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A Method to Identify Main Paths of Knowledge Diffusion for Collaborative Innovation Projects

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Abstract: The main paths of the knowledge diffusion network can reveal the important actors and diffusion process, which has an important significance in improving the efficiency of knowledge diffusion. Due to the independent path choice of project actors, knowledge diffusion networks show a dynamic characteristic in collaborative innovation projects. Taking into account this dynamic characteristic, dynamic main path analysis method for project context is proposed. The method, constructed by MATLAB simulation modeling, proposes calculation index and analysis strategies. Contrastive application of two main types of path analysis (the main path analysis method and dynamic main path analysis method) is carried out through a collaborative innovation project case, in order to verify the effectiveness and applicability of this method. The comparison results show that the main paths identified by the new method are more consistent with the actual main paths in knowledge diffusion practice, and the level of knowledge flow through main paths is higher. Therefore, our conclusion is that the dynamic main path analysis method proposed in this research has high applicability and accuracy for identifying the main paths in the collaborative innovation projects.

Keywords: dynamic main paths analysis method; main path analysis; collaborative innovation projects; knowledge diffusion; network

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1. Introduction

Knowledge diffusion in collaborative innovation projects is a key process for integrating knowledge resources from multiple parties to achieve innovation. The knowledge diffusion process in projects is affected by multiple actors, which means that it has high uncertainty [1]. Relying solely on the spontaneous behavior of the actors is not enough to achieve effective knowledge diffusion. In practice, the results of knowledge diffusion in projects are actually often difficult to meet the resource demand for innovation [2]. In collaborative innovation projects, there are multiple knowledge entities with complex and diverse knowledge resources, and the process of interaction of knowledge resources is often invisible and inaccessible during project implementation. Who is the important knowledge entity in the project? With whose knowledge should resources should be integrated? How efficiently do they diffuse knowledge? These questions are difficult to answer in project management practice. Main path analysis in knowledge diffusion can reveal the important knowledge entities and diffusion paths [3], which is of great significance to the effective governance of knowledge diffusion [4]. Therefore, a quantitative main path analysis method is proposed in this research for solving the practical problems of knowledge diffusion in collaborative innovation projects.

The dynamic nature of knowledge networks in collaborative innovation projects should be considered for the construction of analysis method. The knowledge diffusion process in projects is shown as the flow of knowledge among entities (i.e., project actors) by the dissemination and value-added of knowledge, with the purpose of the integration and innovation of knowledge [5,6]. Project knowledge, involved knowledge generated and used in the process of project implementation, is mainly attached to project actors [7]. That is, the process of knowledge diffusion is realized by the interaction of project actors [8]. The interactions of projects actors are shown as knowledge networks. Nodes of knowledge networks in projects represent the project actors, and network links represent the relationships among them, which are the potential paths for knowledge diffusion [9]. Knowledge diffusion in networks is realized by the spontaneous behavior of nodes. Any network nodes can relatively independently select the paths for knowledge diffusion [10]. This leads to some network relationships being hidden rather than selected as diffusion paths at some times. That is, the knowledge network in projects changes in the process of knowledge diffusion due to the path choice of nodes [11]. Therefore, the dynamic characteristic of knowledge networks is remarkable for main path analysis in the knowledge diffusion of projects.

Due to the dynamic of knowledge network in projects, the existing main path analysis methods are difficult to apply to project situations. Main path analysis (MPA) is a widely used method for analyzing main paths in existing research, generally oriented to the knowledge diffusion in citation networks, patent networks, etc. [12]. For example, scholars are employed MPA in citation networks for revealing knowledge interaction [12], key research issues [13] and knowledge evolution [14,15] in certain research fields. However, knowledge networks in projects are significantly different from citation networks, and it is difficult to apply MPA methods in the context of projects due to the dynamic characteristic. That is, the lack of applicable methods is the main obstacle for the study of main paths in the knowledge diffusion of projects. Therefore, a dynamic math path analysis method (for short named DMPA) is proposed in this research for the main path analysis in collaborative innovation projects.

The contribution of this research can be described as the following three aspects. Firstly, this study provides methods and ideas for analyzing the main paths of knowledge diffusion in project contexts. The new method enables the complex knowledge diffusion process to be analyzed, and the knowledge diffusion process can be demonstrated by quantitative data. The mechanism of the knowledge diffusion path selection process is revealed, which is of great significance for understanding the knowledge diffusion process of collaborative innovation projects. Secondly, the main path analysis method proposed in the research not only provides theoretical support for the subsequent analysis of the project knowledge diffusion process, but also expands the application scope of MPA methods in the field of knowledge diffusion research. Thirdly, the key project actors and diffusion process in project management practice can be extracted by the DMPA method, which is invaluable in developing targeted governance strategies. The method proposed in this research is of great significance for providing project managers with quantitative decision data to make knowledge diffusion process efficient and orderly.

Our research constructs a DMPA method for collaborative innovation projects by improving the existing MPA method. We employ a simulation to depict the dynamic knowledge networks in projects based on the path selection process of project actors. Then we suppose the dynamic index to evaluate the main paths, and then combine the three strategies to analyze the main paths of the knowledge diffusion in projects. In order to verify the applicability and effectiveness, the DMPA method is applied to a collaborative innovation project case compared with MPA method. The rest of this article is organized as follows. The "Theoretical Background" in Section 2 summarizes the existing research about main paths in projects and explains the theoretical basis of MPA. DMPA method is presented in the "Construction of Dynamic Main Path Analysis Method" in Section 3. The "Case Application of Dynamic Main Path Analysis Method" in Section 4 applies the DMPA method in a project case and compares the results of the two analysis methods (MPA and DMPA). Finally, the "Conclusions and Future Research" in Section 5 concludes the research and propose future research directions.

