mathematics

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A Double-Layer Coupled Network Model of Network Density Effects on Multi-Stage Innovation Efficiency Dynamics: Agent-Based Modeling Methods

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Abstract: This paper proposes a double-layer coupled network model to analyze the multi-stage innovation activities of online, and the model consists of two layers: the online layer, which represents the virtual interactions among innovators, and the offline layer, which represents the physical interactions among innovators. The model assumes that the innovation activities are influenced by both the online and offline network structures, as well as the coupling effect between them. And it simulates the entire innovation process including knowledge diffusion and knowledge recombination. The model also incorporates the concept of network density, which measures the degree of network connectivity and cohesion (network structure). Observing the network density influence on innovation efficiency during the innovation process is realized through setting the selection mechanism and the knowledge recombination mechanism. The coupling relationship between the two layers of network density on the three stages of innovation is further discussed under the theoretical framework of the innovation value chain. Simulation and experimental results suggest that when the offline network density is constant, a higher online network density is not always better. When the online network density is low, the sparse structure of the online network reduces innovation efficiency. When the online network density is high, the structural redundancy caused by the tight network structure prevents innovation efficiency from improving. The results of the study help enterprises to adjust and optimize the internal cooperation network structure at different stages of innovation in order to maximize its effectiveness and improve the innovation efficiency of enterprises.

Keywords: online social media; double-layer coupled network; network density; multi-stage innovation

MSC: 91D30; 68V30

Citation: Han, J.; Zhang, W.; Wang, J.; Li, S. A Double-Layer Coupled Network Model of Network Density Effects on Multi-Stage Innovation Efficiency Dynamics: Agent-Based Modeling Methods. *Mathematics* **2024**, *12*, 337. https://doi.org/10.3390/math12020337

Academic Editors: Wen Zhang, Xiaofeng Xu, Jun Wu and Kaijian He

Received: 14 October 2023
Revised: 22 November 2023
Accepted: 23 November 2023
Published: 19 January 2024

1. Introduction

With the development of information technology, Online Social Media (OSM) has enabled knowledge flow activities to a large extent, and organizations are witnessing yet another revolution in their paradigm of knowledge flow [1]. More and more organizations are adopting social and office software for online communication and work. Employees in enterprises often share knowledge in an online manner through enterprise social media, WeChat groups and other social networking platforms. Compared with offline face-to-face communication, employees can communicate online across time, space and organizational hierarchical barriers, more conveniently and with timely interaction [2]. Through online communication, employees can share knowledge, information, and ideas with many colleagues at the same time to conduct innovation activities [3–5] and form an online cooperation network [6], However, some scholars have pointed out that for knowledge that is more difficult to share, such as ideas and know-how, employees rely solely on online communication, which is less efficient in terms of dissemination; additionally, in person (offline) face-to-face direct communication is still needed to improve the performance of knowledge dissemination [7]. Nowadays, online and offline social networks are the two main channels for members of an organization to exchange knowledge, and the dissemination and innovation of knowledge in an organization is increasingly characterized by the "interaction between online and offline" [8]. Furthermore, the innovation process is evolving in switching and interacting between the two network platforms.

The online cooperative network, established through OSM, is coupled with the offline cooperative network, which implies that the two still interact with each other despite their independent structures. In particular, when one network forms a tight connection, the tightness of the two networks will inevitably affect the tightness of the other. The close-knit network of relationships formed among an organization's employees is the social capital that employees possess, and it is this particular social capital that supports organizational innovation, change capacity, and knowledge integration in cooperation networks [9]. Additionally, the tightness of the organization can laterally reflect the local network characteristics [10]. Meanwhile, it has been shown that network characteristics impose a significant impact on organizational innovation performance [11]. Therefore, with online and offline cooperative networks coupled, it is necessary to explore the innovation efficiency of organizations by using the tightness of cooperative networks (hereafter referred to as network density), which both reflects the network characteristics and has an impact on innovation performance. Furthermore, the need for network density at different stages of innovation is dynamic, due to the differences in the main needs at different stages of innovation. The impact of organizational cooperation network density on innovation must not neglect the multi-stage differences in innovation and the multi-dimensional characteristics of the network [12,13].

In this study, we introduce the coupling network method, then build a definite model under the selection mechanism of knowledge flow and recombination. Through simulation experiments, the effects of online network density, offline network density, and the density relationship between double-layer networks on innovation efficiency were explored, where the innovation efficiency was measured by the number of knowledge owners and the frequency of exchanges. The simulation results provide numerical support for the integration of enterprise online cooperative network and offline cooperative network as two knowledge communication channels for organizations, thereby revealing the effect of OSM on innovation. The key contributions of this study are summarized as follows.

First, this study clarifies the realistic background of online cooperative networks embedded in offline cooperative networks in the OSM context. According to the behavior of members in the organization through OSM communication, an online–offline double-layer coupling network model is constructed to simulate innovation behavior in the organization.

Second, differing from previous research models that only focus on the influence of offline cooperative networks on innovation, our study analyzes the relationship between online cooperative networks and offline cooperative networks and reveals their interaction. By constructing a knowledge vector, our study extends the dimension of the knowledge state based on the original research.

Third, by comparing the innovation efficiency of the online–offline double-layer coupling network with different structural combinations, we explain the differences and causes of innovation efficiency under different structural combinations. Based on the innovation value chain theory, the promotion of innovation by online and offline cooperative networks and their different functions at different stages are further explored from the multi-stage perspective of innovation, and the relationship between the double-layer networks is elaborated.

Based on social network theory and knowledge dissemination theory, this study constructs an online–offline double-layer coupled network model by combining the structure and characteristics of the internal cooperation network of the organization, and proposes a selection mechanism and a knowledge restructuring mechanism to study the mechanism by which the double-layer cooperation network of the organization has an impact on the innovation efficiency. These provide theoretical basis for the relevant subjects to optimize the organizational structure and improve the implementation measures of innovation efficiency, expand the application of multi-layer network theory in innovation research, enrich the research method of technological innovation, and further deepen the influence of cooperative network structure on innovation efficiency.

The remainder of the paper is organized as follows. Section 2 provides a comparative discussion of prior studies that are highly relevant to our study and presents the research hypotheses of this paper. Section 3 introduces the appropriate notation and formulas to accurately describe the decision model. Section 4 formulates the innovation process model and the algorithm employed to derive the simulation results. Section 5 analyzes the results of the numerical experiments and derives management insights. Section 6 summarizes the conclusions and further recommendations of this study.

