in Barney's three major interorganizational competitions. However, both are suited to industries where the business environment is fairly stable and the future is reasonably foreseeable. However, the current business environment may be different. Globalization, deregulation, and, above all, rapid development and digitization of IT have accelerated change in the business environment. D'aveni (1994) refers to this environment as "hypercompetition," meaning that the type of competition is adapting to the Schumpeterian model[14]. This study attempts to gain knowledge on competitive strategies that are appropriate for this hypercompetitive economic situation.

This study categorized the styles of cross-disciplinary fusion into three patterns in big data. Group 1 comprised India, China, and South Korea, with a complete network of chemistry, clinical medicine, and engineering (3–4–7). Group 2 included Spain, Australia, and Italy, with a strong network of biology and biochemistry, and environment/ecology (2–8). Group 3 consisted of Canada, Germany, the United States, and England, with a strong network of clinical medicine, and molecular biology & genetics (4–14). These are considered to be the forms of innovation of those groups.

To summarize the results of this study, in Big Data-related research, Europe and the U. S. are considered to be advancing research that comprehensively combines biological knowledge, while Asia is advancing research that combines scientific and engineering knowledge, with a focus on clinical medicine. In addition, since there are no unexpected connections among the three groups, the results suggest that there is a strong tendency toward the deepening of knowledge.

The limitations of this study and directions for future research are discussed. The style of cross-disciplinary fusion presented in this paper is to examine patterns of connections among currently mainstream research fields and to discuss the exploration of knowledge and the exploitation of knowledge based on the specificity of these patterns. On the other hand, since the exploration of knowledge is a new endeavor, there could be a viewpoint of classifying knowledge by patterns focusing on weak connections and discussing the exploration of knowledge. A possible direction for future research is to discuss the exploration of knowledge by classifying by patterns focusing on weak connections.

Acknowledgments

This research is a project of the Interdisciplinary Innovation Research Group, College of Industrial Technology, Nihon University. This work was supported by JSPS KAKENHI Grant Number 17K04710.

References

1) March, J. G., Exploration and Exploitation in Organizational Learning. *Organization Science*, 2(1), 71-87 (1991). https://doi.org/10.1287/orsc.2.1.71
2) Barney, J. B., Types of Competition and the Theory of Strategy: Toward an Integrative Framework. *Academy of Management Review*, 11(4), 791-800 (1986). https://doi.org/10.2307/258397
3) Mizukami, Y., Honda, K. & Nakano, J., Study on research trends on the Internet of things using network analysis. *International Journal of Japan Association for Management Systems*, 10(1), 27-35 (2018). https://doi.org/10.14790/ijams.10.27
4) Mizukami, Y., & Nakano, J., Using the Academic Literature Database to Evaluate the International Interdisciplinary Fusion in IoT Research Through Coauthor Analysis. *Proceedings of the Institute of Statistical Mathematics*, 68(2), 265-285 (2020). (in Japanese).
5) Chesbrough, H., Open Innovation: The New Imperative for Creating and Profiting from Technology. Harvard Business School Publishing (2003).
6) Rothaermel, F. T. & Alexandre, M. T., Ambidexterity in Technology Sourcing: The Moderating Role of Absorptive Capacity. *Organization Science*, 20(4), 759-780 (2009). https://doi.org/10.1287/orsc.1080.0404

7) Leydesdorff, L. & Ivanova, I., The measurement of "interdisciplinarity" and "synergy" in scientific and extra-scientific collaborations. *Journal of the Association for Information Science and Technology*, 72(4), 387-402 (2021).
https://doi.org/10.1002/asi.24416

8) Mizukami, Y., Honda, K., Suzuki, S., Nakano, J. & Otabe, A., Co-author information and authors' affiliation information in scientific literature using centralities: The researchers who act as mediators between organizations. *International Journal of Japanese Association for Management Systems*, 8(1), 1-8 (2016).

9) Leifer, R. & Delbecq, A., Organizational/Environmental Interchange: A Model of Boundary Spanning Activity. *Academy of Management Review*, 3(1), 40-50 (1978).
https://doi.org/10.5465/amr.1978.4296354

10) Ancona, D. G. & Caldwell, D. F., Bridging the Boundary: External Activity and Performance in Organizational Teams. *Administrative Science Quarterly*, 37(4), 634-665 (1992).
https://doi.org/10.2307/2393475

11) Friedman, R. A. & Podolny, J., Differentiation of Boundary Spanning Roles: Labor Negotiations and Implications for Role Conflict. *Administrative Science Quarterly*, 37(1), 28-47 (1992).
https://doi.org/10.2307/2393532

12) Zupic, I. & Cater, T., Bibliometric methods in management and organization. *Organizational Research Methods*, 18(3), 429-472 (2015).
https://doi.org/10.1177/1094428114562629

13) McCain, K. W., Mapping authors in intellectual space: A technical overview. *Journal of the American Society for Information Science*, 41(6), 433-443 (1990).
https://doi.org/10.1002/(SICI)1097-4571(199009)41:6<433::AID-ASI11>3.0.CO;2-Q

14) D'aveni, R. A., Hypercompetition. Free Press (1994). ISBN-13: 978-0029069387.

研究能力評価におけるシュンペーター的競争の新たな指標
：学術文献データベースを用いた著者分析

水上祐治

要　旨

本稿は、学術論文の専門分野に着目して、研究活動におけるイノベーション戦略の国・地域別比較からその分類を試みるものである。分析では、ビッグデータ技術の論文を題材として、国・地域別のビッグデータ技術の適用・応用分野を示して考察を展開している。経営学におけるイノベーションとは、既存知と既存知の新たな組み合わせによるシナジー効果の探究と捉えることができる。本稿では、その既存知の組合せ方法の分類方法として、新たに「両効きの経営」のフレームワークを適用した。「両効きの経営」は、新たな知を求めて異分野との融合を求める「知の探索」、分野内または親和性の高い知を活用する「知の深化」の２つの戦略から構成されており、本稿では、その戦略の違いを抽出し考察している。本稿の分析は２段階で構成されている。まず、シュンペーター的競争のイノベーション戦略における「人的多様性」という概念を元にして個人のイノベーション力を抽出している。そして、それら個人の能力を地域・国別に積み上げることで、地域・国別等の組織別のイノベーション力を抽出している。分析データは、ビッグデータ技術の論文数上位 10 カ国の３年間の学術論文データベース（2016～2018 年）を使用している。データは、筆者らが提案した共著者分析法と、新たに提示した分野横断的な連携表示法を用いて処理している。分析の結果、ビッグデータ研究における分野横断的な融合のスタイルを３つのパターンに分類することができた。

Biographical Sketches of the Authors

Yuji Mizukami is a researcher with more than 10 years of experience in the field of empirical research on management theory and evaluation index development. Doctor of Business Administration. He is a professor at the Department of Management Engineering, College of Industrial Technology, Nihon University. He is also the founder of the Innovation Research Group of the Department of Industrial Engineering, Nihon University. He is also a board member of the Japan Society of Management Systems. He is also a board member of the Japanese Society of Hospitality Management.