2. Theoretical Background

2.1. Main Path Analysis Method

The main path analysis method (MPA) is a primary method adopted by the existing research for identifying main paths in knowledge diffusion [16,17]. Application of MPA is mainly applied in the research of citation networks and patent networks. For instance, Yu and Sheng [18], Lathabai et al. [19] and Fu et al. [20] employed MPA to analyze main paths in citation networks and to reveal the development of research domain and evolution of knowledge. It follows that the MPA method is commonly used for main path analysis of static networks.

However, MPA is rarely applied in the issue of knowledge diffusion of collaborative innovation projects. Why the MPA method difficult to apply in the context of collaborative innovation projects is as follows. MPA is a method applicable to the path analysis in static networks based on the overall connectivity of network [16]. To be specific, calculation of the indicators (i.e., SPC) in MPA is based on the network structure, which is only related to the position of nodes in networks, without considering the influence of dynamicity. The network of knowledge diffusion in projects is dynamic along with project implementation [21]. Each node in the network (i.e., actors of project) can choose the diffusion paths due to a certain degree of autonomy [8]. As a result, the network formed in collaborative innovation projects at a certain time is composed of the paths selected by each network's nodes. In other words, the knowledge diffusion network of collaborative innovation projects is different at any time. Therefore, the MPA method is difficult to directly apply to the project knowledge network. A new main path analysis method should be proposed for the main path analysis of knowledge diffusion in the project context.

2.2. Existing Research about Knowledge Diffusion Main Paths in Collaborative Innovation Projects

In the existing research, it is generally agreed that knowledge diffusion is of great significance to the innovation goals in collaborative innovation projects [22,23]. In the beginning, scholars define how the knowledge diffusion process occurs in projects, and the internal mechanism of this process. It is generally believed that knowledge diffusion in projects that happens among project actors (i.e., the knowledge entities in projects) can be described by the interaction process of project actors [24,25]. And then some scholars explained this process from different theoretical perspectives. Based on resource dependence theory, Sanders and Wong [26] discussed how to choose partners for more efficient acquisition paths of knowledge resources. Based on the organizational context perspective, Ren et al. [27] analyzes the inter-project knowledge transfer within the project-based organizations. As the research progresses, scholars increasingly pay attention to knowledge diffusion based on the network perspective, mainly on the overall network structure, network relations and other issues. Xu et al. [2] explored the influence of network relationships' characteristics on diffusion efficiency in knowledge diffusion. And Mao et al. [1] compared the speed of knowledge growth in different network topology and proposed a suitable network structure for knowledge diffusion. It can be seen that scholars in the field of knowledge diffusion gradually pay attention to the influence of interaction path selection and network diffusion paths on knowledge diffusion. These studies provide a theoretical basis for further research of knowledge diffusion paths. And, this indicates that the path analysis for project scenarios is still in the initial stage.

Main paths of knowledge diffusion in projects reveal the important interaction process of knowledge entities, which is of great value for governance of knowledge diffusion. What needs attention is the complex system characteristics of the knowledge diffusion process in collaborative innovation projects [10]. In particular, multiple actors interact with each other and constantly adjust their behaviors, resulting in the continuous change of entire system over time [28]. It causes the knowledge network in projects to be different from other types of knowledge networks (i.e., citation networks and patent networks), and show significant dynamic characteristics [28]. This feature makes it difficult and more valuable to analyze the main paths of knowledge diffusion network in projects. Identification of main paths can analyze the key actors and diffusion process in knowledge diffusion process, which play an important role in understanding the mechanism of knowledge diffusion process [4]. It can be seen that the main paths of knowledge diffusion in collaborative innovation projects gradually received attention, and the important value of that has also been generally recognized. However, the study of main paths in projects has not been discussed deeply in the current research of knowledge diffusion.

Based on the above literature review, it can be found that: (1) the existing main paths method is difficult to apply in the context of collaborative innovation projects for the main path analysis of knowledge diffusion. (2) Due to the lack of an applicable main path analysis method, scholars are less involved in the study of knowledge diffusion paths in collaborative innovation projects. Therefore, it is necessary to propose a new main path method suitable for the context of collaborative innovation projects.

3. Construction of Dynamic Main Path Analysis Method

3.1. Theory Construction

Considering the characteristics of projects contexts, a dynamic main path analysis method (DMPA) is constructed using for reference the MPA method. Theory construction mainly consists of two parts. To begin with, dynamic search paths count of each network link should be defined and measured. Then, path search strategies are constructed to identify the main paths accordingly [29]. The process of theoretical construction will be described in detail below.

(1) Dynamic search paths count (DSPC) is proposed to calculate the search times of network links in collaborative innovation projects. The SPC value in MPA is obtained by analyzing the connectivity of the network [29]. However, the path choice of actors in collaborative innovation projects is dynamic [30,31], so it cannot be analyzed only based on static network connectivity. Thus, DSPC is proposed to calculate the real-time search times of network links for collaborative innovation projects.