2. Materials and Methods

A social network is a collection of social members based on their relationships, which can be formed spontaneously or naturally. The role of social networks is a necessary element of research innovation, providing social members with different ways and means to integrate and apply knowledge, thus promoting knowledge innovation. Social networks, through their unique network structure, can effectively facilitate cooperation work between groups [14]. In a social network, each individual can connect with any other individual, forming a complex network structure. This network structure allows information to spread quickly through the network, reducing the negative impact of most users hitching a ride and not wanting to reciprocate [15], thus facilitating inter-group collaboration [16]. Online social networks are where members of a social network create and exchange content through online social media, and since online social networks can be realized with the help of convenient carriers, such as smartphones and computers, they can transmit information to any member of the online social network, and this is a very important aspect of social networking, such as for members in the online social network, which greatly reduces the cost of information transfer. Face-to-face interactions in offline social networks help to build and strengthen trust [17], build stronger teamwork and deeper personal relationships [18], thus promoting better cooperation, integration and synergy among unaffiliated groups [15]. A study by Schötteler et al. suggests that online social networks facilitate communication, collaboration, and knowledge sharing among employees in an organization [19]. A study by Pee et al. suggests that individual employees utilize online social networks to cross traditional hierarchical boundaries or organizational departmental boundaries for intra-team knowledge sharing, collaboration, or cross-organizational communication and collaboration with extra team members to obtain more heterogeneous information [20]. Leonardi's study found that employees can establish a good communication and collaboration relationship with other members of the organization through online social networks, and at the same time, in the context of the widespread use of digital concepts in the enterprise, online social networks provide an opportunity for employees to express their views. Since the members of online social networks are all employees within the organization, the information posted can resonate with members and enhance the sense of belonging [21]. Pillet and Carillo found that employees' use of online social media positively contributes to the organizational effectiveness of the organization, based on the data collected from a large international IT services company that was one of the first in the world to undergo a digital transformation. Online social media positively contributes to the formation of member connectivity in an organization's social network, and employees' communication habits are positively influenced by comparative advantage and perceived ease of use, while comparative advantage positively affects the ability to share knowledge [22]. By exploring the impact of social networks on the perceptions of speedy relationships and institutional mechanisms, Chong et al.'s study found that speedy relationships built on interactivity and presence in a social network strengthened member trust, which further increases members' willingness to share [17]. Pollet et al. investigated the relationship between social networks, network size, and emotional closeness in a sample of 117 individuals between the ages of

18 and 63, and the experiment showed that individuals were emotionally closer to members of offline social networks [18].

2.1. Online–Offline Cooperation Network Coupling

2.1.1. Online Social Media-Related Research

OSM is an Internet application based on Web 2.0 concepts and technologies. OSM allows users to create and exchange content. This public social media allows information to be delivered to any member using OSM with the help of more convenient carriers, such as smartphones, etc. It greatly reduces the cost of information dissemination, and hence, is rapidly gaining wide acceptance in the work scenario [23]. According to research, the use of OSM facilitates communication, collaboration, knowledge sharing, and knowledge diffusion among employees in enterprises [24].

The original OSM was for the public, that is, anyone could use it, for example, Facebook, Twitter, etc. Employees can communicate with employees within the organization through OSM. Some enterprises develop or customize OSM software for enterprise users according to their own needs to support internal communication and collaboration [23]. As for the definition of enterprise online social media, researchers generally agree with the definition proposed by Leonardi: enterprise online social media is an integrated platform that integrates many social media functions based on the Internet [25]. Organizations hope to increase discussion among employees through enterprise online social media, promote knowledge flow, stimulate employee innovation vitality, and add value to the organization. A large number of studies have focused on the positive effects of using OSM [26]. However, some studies exploring the relationship between OSM and innovation performance have found that OSM does not always promote employees' innovation performance and may have some negative impact on it. According to the study [27], rules and standardization can be powerful tools for promoting OSM within an organization, but overly strict policies limit employees' autonomous exploratory behaviors, which may lead to the stagnation of their innovative behaviors. Therefore, while encouraging the use of OSM to promote innovation, excessive and inappropriate use of OSM should be prevented, and the combination and interaction between OSM and offline cooperation networks should be considered.

2.1.2. Offline Cooperation Networks Related Research

In recent years, scholars have extensively studied the concept of innovation from the perspective of cooperative networks, where knowledge diffusion as a network-level phenomenon is a necessary condition for innovation. Different aspects of knowledge transmission within an organization have been studied, including the influence of both extrinsic and intrinsic motivational drivers, where anticipated reciprocal relationships [11] and interpersonal trust [28] contribute to developing favorable attitudes of members regarding knowledge sharing behaviors. Social relationships are determinants of organizational members' attitudes toward knowledge seeking and knowledge sharing [11,29], and scholars have developed a generic model by incorporating the degree of forgetting in the knowledge dissemination process in complex networks; their simulation results indicate that different network structures have different degrees of influence on knowledge dissemination and diffusion [30]. Researchers focused on the topology of cooperative networks. Simulation experiments with different network characteristics are conducted around offline cooperation networks, and the experimental numerical results show that scale-free networks are the most effective network structure for knowledge growth and diffusion [31]. The connectivity of the content network between researchers was demonstrated to be conducive to creative diffusion through a network-linking approach [32]. From a network relational perspective, it is argued that weak relational connectivity provides access paths to non-redundant knowledge on a non-redundant network structure, which allows for stronger divergent thinking and thus facilitates the creation of ideas [33]. On this basis, scholars further explore the relationship among network location, social capital, knowledge transfer, and innovation ability [34], and considered the knowledge flow through offline cooperative network channels [35], but the perspective of the single-layer network has certain limitations, multi-level and multi-dimensional discussion of knowledge flow in different channels is ignored, and there is a lack of discussion on the relationship between online and offline cooperation networks.

2.1.3. Online–Offline Cooperation Network Coupling: Implications for Organizational Knowledge Communication

As OSM promotes employee communication within organizations, it also creates new contacts among employees, which changes the original social network structure of organizations to a certain extent. One scholar's research focuses on how social media affects the structure within organizations [36]. His research shows that the use of OSM creates a complex organizational structure that is different from offline cooperative networks, and, at the same time, the use of OSM increases the competitiveness of enterprises. The change in organizational cooperation network structure brought by OSM is of practical significance, because the understanding of cooperative network structure can help enterprises understand the influence of social media degree on organizational performance, and it is the interaction of social and technical factors, which determines users' participation in OSM. Online cooperative networks can provide a wider range of communication options [37] and long-term cooperative relationships [9].

Different from stable member relationships in offline cooperative networks, members in online cooperative networks are more flexible. The flexible structure enables employees to transfer the main channels of communication from offline to online, forming a scene of interactive coexistence of online and offline cooperation networks. Therefore, this paper proposes that there is a coupling between online and offline cooperation networks and that this coupling affects knowledge exchange within an organization. The relationship between the two may be diverse and complex. The online network can either supplement the offline cooperative network or replace the offline cooperative network under certain conditions. At the same time, some innovative activities are naturally better suited to online cooperation networks. Therefore, the coupling problem of double-layer networks is very novel.

2.2. The Impact of Network Density on Innovation Efficiency

2.2.1. Network Density Reflects Network Structural Characteristics

Previous studies have focused on "hubs" in organizations, that is, key employees with a lot of connections. Employees in such a central location are surrounded by enormous potential for communication. However, the connection in the real organization is not only the social links of users, but also highly related to the actual communication activities of users, that is, the exchange of information. Previous research has highlighted the importance of user communication activities: "in the absence of communication activities, regardless of the structure, the structural resources in the organization will remain dormant and provide no benefits" [38]. This means that the network resources occupied by employees are dormant when they do not communicate, so the centrality of employees does not affect the knowledge exchange within the organization in real-time.

Current research also focuses on the network of users based on actual interaction. In the network related to OSM, researchers point out that social capital within an organization is constantly changing, not only through fixed social connections, but also through real-time communication, which is often referred to as the dynamic network. Some of the characteristics of organizational structure change dynamically, so it is difficult to accurately capture the dynamic organizational structure data, and the impact of periodic organizational structure change on innovation becomes difficult to describe. However, since the overall structure within the organization will have a certain influence on the local structure, we can still reflect the local characteristics of nodes in the organization on the side through the tightness of the organization. Some studies have shown that in more close-knit organizations, other employees are more likely to connect with employees with high centrality, and it is easier to generate new center members [39]. Since it is easier to produce "central" employees in a tight structure, and employees in a tight network may have a higher centrality, the study on the degree of tightness of an organization may also reflect the centrality of nodes in an organization. The sparse organization tends to have more structural holes and is less prone to structural redundancy. Therefore, the measurement of the loose organizational structure reflects the non-redundant structure in the organization. Exploring the influence of organizational tightness on innovation efficiency and considering the possibility of other structures in an organization does not ignore the network structure concerned in previous studies.