DSPC of a network link is the times that all diffusion paths from all source points (i.e., knowledge senders) to all sink points (i.e., knowledge receptors) traversed through the link before a certain moment of knowledge diffusion process [3]. The calculation of DSPC value needs to analyze all diffusion paths in network at all times, so we depict the dynamics process of path selection in knowledge diffusion by simulation. Modeling simulation is an effective method to describe and solve complex system problems by abstracting and simplifying the real world. Thus, a simulation model is constructed to describe the dynamic path selection process of knowledge diffusion in projects [1]. Our model is constructed using for reference the existing knowledge diffusion model [30], based on the characteristics of collaborative innovation projects. The detail of the simulation model is shown in the section "method implementation".

(2) Dynamic path search strategies are proposed in DMPA, which are dynamic local search, dynamic global search and dynamic key-route search [16,18]. We redefined the meaning of the three analysis strategies and explained their management implications in the project context.

To begin with, source and sink in the network should be refined according to the difference between project networks and citation networks. Knowledge usually flows from a project actor with high level of knowledge to another project actor with low level of knowledge in the process of knowledge diffusion [1]. Therefore, the node with highest level of knowledge in network that only diffuses knowledge to other nodes (that is, the in-degree is zero) is the source of network, the node with lowest amount of knowledge that only accepts knowledge without diffusing knowledge to others (that is, the out-degree is zero) is the sink of network. Knowledge in network flows from the source to the sink.

Dynamic local search, starting from the sources in network, refers to always selecting the link with the highest DSPC value as the next link to the sinks in the process of forming main path. Dynamic global search refers to the main paths from sources to sinks with the highest sum of DSPC in the selected paths. Dynamic critical path search strategy is to avoid the main path analyzed by local search and global search losing important links during knowledge diffusion process. Dynamic critical path search is one of the important strategies for analyzing main paths of knowledge diffusion, which includes the key actors and their links in the knowledge diffusion. A link with high DSPC indicates that two nodes of the link have a high frequency of knowledge diffusion, and the two nodes are key knowledge entities in project. The main paths by dynamic key-route search are obtained starting from the link of highest DSPC value and selecting the links forward and backward.

In summary, the theory of DMPA method is constructed based on two aspects. More specifically, DSPC is proposed to measure the search times of network links and three analysis strategies of main paths were redefined for searching main paths, correspondingly. The following parts of the article will realize the method by modeling and simulation based on the theoretical basis.

3.2. Method Implementation

(1) Calculation of dynamic search paths count

DSPC value of network links can be calculated by simulating the path selection process of project's actors in knowledge diffusion. Assuming that actors participating in knowledge diffusion are denoted as N, network links among the actors are denoted as E, and the network formed by them can be expressed as a graph G, G = (N, E), N = (1, 2, 3 . . . , n), E = (e_1, e_2, . . . , e_l). The knowledge level of node i is denoted as k_i.

Path selection can be shown by depicting the behavior of knowledge searching and knowledge sharing [8,32]. These two behaviors of each node iterate continuously, forming the entire path selection process in network. The process in the project can be described in detail as follows. If node i in the network is a project actor, node i will select the most knowledgeable one as the knowledge sender from the nodes connected to it, according to the behavioral characteristics of knowledge searching in project practice [8]. Assuming that node j is the neighbor node with the largest amount of knowledge, subsequently, node j, as the knowledge sender, will share knowledge with the knowledge receptor i. Then, the knowledge receptor i absorbs the knowledge shared by the knowledge sender j, which leads to an increase in its own knowledge level [30]. In the time interval [t, t + 1], the knowledge level of the knowledge sender j and the knowledge receptor i are changed with the diffusion process, expressed by Equation (1) and Equation (2), respectively. If there is no diffusion in the network at time t, that is, $k_j(t) - k_i(t) \leq 0$, the actors' search behavior ends and the system reaches a stable state. In addition, the knowledge diffusion process only occurs during project implementation, so the knowledge diffusion process ends when the project ends [23]. Assuming that project time is T, when the model runs at time $t \geq T$, the simulation process stops.

$$k_j(t+1) = k_j(t) \tag{1}$$

$$k_i(t+1) = k_i(t) + \alpha_{i,j}\beta_{i,j}[k_j(t) - k_i(t)], 0 < \alpha_{i,j}, \beta_{i,j} < 1 \tag{2}$$

where, $k_i(t)$ and $k_j(t)$ are the knowledge level of node i and node j at time t, respectively, $\alpha_{i,j}$ represent the willingness of node j to share knowledge with the node i, and $\beta_{i,j}$ represents the absorptive capacity of node i to the knowledge of node j.

Dynamic search paths count (DSPC) of each link in network is recorded during the process of knowledge diffusion. If there is a link between node i and node j in the network, the times of knowledge flowing through the link i-j at time t is denoted as $c_{ij}(t)$. DSPC value of link i-j is the sum of flow times before a certain moment of diffusion process, which is calculated by Equation (3). DSPC is an indicator that reflects the importance of a link in knowledge diffusion process, indicating the extent to which a link contributes to efficiency.

The larger DSPC of a link between two nodes, the more times knowledge flows through the link during diffusion process.

$$\text{DSPC} = \sum_{0}^{T} c_{ij}(t)(i,j = 1,2,\cdots,n) \tag{3}$$

where $c_{ij}(t)$ is the amount of knowledge flow through the link *i*-*j* at time t, and T is the total simulation time.

(2) Mechanism of main path analysis strategies

Three dynamic analysis strategies (dynamic local search, dynamic global search and dynamic critical path search) are employed, based on the DSPC value output by the simulation process. The network in Figure 1 is taken as an example to simulate the three main path analysis strategies. Assuming that nodes in the network are denoted as Ø, Ø = (A, B, C . . . , P). Among them, node A, B, C, and D in the network are sources of the network, and node M, N, O, and P are all sinks. DSPC value of each link are outputted by simulation of path selection, denoted as $C = (a,b,c,d,e)(a < b < c < d < e < f)$, shown in Figure 1.

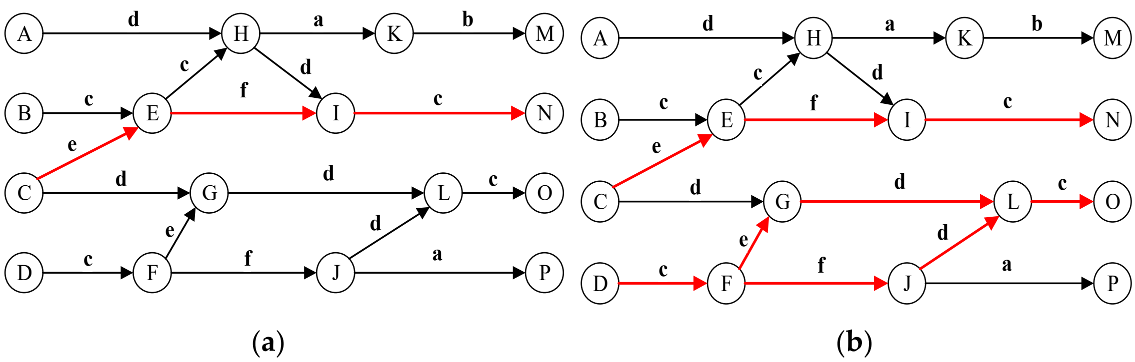

Figure 1. A graph showing how to analyze main paths by dynamic local search strategy. Circles with letters A, B, C . . . , P are nodes in the network, among them, node A, B, C, and D in the network are sources of the network, and node M, N, O, and P are all sinks. The paths composed of red links are the main paths identified by dynamic local search strategy. (**a**) Dynamic forward local search strategy, (**b**) dynamic reverse local search strategy.

The mechanism of dynamic local search strategy can be elaborated as follows. Dynamic local search in project is to select the link with largest DSPC as next link each time. That is, the main paths selected by dynamic local search strategy are the paths with the maximum sum of DSPC. For example, Figure 1a is the main path formed by forward dynamic local search. Staring from the sources, link C→E has the largest DSPC value among the links connected to the source (A, B, C, D). Along with the link C→E, the link with largest DSPC is selected step by step, that is E→I and I→N, and until the sinks (M, N, O, P). Thereby, a main path is generated by forward dynamic local search, namely C→E→I→N. In addition, Figure 1b shows the main paths searched by the reverse dynamic local search strategies. Let the sinks (M, N, O, P) be the starting points searching for main paths, we select the links N→I and O→L with the largest DSPC, and continue to select the link I→E as the outgoing edge from node I, until it arrives at the source node. Starting from node L, the links L→G and L→J with the largest DSPC value are reversely selected, which have the same DSPC value. Finally, three main paths are identified by the strategy of reverse local search based on DSPC, that is C→E→I→N, D→F→G→L→O and D→F→J→L→O.

The path with the highest DSPC generated in all diffusion paths is selected as the main path by dynamic global search strategy. DSPC values of all paths are added for selecting the path with largest one as the main path by dynamic global search strategy. The path D→F→J→L→O is the one with the largest DSPC among all diffusion paths.

Through dynamic forward and reverse searches, main paths are obtained starting from the links with high DSPC. Dynamic critical path search strategy avoids the main path analyzed by local search and global search losing important links during knowledge diffusion process. The top two links with high DSPC in the network are E→I, F→J, C→E and F→G. Starting forward and reverse search with these four links, links with the largest DSPC are selected as the outgoing edges, until it reaches the sources and sinks, separately.

Calculation of dynamic search paths count and the mechanism of three dynamic main path analysis strategies, shown in this section, are realized through computer programming using software MATLAB R2021b. In the following article, our research will apply DSPC method on a project case for verifying the applicability and effectiveness in the context of collaborative innovation projects.

4. Case Application of Dynamic Main Path Analysis Method

This section will be a case application of a collaborative innovation project adopting the DMPA method. There are two purposes of the case application. Firstly, the process and results of the application of the DMPA method can be shown clearly. Secondly, it can be verified that the new method (DMPA) proposed in this research is applicable in collaborative innovation projects and the application results can be compared with that of MPA method.

4.1. Data Source

Data come from a mega collaborative innovation project in China for technology research and development—"Key Technology and Industrialization of Insulated Containers on the *Belt and Road*"—as a research case. The project task is the research and development of insulated containers for the transportation on the Belt and Road. In order to successfully achieve the R&D goal of insulated containers, the project brought together a number of participants, including scientific research institutes, universities, suppliers, manufacturers and others. It is expected that by integrating the knowledge resources of these participants, the technical difficulties in the R&D process can be solved, and the development of insulated containers can be realized and put into the market. This project has successfully obtained a national technology patent, which is a knowledge-intensive collaborative innovation project. Therefore, main path analysis of the knowledge diffusion process in the project is highly representative and suitable as an application case.