2.2.2. The Impact of Network Density on Innovation Efficiency: The Double Edged Sword of Social Capital

Research has shown that a closely connected cooperative network is an essential social capital for employees [9]. The special social capital of employees supports innovation in co-operation teams [40]. The amount of social capital owned by individuals in an organization is closely related to the degree of connection among members of the organization. When the degree of familiarity between employees is low, the connection between members is loose and the communication between employees is correspondingly less. It is difficult for organizations to achieve network sanctions through mutual constraints such as trust, which increases the opportunism risk brought by information asymmetry and leads to employees' reluctance to share their knowledge and information, further reducing the efficiency of innovation [41]. With the increasingly frequent interaction among employees, members can communicate with mutual friends to reduce the risks brought by information asymmetry and reduce opportunistic behaviors within the organization, thus improving employees' willingness to transfer complex silent knowledge related to core technologies. At the same time, close member relations provide more diversified transmission paths for knowledge transmission within the organization, expand the channels of knowledge transmission, and further promote the flow of knowledge within the organization [42,43].

To sum up, the degree of organizational closeness has an important impact on innovation performance, and the degree of closeness among organization members also reflects the communication cost within the organization. To maintain social relations, employees need to pay a certain amount of energy cost, and organizations with close members need to pay more relationship costs than those with loose members. Previous studies have proved that knowledge transmission is more efficient in tighter organizations than in loose organizational structures. However, some studies have pointed out that the higher the investment, the higher the return; if an organizational structure is too tight, it may hinder knowledge transmission. When the organization's social network is too dense, further improving the connections among organization members will increase the cost of repeated management, enhance the difficulty of information screening, accelerate the knowledge convergence among nodes, and bring about the risk of relationship locking and behavioral consistency pressure, which will hinder the knowledge diffusion and knowledge innovation of cooperation research and development network. In the sparse enterprise social network, increasing the network density can effectively promote the diffusion and knowledge innovation of network tacit knowledge, help members to obtain rich and high-quality information, and carry out in-depth understanding and development of complex knowledge in the network to improve the lack of existing knowledge and technology.

2.2.3. Research Hypotheses on the Impact of Network Density on Innovation Efficiency

This study chooses the tightness of organizational structure as the main organizational structure variable for analysis and measures the tightness of connections among organizational members through enterprise social network density to explore the influence of organizational structure cost on innovation efficiency [44]. When the level of familiarity between employees in an organization is low, there is less communication between employees, which is manifested in low network density in cooperative networks. Less connection between members in the organization makes it difficult for mutual constraints, such as trust, to work. A loose organizational structure attenuates the effect of network sanction in the organization: employees are difficult to trust each other, and Shadow Spur is reluctant to share the knowledge and information they possess, reducing the willingness of employees to transfer complex knowledge involving core technology, thus impeding the exchange and integration of critical knowledge in the organization. With the increasingly frequent interaction among employees, members reduce the risk of information asymmetry by communicating with mutual friends, thus curbing opportunistic behaviors such as "free riding" within the organization. It provides a good information exchange environment for the organization, thus improving the employees' willingness to transfer complex tacit knowledge related to core technologies [45]. The closeness of the connection between members of an organization also reflects the communication cost within the organization. To maintain social relations, employees need to pay a certain amount of energy costs. Organizations with close members need to pay more relationship costs than those with loose members.

The online cooperative network is different from the offline cooperative network due to the use of OSM. Both online and offline cooperative networks will have an impact on the communication of members, thus affecting the innovation efficiency of the organization. Although the variation in the degree of tightness in the two networks may be the same, the cost of the isomorphic two networks is different. For the online cooperative network with the same structure and the offline cooperative network, the cost of constructing the online cooperative network is much lower than that of the offline cooperative network with the same structure because online communication is more convenient.

Based on the above demonstration, this study proposes hypotheses about the impact of double-layer coupled networks on innovation efficiency:

Hypothesis 1 (H1). *When the density of the online cooperation network is constant, the time required for innovation shows a U-shaped change with the increase of offline cooperation network density.*

Hypothesis 2 (H2). *When the density of the offline cooperation network is constant, the time required for innovation shows a U-shaped change with the increase of online cooperation network density.*

2.3. Comparison of Research Methods

The process of innovation evolution is complex and subject to many uncertainties, and there are two main existing approaches to portraying the process of innovation evolution, one being an extreme, thick description of an in-depth case study analysis of a firm's actual situation. Bernstein and Singh, based on a multi-case study design of nine biotechnology firms and one peak industry organization from Australia, proposed the intentional stage process model as the backbone of the conceptual model and incorporated the dual mechanisms of market pull and technology push into the model [46], which reveals the complex causal processes involved in the innovation process, but cannot be easily generalized.

The other is a thin description of the results of sample survey-type studies, which are more generalized, but are generally abstract studies regarding the mechanisms, processes, events, or choices by which different types of variables interrelate and influence outcomes. Most of the articles on sample survey type of research use two methods, one of which is the traditional method using statistical models such as regression modeling or structural equation modeling. Roper et al. conducted a questionnaire survey of a large group of manufacturing firms in Ireland and Northern Ireland, and analyzed the recursive process of knowledge acquisition, knowledge transformation, and knowledge utilization to form an innovation value chain [47]. Chen and Guan introduced structural equation modeling to study the non-sustainability and interdependence of causal effects during the innovation production process, and investigated the operation mechanism of the innovation production process based on systemic thinking [48]. Another mathematical approach includes differential equations as well as equilibrium and limiting behavior analyses. Guidolin and Manfredi proposed a system of ordinary differential equations with a one-way stage and a decision-making stage to describe the interactions between subjects in the diffusion of innovations [49]. Liu and Liu constructed an evolutionary game model of the knowledge transfer behavior of team members who have reciprocal preferences in the team's innovation activities, behavior in an evolutionary game model, and simulated the evolutionary equilibrium strategies of the model under different parameter changes, analyzing equilibrium and limit behaviors from the perspective of behavioral economics, which extends the mutual cooperation of knowledge teams [50]. However, these approaches do not formalize the overall characteristics of how individual employee behaviors and decisions bring about innovations during the innovation process, which occurs through the interactions between individual employees; this formalization is particularly important.

Whereas the Agent-Based Modeling approach (hereafter referred to as ABM) is the middle ground between thick description and thin description [51]. ABM reflects the performance of the system as a whole by explicitly defining the microscopic features in a complex system and utilizing a large number of interactions between microscopic subjects on the basis of macroscopic features. Through ABM, the dynamic process of knowledge exchange between individuals can be well modeled, and the information implied in the dynamic interactions of individuals can be further explored, and the interactions between subjects are not affected by external human operations, and are only related to the initial setup of the system [52]. Therefore, the use of the ABM methodology can be more realistically and intuitively modeled, and the overall changes of the system can be fully reflected, which can lead to a more effective study of the innovation process. In conclusion, the modeling by ABM in this study can effectively simulate the innovation process in the organization and better characterize the behavioral characteristics of knowledge interaction among members, thus exploring the internal mechanism of knowledge flow within the organization.