Our research constructs the initial knowledge network mainly based on the work breakdown structure (WBS) and responsibility allocation matrix (RAM) of project [33]. The initial knowledge network will certainly change due to the path selection of project actors. First of all, the network nodes for knowledge diffusion can be identified by the WBS and RAM, that is, all project actors participating in the knowledge diffusion. Based on WBS and RAM of the case, we identified 38 important project actors participating in the knowledge diffusion, including project owners, management consultants, equipment manufacturers, material suppliers, colleges, research institutions, designers, engineers, contractors, production companies, users, etc. Thus, these 38 project actors are denoted as 38 network nodes in the network. Secondly, identifying the relationships among actors based on the RAM of project. Incidentally, the relationships identified are the potential knowledge diffusion paths, not the real diffusion paths, and the real diffusion paths can be obtained through the simulation of the knowledge diffusion of the project. To be specific, if there is a direct relationship of task collaboration between two actors, which is expressed as "1" in the adjacency matrix, otherwise it should be expressed as "0". The directions of the network relationships are determined by the knowledge level of nodes at both ends of the link. Specifically, if there is a relationship between two nodes, the direction of network link is from the node with high level of knowledge to that with low level of knowledge.

The knowledge level of project actors in a network can be quantified by the experts' grading method. The grades evaluated are mainly based on papers, topics, patents and project experience of each actor [2]. The range of knowledge level in the case is set as [1,10] in our model, using for reference of the existing simulation models [1,32,34], and experts score the knowledge level of each actor in this range. Following the operation process of expert grading method, we invited 15 experts including five experts in the field of knowledge management, five experts in the project management field, and five mangers in charge of the project. Among them were experts in the field of knowledge and project management are all from colleges and universities with more than 10 years of research experience in this field. Firstly, initial evaluation of knowledge level of actors was made by all experts based on papers, topics, and works of actors. Then, we distributed the project files to experts about the performance of actors in the project for deepening the understanding of knowledge level of each actor. After that, we once again invited all experts to revise the initial scores of all actors. The knowledge level of each actor was obtained by taking the average value of 15 scores.

Then, source nodes and sink nodes of the case should be identified before main path analysis. According to the definition of source and sink in DMPA, the node with the highest level of knowledge that only diffuses knowledge to other nodes is the source in the network, the node with the lowest amount of knowledge that only accepts knowledge without diffusing knowledge to others is the sink of the network. Through social network analysis method, in-degree and out-degree of the network nodes are analyzed. The analysis results show that the nodes with an in-degree of 0 are N12 and N30, the nodes with an out-degree of 0 are N5, N21, N26. Based on the knowledge level of network nodes, the knowledge level of N12 and N30 are highest and the knowledge level of N5, N21, and N26 are lowest in the network. That is, N12 and N30 are the sources, N5, N21, and N26 are the sinks.

The practical role of the source and sink in the case are also confirmed through in-depth interviews with the project manager. In the case practice, it is found that N12 and N30 are the project actors from universities and research institutes, respectively, who are responsible for the development and transformation of the container's insulation technology. These two project participants are responsible for the knowledge diffusion of insulated containers' technologies to the other participants, and for the joint knowledge transformation and technology innovation. These two nodes do assume the role of knowledge source in the implementation of the project. In addition, N5 and N21 are two material suppliers, and N26 is the manufacturer of containers in practice. These three participants are mainly involved in the final implementation phase of the project, responsible for gaining technical solutions from other participants and implementing them. In other words, the main task of N5, N21, and N26 is to absorb the knowledge resources passed on by the other participants, and they are not responsible for transmitting knowledge outwards. In addition, other nodes of the case, except for the sources and sinks, all show the behaviors of receiving knowledge from others and transmitting knowledge to others.

Subsequently, our research uses software MATLAB R2021b for realizing network construction, outputting DSPC values and analyzing main paths. Initial knowledge network in the case is shown as Figure 2. The network relationships constructed are potential paths for knowledge diffusion in project, but the actual paths need to be obtained by simulating the dynamic process of knowledge diffusion in the case. The project data and knowledge level of nodes are inputted as the initial data in the simulation model for obtaining DSPC value of network links. Subsequently, dynamic local search, dynamic global search and dynamic critical path search based on DSPC value are performed to extract main paths of knowledge diffusion in the case. The following part of article will compare and analyze the application process and results of the two main path analysis methods (MPA and DMPA).

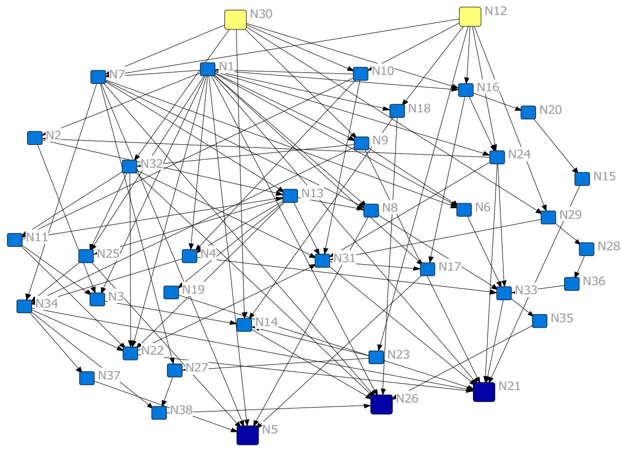

Figure 2. Initial knowledge diffusion network based on work breakdown structure (WBS) and responsibility allocation matrix (RAM) of the project case. The yellow nodes are sources and the dark blue nodes are sinks.