3. Methods

Innovation is accompanied by a combination of knowledge. As the innovation process is affected by many factors, the success of innovation is also affected by many uncertainties, for example, subject diversity (including subject knowledge diversity, subject network location diversity, diversity of communication methods), subject intelligence initiative, and technical complexity [53]. The ABM can well simulate the dynamic process of inter-individual knowledge exchange, and further explore the information implied in the dynamic interaction of individuals, and the interaction between subjects is not affected by external human operation, only related to the initial setting of the system, so the use of ABM can provide a more realistic and intuitive modeling and fully reflect the overall changes in the system, so as to more effectively study the innovation process [54].

3.1. Double-Layer Coupled Network

Employees of the enterprise have the opportunity to use corporate OSM for both online communication and face-to-face offline communication, so all employees can appear in any network; here, we define the double-layer coupled network model $\mathrm{G} = \{\mathrm{G_o}, \mathrm{G_f}\}$, where $\mathrm{G_o} = \{\mathrm{V_o}, \mathrm{E_o}\}$ represents the online social network layer formed by employees using enterprise social software, and $\mathrm{G_f} = \{\mathrm{V_f}, \mathrm{E_f}\}$ represents the offline cooperation network formed by face-to-face communication among employees, where $\mathrm{V_f}$ in the offline cooperative network is the set formed by all nodes, and $\mathrm{E_f}$ represents the set formed by all connected edges in the network. Additionally, $\mathrm{V_o}$ represents all nodes in the online cooperative network, and $\mathrm{E_o}$ represents all connected edges in the online cooperative network. Some studies consider the situation where offline individuals do not participate in online social networks due to factors such as not being able to access the Internet in time and set up a network model for the situation where the nodes in the online and offline networks are not identical, namely, $\mathrm{V_o} \neq \mathrm{V_f}$. However, failure to participate does not imply never participating in online innovation activities, so our proposed model will make adjustments to the mechanism of knowledge exchange in the node. Therefore, the nodes of the double-layer network in the double-layer coupled network model in this paper are consistent. This suggests that the set $V_o = \left\{V_{o(1)}, V_{o(2)}, \ldots, V_{o(N_o)}\right\}$ composed of all nodes in the online social network is equal to the set $V_f = \left\{V_{f(1)}, V_{f(2)}, \ldots, V_{f(N_o)}\right\}$ of the replica in the offline cooperative network, which represents the total number of nodes in the two networks in the initial instance, respectively, whereas not all nodes participate in the communication during the simulation. $E_o = \left\{e_{(V_{c(i)}, V_{c(j)})}, V_{o(i)}, V_{o(j)} \in V_o\right\}$ represents a collection of connections in an online cooperation network. Employees (subjects) are represented by nodes in the network, and each employee participates in online and offline innovation activities of the enterprise through online cooperation networks and offline cooperation networks. Therefore, we can regard the complex system in which the subject participates in innovation as a set of double-layer coupled networks. The framework diagram of a double-layer coupled network is shown in Figure 1. As we all know, Google is a company known for Its innovation, and its products and services cover a wide range of fields such as search engine, cloud computing, and advertising technology. Within Google, there is an online collaboration platform called "Google Docs", which allows employees to edit and comment on the same document in real time, no matter where they are. Google also encourages face-to-face communication and collaboration. Their office environments are designed to be very open to facilitate interaction between employees. They even have a tradition known as "TGIF", where every Friday all Google employees get together for face-to-face interaction and discussion. At this time, the company's employees have the opportunity to use "Google Docs" online collaboration platform for online communication as well as face-to-face offline communication, so all employees can be present in any network to participate in innovative activities. This coupling of online and offline social networks creates a powerful double-layered cooperative network within Google, which greatly improves their innovation efficiency. Online platforms allow employees to collaborate anytime, anywhere, while face-to-face interactions help build stronger teamwork and deeper personal relationships. The coupling of online–offline networks allows Google to generate and implement innovative ideas in a short period of time, thus maintaining its leadership position in the global technology industry [55]. The nodes of the online and offline collaboration network layers are identical because all employees in the company participate in the online collaboration platform "Google Docs", as well as in offline face-to-face communication, and the nodes represent the company's employees. The inner edges of the layers represent the connections between employees through online or offline communication. The inter-layer edges are connected only by each employee and his/her copy in the other network layer. In a double-layer sub-network, weights and directions are not even considered, so both online and offline cooperative networks are incapacitated and un-directed. Since the number of face-to-face communication per unit time of each employee at work is the same, it is assumed that the offline cooperation network is regular. However, the number of employees communicating online is greatly influenced by their work content. For example, some employees may need to communicate with colleagues frequently concerning work-related content, while others may rarely need to communicate with other colleagues. Therefore, it is assumed that the online cooperation network of employees is random. In the experiment, the number of nodes in both networks was $N = 100$. To further reveal the coupling relationship between the two networks, the number of connected edges in the network will be adjusted according to the network density.

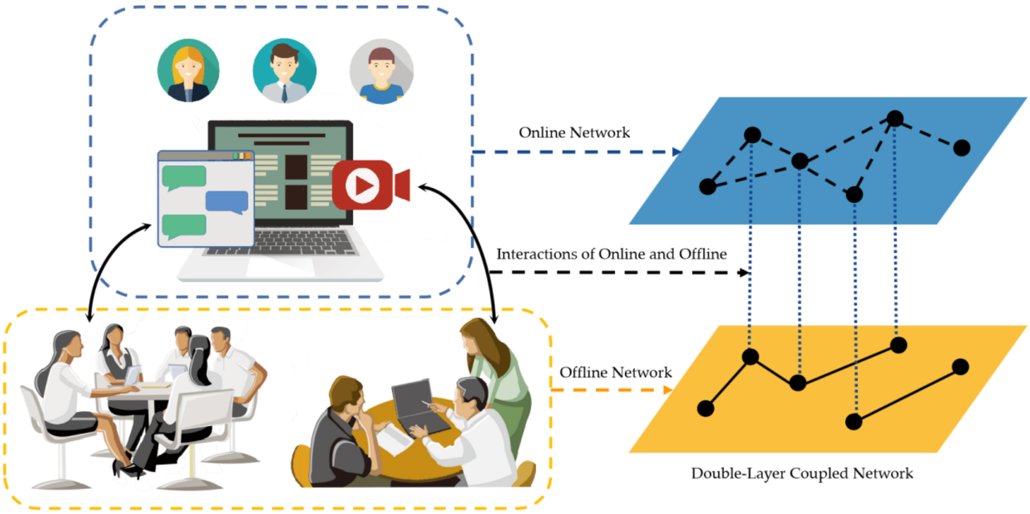

Figure 1. Overall model design and framework of the multi-layer network model. The model contains two sub-networks, online and offline, which correspond to two communication modes, respectively.

3.2. Selection and Recombination Mechanisms

Based on the idea that innovation is a process of searching, recombining, and selecting knowledge of existing literature, we therefore construct an innovation model consisting of two parts, namely (1) the selection mechanism, and (2) the recombination of knowledge. Before providing the details of the model settings, we present a simple description of these two parts of the model. The expressions of relevant parameters used in this research model are shown in Table 1.

Table 1. Related parameters used in this experiment.

Parameters	Definition
N_1	The number of an online network subjects
N_2	The number of an offline network subjects
L_1	The number of edges in online network
L_2	The number of edges in offline network
d_{on}	The density of online networks, which is expressed as $d_{on} = \frac{2L_1}{N_1(N_1-1)}$
d_{off}	The density of offline networks, which is expressed as $d_{off} = \frac{2L_2}{N_2(N_2-1)}$
λ	Vector expression of knowledge, $\lambda_i = (k_1, k_2, \ldots, k_m)$
k	The value of a knowledge component in a knowledge vector
m	The number of knowledge components in the knowledge vector
p	Probability of communication between subjects
q	The probability that the subject chooses online channels for communication
$1 - q$	The probability that the subject chooses offline channels for communication
α	The probability of acquiring knowledge after communication
θ	The coefficient of innovation achievement

N_1 is the number of subjects in the online network, and N_2 is the number of subjects in the offline network. Technological innovation is often difficult to be accomplished independently by one researcher, and often requires multiple subjects to collaborate with each other to accomplish it. The communication methods of the subjects are also diversified. In the digital age, the subjects can use online social media communication, then belong to the subjects in the online network. At the same time, they can also use face-to-face communication, which belongs to the subjects in the current network.

L_1 represents the number of connected edges actually measured in the online network. L_2 represents the number of connected edges actually measured in the offline network. Reflects the number of interactions between subjects in the network, the more interactions occur between subjects, the more edges are connected in the network.

d is the network density, which is the ratio between the actual number of edges and the possible number of edges in the network, where "possible number of edges" refers to the maximum number of edges that the network may have. d_{on} is the online network density, and d_{off} is the offline network density, and the value range is [0, 1]. The larger the value of, the more closely the nodes are connected in the network.

λ is a knowledge vector that describes the knowledge level of the organization members. The expression $\lambda_i = (k_1, k_2, \ldots, k_m)$ denotes that each subject i is assigned an m-dimensional knowledge vector at the initial stage of the model, where the knowledge vector is λ Each component in k_m ($k_m \succcurlyeq 0$) denotes the degree of the m-th knowledge in the knowledge vector possessed by subject i. k on denotes the value of the knowledge component in the knowledge vector when $k_m = 0$ indicates that subject i does not currently possess the m-th kind of knowledge.

m is the number of knowledge components in the knowledge vector, and reflects the richness of knowledge in the organization and the breadth of knowledge elements included in the innovation. When the number of categories owned by the subject is small, the type of knowledge in the organization is relatively homogeneous; when the number of knowledge categories owned by the subject is too large, not only does it not correspond to the reality of innovation activities, but also greatly increases the amount of calculations in simulation experiments. Therefore, the number of categories owned by the subject m should not only reflect the richness of knowledge in innovation, but also take into account the difficulty of innovation.

p denotes the probability of communication between subjects, in reality it is not necessary that all employees communicate online or offline at the same time, so this study sets the communication probability. The communication probability allows a portion of employees not to communicate in a time step, ensuring that the model is more in line with the reality that members of an organization need to have a certain amount of time to digest what they have learned. Also the communication probability allows the model to better simulate innovation activities at multiple organizational scales.

q is the probability that the subject chooses the online channel for communication, then $1 - q$ is the probability that the subject chooses the offline channel for communication. In order to prevent employee communication preferences from affecting the interaction between the organization's online and offline cooperation networks, this study does not set the online communication preferences and offline communication preferences of employee communication species, so the probability of employees using online communication and offline communication is equal.

α for the probability of acquiring knowledge after communication, in the stochastic network model, the probability of each subject acquiring knowledge depends on the state of its neighbors. When the more neighbors a subject has, or the more subjects in its neighbors who have already acquired knowledge, then the probability of this subject acquiring knowledge will be larger. So, the size of the probability of acquiring knowledge after exchange is related to the number of subjects in the network, the connected edges, and the probability of exchange between subjects.

θ is the innovation outcome coefficient, which indicates the degree to which the innovation has been completed, and when the innovation outcome coefficient is 1, it means that the innovation has been produced.

3.2.1. Selection Mechanism

In the process of innovation, the subject will constantly acquire new knowledge to improve their knowledge stock before realizing innovation. The major way to acquire knowledge between subjects is communication, and every subject can only communicate with its neighbor in the network, so the structure of the network will influence the manner and results of the subjects significantly. Since the subject's energy is not infinite, it is difficult for the subject to participate in offline and online innovation activities simultaneously. In this study, we assume that the probability of subjects participating in innovation activities via the online network is q, and the probability of subjects participating in innovation activities via the offline network is $1 - q$. Each of the subjects possesses different knowledge, and learns from each other in communications, making knowledge recombine.

3.2.2. Recombination of Knowledge

As pointed out by Frederik [45], not all new ideas are feasible, so there needs to be a mechanism of recombination to filter the results that satisfy the environmental requirements. The model assumes that the implementation of an innovation requires m different types of knowledge. Initially, all knowledge is distributed among different innovation subjects in the network. During the process of knowledge transmission and recombination, the innovation subject will constantly acquire new knowledge to improve their knowledge combination. Innovation occurs when a subject's knowledge mix is consistent with the knowledge mix required for innovation.

To model the above discussion, each node i is given an m-dimensional knowledge vector $\lambda_i = (k_1, k_2, \ldots, k_m)$, each component of λ, $k_m \succcurlyeq 0$ represents the knowledge level of the m-type knowledge possessed by the innovation subject i, when $k_m = 0$, it means node i does not possess m-type knowledge at present. The level of knowledge possessed by nodes in online and offline networks is synchronous in real-time, that is, when nodes acquire knowledge of a certain dimension in online networks, they also acquire such knowledge in offline networks immediately.

At the initial state, knowledge elements are randomly assigned to nodes in the network. m nodes are randomly selected from N nodes $(m < N)$, and the m nodes are set as follows: select a dimension from the m-dimension vector of each node, then set the knowledge content of this dimension as k and that of other dimensions as 0, make all m vectors linearly independent, and the knowledge vectors of other $N - m$ nodes as 0 vectors. The specific explanation of the above settings is that at the beginning of the experiment, all kinds of knowledge shall meet the technical opportunities that are distributed among different subjects of the network, and m subjects have only one of the m kinds of different knowledge. When $m > N$, the knowledge m-dimension required for innovation is greater than the total number of network nodes N, and each knowledge vector is linearly independent, which will lead to the lack of necessary knowledge elements in the network, which may cause failure in the innovation. Therefore, the initial number of nodes with knowledge elements m must satisfy $m < N$. At time T, each node preferentially selects an online or offline communication mode, and then selects one of its adjacent idle nodes in the online (offline) social network in turn for communication. In this model, there are mainly two ways to communicate and acquire knowledge between nodes; the examples are presented as follows.

$$\lambda_i = (1,0,1,0) + \lambda_j = (1,0,1,1) \rightarrow \lambda'_i = (1,0,1,1) + \lambda'_j = (1,0,1,1) \tag{1}$$

Equation (1) represents the situation where the corresponding knowledge vector $\lambda_i = (1,0,1,0)$ of node i without knowledge of one dimension acquires knowledge elements of this dimension after communicating with node j($\lambda_j = (1,0,1,1)$), thus possessing the knowledge of that dimension [56].

$$\lambda_i = (1,0,1,0) + \lambda_j = (1,0,3,0) \rightarrow \lambda'_i = (1,0,2,0) + \lambda'_j = (1,0,3,0) \tag{2}$$

Equation (2) denotes that node i($\lambda_i = (1,0,1,0)$) has a deeper understanding of its knowledge after communicating with node j($\lambda_j = (1,0,3,0)$), which is more professional than node i; the value of this dimension in the knowledge vector corresponding to node i has also been improved [57].