4.2. Contrastive Application of Two Main Path Analysis Methods

Contrastive application of two main path analysis methods, MPA method and DMPA method, are applied to the project case for discussing the applicability and effectiveness in the context of collaborative innovation projects.

(1) Application of MPA method

The MPA method is employed to analyze main paths of project case (Figure 2). We used software MATLAB R2021b to obtain the main paths by local search, global search and critical path search, shown in Table 1. The sources are N12 and N30, and the sinks are N5, N21, N26. Three analysis strategies (global search, local search, critical path search) are adopted for analyzing main paths separately. The links with the largest SPC that from the sources to sinks are N10-N1 and N17-N5 according to the simulation results. Starting with the two links, forward researching and reverse searching in critical path search strategy are performed to obtain the main paths, respectively.

Table 1. Results of MPA method.

Analysis Strategies	Results of Main Path Analysis
Global search	N12-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N17-N5 N30-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N15-N5
Local search	N12-N10-N1N-9-N32-N11-N13-N25-N34-N22-N31-N17-N5 N12-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5 N30-N10-N1-N9-N32-N11-N13-N25-N34-N22-N31-N17-N5 N30-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5
Critical path search	N12-N10-N1-N9-N32-N11-N13-N25-N34-N22-N31-N17-N5 N12-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5 N30-N10-N1-N9-N32-N11-N13-N25-N34-N22-N31-N17-N5 N30-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5 N12-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N17-N5 N30-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N17-N5

(2) Application of DMPA

Similarly, our research again adopts the DMPA method for analyzing the main paths of knowledge diffusion in the case. First of all, we inputted project data into the model, and used MATLAB to simulate the dynamic process of knowledge diffusion. The actual paths for knowledge diffusion in the project are shown in Figure 3. The DSPC value of each link in the network is obtained by running the simulation model. The thickness of the network links is to clearly show the relative size of the DSPC value in Figure 3 (the network link with a DSPC value of zero is not shown in the figure). It can be found from Figure 3 that the paths actually selected by actors are quite different from the paths in the initial network (shown in Figure 2). That is to say, the DSPC of many links in in the initial network are zero. For example, link N17-N5 is an important link based on SPC in MPA method, however, the DSPC value of N17-N5 is zero, that is, no actors choose it for knowledge diffusion in actuality. On the contrary, it can be seen that link N7-N5 has a large DSPC value in Figure 3, which means that the actors selected the link multiple times during the knowledge diffusion process; however, N7-N5 is not an important network link based on SPC.

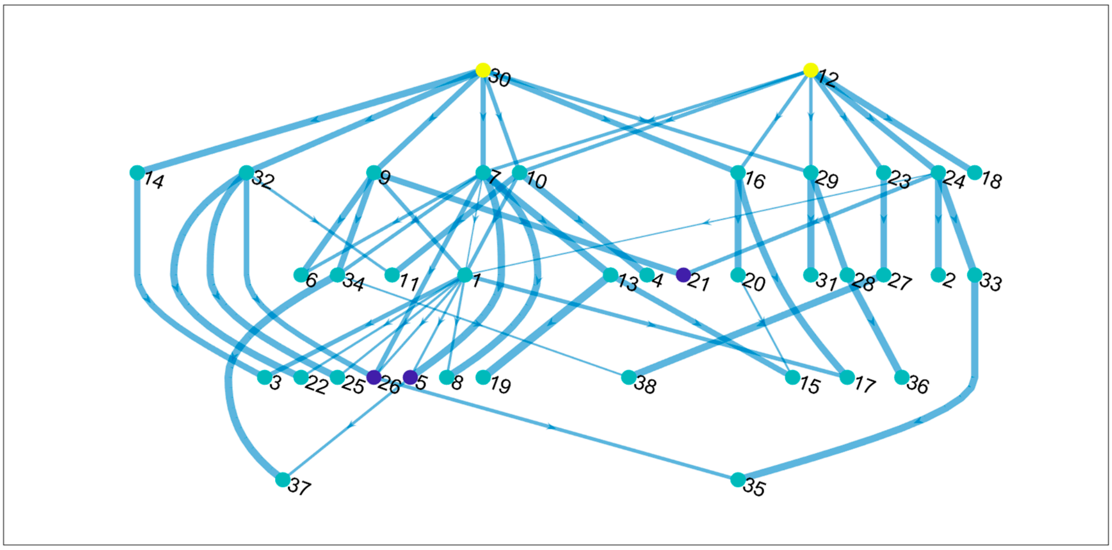

Figure 3. Dynamic search path counts of network links in the case are outputted by application of dynamic main path analysis method. The dots labelled with numbers 1, 2, ..., 38 correspondingly represent nodes N1, N2, ..., N38 in the network. The yellow nodes are sources and the dark blue nodes are sinks.

Secondly, the main paths are obtained by the three search strategies (dynamic local search, dynamic global search and dynamic critical path search), which is shown in Table 2. Among all paths from sources to sinks, path N12-N7-N5 is the most frequently selected one for knowledge diffusion, which is the main paths obtained by dynamic global search. The path N12-N24-N21 is obtained by forward dynamic local search, selecting the optimal DSPC value each step from the sources. The path N12-N7-N5 is the result of reverse dynamic local search, selecting the links with optimal DSPC starting from the sinks. The main paths by dynamic critical path search are selected starting from N7-N5, N12-N24, N30-N32 as key paths.