3.2.3. Suspension Conditions

Since the energy of each subject energy is not infinite, it is assumed that nodes can only discuss one topic (one knowledge dimension) each time they communicate on the premise of non-generality. At each moment T, each node can communicate no more than once. When no nodes in the network can communicate with each other, time T ends. In the above process, knowledge flows through the network in the process of communication between subjects, which enables subjects to increase their existing knowledge level while acquiring new knowledge needed for innovation through the network. This is the process of knowledge recombination. Assume the knowledge element required for innovation is m-dimensional vector $A = (k_1, k_2, \ldots, k_m)$, the nodes in the network continuously communicate and learn from each other; when the knowledge vector of a node i in the network becomes $\lambda_i = (k_1, k_2, \ldots, k_m) = A$, innovation is generated. This is because the knowledge vector of this node is consistent with the requirement of generating this innovation.

3.2.4. Model Simulation

Due to a certain degree of randomness of a single experiment, in order to network the error generated by the randomness, 10 simulations of the innovation process under each group parameter are carried out, and the average value of the 10 simulation results is finally taken as the final data. The simulation process is as follows (Algorithm 1).

Step 1: Set the network model parameters and the initial knowledge vectors for each node;

Step 2: Each node first chooses whether or not to communicate (communicate or not), and if it chooses to communicate then it again chooses the method of this communication (online or offline);

Step 3: Communicate with a random neighbor node but satisfy the knowledge diffusion condition with the probability of α. Knowledge diffusion occurs and records the node where knowledge diffusion occurs. When the condition is not satisfied, the knowledge vectors of both parties do not change.

Step 4: Go to Step 2 until the first innovation appears in the network and record the total number of hours to complete the innovation.

Step 5: Change the network parameters and repeat the experiment.

Algorithm 1 STVMD based on STFT (Note: Set different initialization according to different situations).

Initialization: $\{\lambda_1, \lambda_2, \ldots \lambda_m\}$, α, $G_{on} = \{N_1, L_1\}$, $G_{off} = \{N_2, L_2\}$
results $\leftarrow$ { }
repeat
  $G \leftarrow$ Choose(G_{on}, G)
  for $n \in G$ **do**
    if $n \notin$ results & Random( ) >= α then
      m $\leftarrow$ Random(n.neighbor)
      communicate(n, m, G, λ_n, λ_m)
      Update $\lambda_n, \lambda_m \leftarrow \mathrm{Max}(\lambda_n, \lambda_m)$
      results.append(n, m)
    end if
    Update G_{on}
    Update G_{off}
  end for
until Sum(λ_{Gon}) = N_1

3.3. Variable-Network Density

The tightness of organizational structure can be obtained by measuring network density. The density of a network refers to "the ratio between the actual number of edges in the network and the possible number of edges", whereas "the possible number of edges" refers to the maximum number of edges that can be had in the network. The maximum number of edges that can exist in a network is equal to $N(N-1)/2$ [58]. Therefore, the density calculation formula can be expressed as:

$$D = \frac{L}{N(N-1)/2} \tag{3}$$

where L represents the number of connected edges measured in the network, and N is the number of nodes in the network. The value range of network density D is $[0, 1]$. The larger the network value is, the closer the relationship between nodes is. When the density is 1, it means that all nodes in the network are closely connected. When the density value is 0, it indicates that there is no connection between any two nodes in the network.

Density Relations for Double-Layer Coupled Networks

In multi-layer networks, the attributes of nodes are multidimensional and multi-layered, and there is a hierarchical relationship between the layers of the network and relationships, so describing the structural attributes through a single-layer network may neglect the relationships between different layers. Therefore, this study introduces the concept of a double-layer coupled network density relationship to explore the overall network structure relationship between online and offline cooperative networks in order to better understand the relationship between online–offline double-layer coupling networks. This study starts from the network density calculation formula, and describes the relationship between the two layers of the coupled network through the ratio of their densities:

$$V = \frac{D_{on}}{D_{off}} = \frac{N_{off}(N_{off}-1)}{N_{on}(N_{on}-1)} \times \frac{L_{on}}{L_{off}} \tag{4}$$

When the value of V is 0, it indicates that the online cooperative network does not exist, and then the model is the offline single-layer network. When the V value is greater than 0 but less than 1, it indicates that the online network exists, but the density of the online network is less than the density of the offline cooperative network. At this time, the structural resources in the offline cooperative network are richer, and the path of knowledge flow between members is richer than that in the online cooperative network. When the value of V is greater than 1, it means that the density of the online cooperation network is greater than the density of offline cooperation network; at this time, the structure of online cooperation network is more compact than the offline cooperation network. According to the above discussion, at this time, the knowledge flow paths in the online cooperative network are richer and more likely to produce more efficient paths than the offline cooperative network.

This study measures the time step to finish innovation and the frequency of communication during innovation. Innovation time is used to describe the total simulation time step required by the organization to finish innovation, and the time step can be used to reflect the innovation efficiency of our model. The communication frequency in the innovation process is used to describe each communication in the simulation model, and the communication frequency can be used to measure the total cost of innovation. Both variables can be obtained directly from the simulation model.

3.4. Robustness Test

In this experiment, the initially assigned knowledge vector and innovation vector have equal rank, the innovation could finish if communication reasonably occurs. When the network is too sparse, the presence of isolated regions in the network makes the completion of innovations difficult or outright avoidable. To prevent this from occurring in the model, this study uses the backtracking search algorithms in distributed constraint satisfaction problems to calculate the maximum time of the innovation process [59].

3.4.1. Constraint Satisfaction Problem

The constraint satisfaction problem is the problem of finding assignments for all variables that satisfy their constraint relationships with each other over a certain range of values, consisting of the variables, the value domains of the variables, and the constraints between the variables, which are the density ratios of a double-layer network.

Definition 1. *(Constraint Satisfaction Problem) The constraint satisfaction problem can be formalized as a constraint network, defined by the set of double-layer network density ratios, the set of value domains for each double-layer network density ratio, and the set of constraint relationships between the double-layer network density ratios, denoted as the triad* (V, D, C)*, where:*

V is the set of double-layer network density ratios $\{v_i, \ldots, v_n\}$*;*

D is the set of value domains of all double-layer network density ratios, and $D = \{D_1, \ldots, D_n\}$*,* D_i *are finite domains of all possible values of the double-layer network density ratio* v_i*;*

C is the set of constraint relations between the density ratios of the double-layer network $C = \{C_1, \ldots, C_m\}$*, where each constraint contains a subset of V,* $\{v_i, \ldots, v_n\}$ *and a constraint relation* $R \subseteq D_i \times \ldots \times D_j$*.*

The constraint satisfaction method is an efficient problem solving method that finds an assignment for each double-layer network density ratio in its value domain such that all constraints are satisfied.

Definition 2. *(Solution of Constraint Satisfaction Problem) A solution of a constraint satisfaction problem is a set of assignments to all the double-layer network density ratios in the problem that do not violate any constraints. That is, a set of assignments to all double-layer network density ratios* $S(v_i, \ldots, v_n) = \{d_1 \in D_1, \ldots, d_n \in D_n\}$*,* $\forall C_r \in C$ *have* $S(v_{ri}, \ldots, v_{rj}) = \{d_{ri}, \ldots, d_{rj}\} \in R_r$*.*

3.4.2. Distributed Constraint Satisfaction Problem

The distributed constraint satisfaction problem is a constraint satisfaction problem in which both the density ratio and constraints of a double-layer network are distributed among different autonomous subjects (employees). Based on the definition of constraint satisfaction problem, the distributed constraint satisfaction problem can be defined as follows:

Definition 3. *(Distributed Constraint Satisfaction Problem) n subjects denoted as* $N_1, N_2, \ldots, N_n$*, m double-layer network density ratios as* $v_1, v_2 \ldots, v_m$*, m double-layer network density ratios in the value domain of* $D_1, D_2 \ldots, D_m$*, the constraints between the double-layer network density ratios are still denoted by C; each subject has one or more double-layer network density ratios, and each double-layer network density ratio* v_j *belongs to a* N_i *denoted as belongs* (v_j, N_i)*; constraints between the double-layer network density ratios are distributed either within the subjects or between the subjects when* N_l *knows the constraint relation* C_k*, denoted as* $Known(C_k, N_l)$*.*

Constraints distributed within subjects are called local constraints, while inter-subject constraints are called global constraints; local constraints can be handled by the computation of the subjects, whereas global constraints require not only the computation of the subjects, but also inter-subjects communication to handle them, thus requiring the following communication model assumptions:

Assumption 1. *Inter-subject communication is accomplished by passing messages to other subjects when and only when one subject knows the address of the other.*

Assumption 2. *The delay in transmitting messages is random but finite, and the order in which messages are received between any pair of subjects is the same as the order in which they are sent.*

Assumption 3. *Each subject knows only part of the information about the whole innovation.*

Subjects in distributed constraint satisfaction are computational entities that comply with cooperation mechanisms to perform decision-making behavior.

Each subject is responsible for a number of double-layer network density ratios and determines their values, since there are also intrinsic inter-subject constraints that must be satisfied by the assignment. The formal definition of the solution to the distributed constraint satisfaction problem is:

Definition 4. *(Solution of Distributed Constraint Satisfaction Problem) A solution to a distributed constraint satisfaction problem is found if and only if the following conditions are satisfied:* $\forall N_i$, $\forall v_j$ *there exists a relation belongs* (v_j, N_i), *and* $\forall C_k$, $\forall N_l$ *Known*(C_k, N_l) *are both* C_k *satisfied when the assignment of* v_j *to* $d_j \in D_j$. *That is, at this point the assignment of all variables in the problem satisfies all inter-subjective and intro-subjective constraints.*

3.4.3. Backtracking Search Algorithms

The two basic ideas of the backtracking search method are introducing a minimum conflict heuristic in order to reduce the risk of unfavorable assignments, and creating a dynamically changeable priority order of the subjects so that unfavorable assignments can be corrected without exhaustive search.

Because the knowledge vectors of the subjects endowed at the initial stage of the model ground are linearly independent, the problem of studying the avoidance of the presence of isolated regions in the network, which makes it difficult to complete the innovation, can be understood as the problem of solving a chi-square linear equation, and since the matrix formed by the knowledge vectors of the subjects and the innovation vectors are equal-ranked, there is a solution to the model, i.e., the innovation can be achieved in the organization.

The probability of two nodes communicating and acquiring knowledge is p. For a knowledge vector with m-dimensions, the probability that all dimensions participate in the communication (considering the longest innovation time) is $p^{\frac{m(m-1)}{2}}$. The components of each knowledge vector have k values, so there are k^m possible values in m-dimensions. Therefore, the expected value of the node knowledge vector value that forms after communication is $k^m p^{\frac{m(m-1)}{2}}$. In the whole system, the probability of failing to reach innovation after i check is $p^{i-1}(1-p)$. Therefore, for I checks, the communication frequency of each node can be expressed in Equation (5):

$$\sum_{i=1}^{m-1} ip^{i-1}(1-p) + (I-1)p^{m-1} = \frac{1 - mp^{m-1} + (m-1)p^m}{1-p} \tag{5}$$

The expected communication frequency is equal to the number of nodes multiplied by the frequency of communication performed by the nodes; the total communication frequency required for the innovation process is the sum of the expected communication frequency from 1 to I for the backtracking search process:

$$\sum_{i=1}^{m} \frac{1 - mp^{m-1} + (m-1)p^m}{1-p} k^m p^{\frac{m(m-1)}{2}} \tag{6}$$

The dimension of the knowledge vector designed in this experiment is $m = 10$ (The number of knowledge categories (m) held by the subject reflects the richness of knowledge in the organization and the breadth of knowledge elements included in the innovation. When m is small, there is just a single category in the organization; when m is large, it not only corresponds to the reality of innovative activities, but also greatly increases the computational volume of the simulation experiment. Therefore, in order to ensure that this experiment can reflect the diversity of knowledge in innovation, set m = 10), and the total number of nodes in the network $N = 100$ (A study states that the number of employees in an organization should not exceed 150 and when the number is exceeded, the organization will face disintegration [60]. Therefore, the number of network members in this experiment is less than 150 people, and, at the same time, the network structure is needed to be measured in the subsequent calculations, so N = 100 is set to reduce the amount of calculations in the subsequent analysis). The maximum communication frequency calculated by backtracking search, according to Equation (6), is 4922. When the communication frequency in the experiment is larger than this value, it indicates that there is an isolated area in the network, which is an invalid experimental result.

4. Results

To verify the influence of the online cooperative network structure on the innovation duration under the condition of ensuring the stability of the experiment, in Experiment 1, keep the offline cooperation network density unchanged, and adjust the online cooperation network density for the simulation experiment; In Experiment 2, the density of online cooperation network was kept unchanged, and the density of offline cooperation network was adjusted for the simulation experiment to meet the requirement of changing the double-layer coupled network density in two ways. The values of the coupling density of the double-layer network were 0.3, 0.6, 0.9, 1.2, 1.5, 1.8, 2.1, 2.4, 2.7, and 3.0 in ten cases. Ten experiments were conducted under each density ratio, and the average value of the ten experiments was taken as the analysis data. Similarly, when the influence of offline cooperation network structure on innovation is verified, the structure of the cooperation network on the control line only changes the structure of the offline cooperation network. Ten experiments are conducted to obtain the experimental results.

According to the simulation results, the effect of network density on innovation time is verified by stepwise regression. In the regression results, the correlation coefficients between the quadratic term of the density ratio R of the double-layer coupled network and the innovation time were 379.9 and 387.1, respectively, in Experiment 1 and Experiment 2, and were verified at the significance level of 1%, indicating that there was a positive U-shaped relationship between the density ratio of the double-layer coupled network and the innovation time. Therefore, the two hypotheses (H1, H2) proposed in this study have been verified (Table 2).

Table 2. A stepwise regression model of network density on innovation times.

Variable	**E1**	**E2**
	ln y_1	**ln y_2**
R	−27.31 *** (−8.12)	−27.83 *** (−7.72)
R^2	379.9 *** (6.96)	387.1 *** (6.62)
cons	4.682 *** (102.01)	4.628 *** (94.11)
N	110	110

Note: *** indicates significant at the 1% significance level.

According to the results of the simulation experiment, the influence parameters on the change of innovation efficiency caused by the change of online and offline cooperative networks in Experiment 1 and Experiment 2 are similar. Although the effect of online and offline cooperative network structure on innovation time is very close according to the results of stepwise regression analysis, the cost of communication through the online cooperative network is lower than that through offline communication, and members who need to pay a huge cost to communicate offline may be easily realized through the online cooperative network. At the same time, the convenience of communication through online cooperative networks also reduces the sunk costs of communication to some extent. Employees cannot obtain useful information in every communication each time. Compared with face-to-face communication, OSM communication, to some extent, hedges the risk that communication cannot bring useful knowledge.