Table 2. Results of DMPA method.

Search Strategies	Main Paths
Dynamic Global Search	N12-N7-N5
Dynamic Local Search	N12-N24-N21 N12-N7-N5
Dynamic Critical Path Search	N12-N7-N5 N12-N24-N21 N30-N32-N26

4.3. Analysis and Discussion

In order to test the effectiveness and applicability of DMPA method, the results of two main path analysis methods in knowledge diffusion will be compared in this section. Main paths are the key paths for knowledge diffusion, that is, the amount of knowledge flow through paths is the key index for evaluating the importance of paths in project. By counting the amount of knowledge transmitted through links included in main paths during the diffusion process, the total amount of knowledge successfully diffused on each main path can be calculated. Assuming that a main path includes m links, the amount of knowledge transferred through one of a link is k_l, and total amount of knowledge flowing through the path, denoted as K_p, can be calculated by Equation (4).

$$K_p = \sum_{l=0}^{m} k_l \tag{4}$$

First, this study uses the MATLAB to output the value of k_l (the amount of knowledge successfully transferred) of each link in the network (Figure 4). The thickness of network link in Figure 4 indicates the level of knowledge flow. Significantly, the links with no knowledge flows through in the network are not shown in Figure 4, that is, k_l of the links are 0. It is worth noting that the diagram of knowledge flow (Figure 4) is highly consistent with Figure 3, no matter whether the network structure and relationships of the two diagrams are basically the same. For example, the knowledge flow through link N7-N5 is relatively large and consistent with the level of DSPC. Or, there is indeed no knowledge flow through link N17-N5 in the knowledge diffusion process.

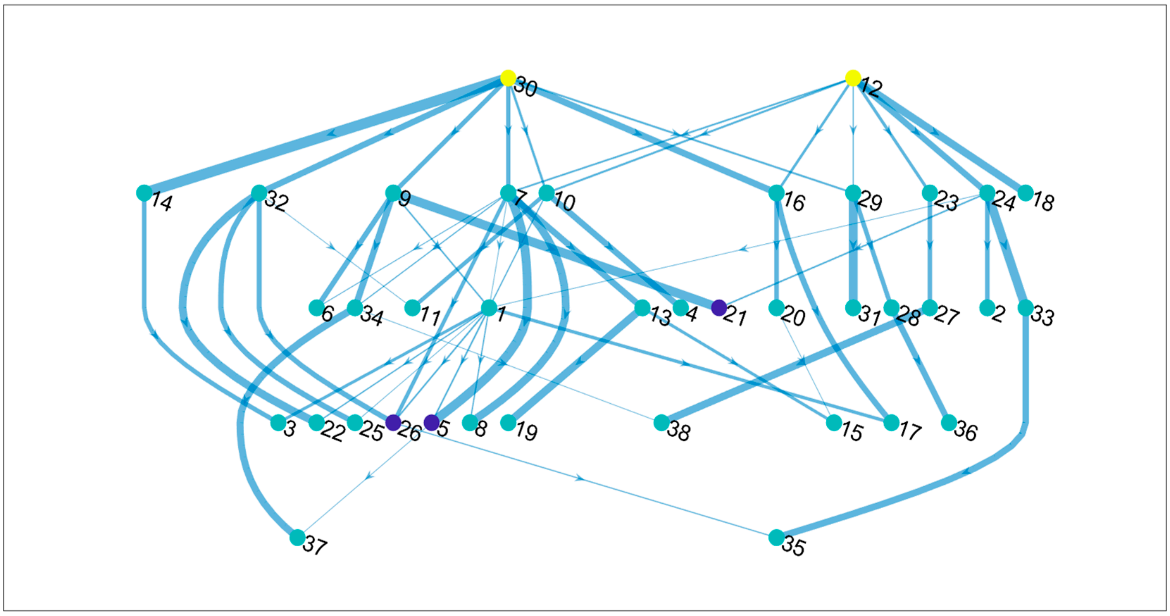

Figure 4. Amount of knowledge flowing through network links during knowledge diffusion in the project case. The dots labelled with numbers 1, 2, ..., 38 correspondingly represent nodes N1, N2, ..., N38 in the network. The thickness of network links indicates the level of knowledge flow. The yellow nodes are sources and the dark blue nodes are sinks.

Second, we calculated the total knowledge K_p flowing through main paths identified by the two main path analysis methods, respectively. Then, we averaged the K_p values of multiple main paths under the three analysis strategies (global search, local search and critical path search). The results are shown in Table 3.

Table 3. Comparison of knowledge flow through main paths.

Search Strategies	MPA Method		DMPA Method	
	Main Paths	K_P	Main Paths	K_P
(Dynamic) Global search	N12-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N17-N5	5.4	N12-N7-N5	10.56
	N30-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N15-N5	4.16		
(Dynamic) Local search	N12-N10-N1N-9-N32-N11-N13-N25-N34-N22-N31-N17-N5	6.62	N12-N24-N21	5.16
	N12-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5	8.41		
	N30-N10-N1-N9-N32-N11-N13-N25-N34-N22-N31-N17-N5	5.38	N12-N7-N5	10.56
	N30-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5	8.17		
(Dynamic) Critical path search	N12-N10-N1-N9-N32-N11-N13-N25-N34-N22-N31-N17-N5	6.62	N12-N24-N21	5.16
	N12-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5	8.41		
	N30-N10-N1-N9-N32-N11-N13-N25-N34-N22-N31-N17-N5	5.38		
	N30-N10-N1-N9-N32-N11-N13-N25-N34-N37-N5	8.17	N30-N32-N26	8.79
	N12-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N17-N5	5.4		
	N30-N10-N1-N16-N24-N2-N13-N25-N34-N22-N31-N17-N5	4.16		

The average K_p values of the three analysis strategies in DMPA method were 10.56, 7.86, 6.98, and the average K_p values of that in MPA method are 4.78, 7.15 and 6.36. In contrast, the main paths identified by the DMPA method successfully transferred more knowledge than the main paths identified by the MPA method, although the main paths by MPA method contains more links. That is, the analysis results by DMPA method are more accurate than that by MPA method in the project case.

In addition, comparing the main paths identified by two methods, it is found that effective knowledge diffusion cannot happen on the main paths identified by the MPA method. For example, the link N1-N16 is a key link in the network based on SPC, and the knowledge level of N1 is higher than that of N16, so a diffusion process occurs theoretically. However, N16 is not only connected to N1 in the network and also connected to N12 (shown in Figure 2). According to the path selection of actors in knowledge diffusion, knowledge receptors will select the node with the largest knowledge difference from the nodes directly connected for knowledge searching. As the knowledge level of N12 is much larger than that of N1, N16 will tend to select N12 for more efficient knowledge searching and the amount of knowledge transferred through the link N1-N16 is 0 (Figure 4), which is consistent with the result of DSPC value (Figure 3). Similarly, the links N2-N13, N22-N31, N17-N5 that included in the main paths identified by MPA method are also not actually diffused knowledge.

In order to verify the practical value of main path analysis results, we showed the results obtained by two methods to the project manager of the case, and again interviewed the project manager. The project manager also stated that the main paths of knowledge diffusion identified by DMPA method were closer to the actual situation of the project, and had higher accuracy than the results of MPA method.

Therefore, comparing results of the two analysis methods, it can be seen that the DMPA method has the following advantages in the main paths identification of collaborative innovation projects. First, the DMPA method, in collaborative innovation projects, has a higher accuracy than MPA method. By comparing the amount of knowledge diffused through main paths, it is found that the main paths identified by the DMPA method are more efficient in the actual diffusion process and indeed play a more important role. Therefore, the DMPA method has higher accuracy than the MPA method for analyzing the main paths in projects. Second, the DMPA method is more applicable in the context of collaborative innovation projects. Specifically, the results by the MPA method are only the main paths in theory, not the actual paths in knowledge diffusion. Main paths identified by the DMPA method are indeed the key paths for knowledge diffusion in projects. Therefore, the analysis results of the DMPA method have stronger practical value and better applicability in the project context.

5. Conclusions and Future Research

In this study, the aim was to propose a main path analysis method for knowledge diffusion in collaborative innovation projects. Knowledge resources' diffusion among projects actors is the basis of implementation of project innovation. Main paths in the knowledge diffusion process of projects can reveal the key process of knowledge diffusion for improving the effectiveness of project governance strategies. However, knowledge diffusion networks in projects show a remarkable dynamic characteristic, as project actors can choose diffusion paths independently. This leads to the difficulty of applying the existing research methods (MPA method) in project situations.

For this reason, a dynamic main path analysis method (DMPA method) is constructed in this study, which describes the path selection process of multiple project actors through simulation and refers to the three main path analysis strategies (dynamic local search, dynamic global search and dynamic critical path search). In order to verify the effectiveness and applicability of the new method, this study takes a collaborative innovation project as the analysis case, comparing with the results of MPA method.

The main conclusions of this study are as follows. Firstly, dynamic main path analysis method (DMPA method) can accurately reveal the dynamic knowledge diffusion paths during the process of project implementation and identify the main path of knowledge diffusion. Second, the comparison of the two methods in the project case shows that the main paths identified by the DMPA method conforms to the project practice of knowledge diffusion paths, and the identification results of this method are more accurate than MPA method.

The importance of this study is mainly reflected in the following aspects. Initially, this study focuses on dynamic characteristics of knowledge diffusion networks in the context of collaborative innovation projects, especially compared with the citation networks and patent networks, and expounds the internal mechanism of dynamic characteristics. Furthermore, the new main path analysis method proposed in this study makes it possible to analyze the complex knowledge diffusion process in projects. Additionally, this study expands the application scope of main path analysis in theory, and provides theoretical methods for the subsequent research on knowledge interaction in collaborative innovation projects. Finally, in practice, by identifying main paths through DMPA, project managers can figure out important knowledge entities, and focus on and maintain them and their interactions in the project implementation process. Capturing the main knowledge resource diffusion process in collaborative innovation projects, the overall knowledge resource integration efficiency of projects can be greatly enhanced, and ultimately, efficient innovation results can be obtained.

However, there are still some limitations in this research. First, the knowledge level of project actors is obtained by expert evaluation method with a certain degree of subjectivity.

Second, the DMPA method proposed in this research only considers one type of knowledge resource in projects, and the influence of multiple knowledge resources in projects has not been discussed in depth. Thus, the issue of main paths analysis for interactive diffusion of heterogeneous resources in projects should be further expanded and explored in future research. Thirdly, the application of the method and universal validation cannot be equated. Although a very representative case has been selected for method application, there is only one case and the results of the application of the case are still somewhat limited. Thus, the effectiveness of the method can be more widely verified if it can be applied in the future with a large number of project cases.

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