The following results are obtained after simulating the innovation process of online–offline networks under different density combination conditions. The total time to finish innovation is the most intuitive indicator to reflect the speed of innovation. Due to the difference in network structure, the frequency of subject communication in a time-step network is also different, so the total time step of innovation is also different under different network structures. The simulation process will be used to explain the influence of network structure in the innovation process. This study analyzes the characteristics of OSM participation in the innovation process, as shown in Figure 2. In the generation phase, the number of knowledge owners in the organization is still very low, and it is difficult for knowledge to be widely spread within the organization, so the communication in online and offline networks is at a low level. The dense online network provides more opportunities for employees to communicate; communication in the online network is more active during this phase. The frequency of communication in both online and offline networks increases synchronously over time. In the elaboration phase, the communication between online and offline networks presents an obvious complementary relationship. The use of OSM makes up for deficiencies in offline communication, and the communication between online and offline networks changes alternately with time. When offline communication is sufficient, online communication will not occupy the time of offline communication. At the same time, when online communication is insufficient, online communication replenishes the vacancy of communication. The apparent interaction between the two communication modes fully demonstrates that the use of OSM complements and promotes the original communication channels of an organization. In the championing phase, the frequency of offline communication is higher than that of online communication, because offline networks can provide more stable connections and necessary support for innovation. In this phase, online communication is not ineffective, but provides a good guarantee and auxiliary role for offline communication. In the last time step of the experiment, innovation has been completed and the terminating condition is satisfied, so communication between nodes no longer occurs.

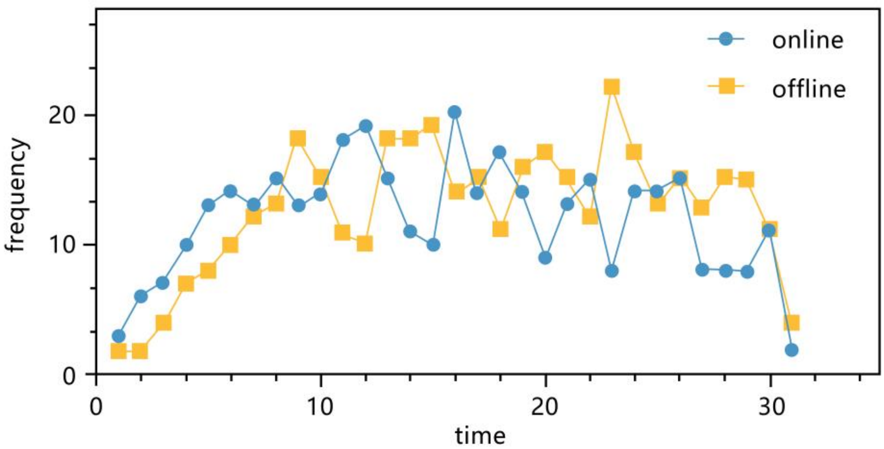

Figure 2. Data graph of communication frequency in online and offline networks during the innovation process.

The process of innovation demands constant interaction among subjects. When the online network has a low density, its structure becomes sparse, and subjects with knowledge often cannot be contacted through the online network, which further results in a longer time for innovation. As its density increases, the online network forms a closer coupling relationship with the offline network, under which circumstance the subject can not only contact an adjacent subject through the offline network, but also the distant one in reality through the online network, which greatly accelerates the propagation speed of knowledge within the organization. Therefore, we further analyze the impact of density coupling on innovation in double-layer networks. Figure 3 shows the data obtained after several tests, which reflects the variation trend of the total time steps of innovation caused by changes in network structure. In Figure 3, the horizontal axis represents the ratio of online network density to offline network density, the vertical axis represents the time step achieved by innovation. It can be observed from Figure 3 that when the density ratio of the online–offline double-layer coupling network is less than 1.5, the time step of innovation consumption decreases sharply with the increase of online network density. When the density value is greater than 1.5, the innovation consumption time slowly rises with the increase of online network density.

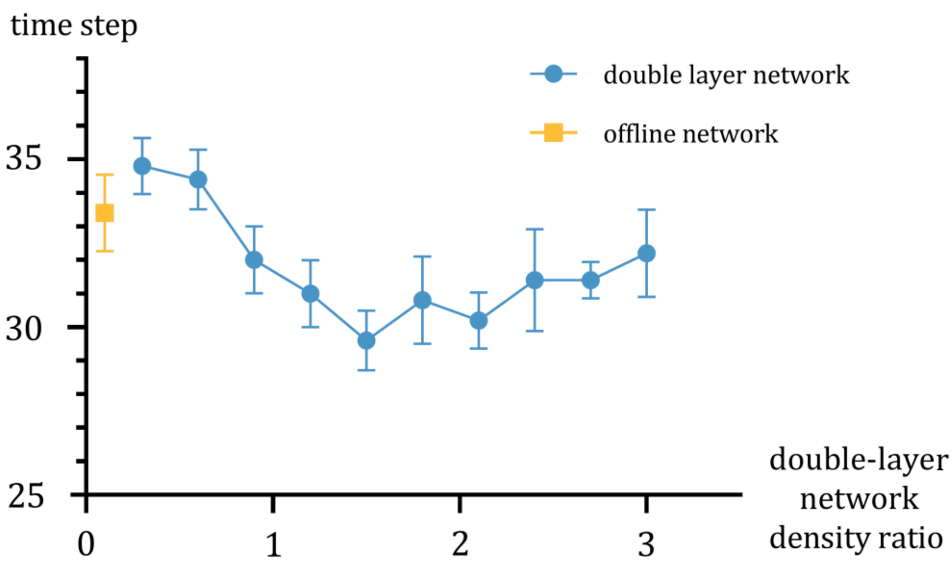

Figure 3. The effect of coupling relation of the density of double-layer network on innovation efficiency. The first group of data is obtained in an offline single-layer network as the control group.

In this experiment, the density ratio between the online network and offline network is 1.5, to which the total time consumed for innovation is the shortest. As the online network further increases, its structure also becomes closer, which increase online network structure and the increase of invalid communication. This is also the reason why the innovation time step gradually increases when the density ratio of the online network to the offline network is greater than 1.5. Although, a redundancy in the network may induce continuous transmission of important knowledge elements in a cohesive subgroup, however, they cannot reach the outside of the subgroup. This generates sufficient information benefits while further reducing the efficiency of knowledge transmission in the network.

In this experiment, the minimum total time consumed by innovation is a 1.5 density ratio of online network to offline network. In organizations, due to the different scales of different organizations, the actual optimal density ratio may fluctuate under the influence of the formed cooperative network scale. It is not feasible for organizations to adjust the density of online or offline cooperation networks, but it can still strengthen innovative behaviors at different stages through a series of activities. For example, in the generation phase, organizations can increase the frequency of online meetings within the organization, or organize external personnel's lectures and other activities within the organization. New activities can strengthen the original connection and form a new connection within the organization. In the elaboration phase, offline knowledge exchange activities should be advocated. Since both online and offline play an important role in this phase, employees are likely to enter a dilemma of choice. Organizations should provide certain guidance to employees' activities to avoid employees from investing too much energy online or offline, affecting their innovative behaviors. In the championing phase, offline activities should be encouraged. One-to-one communication between leaders and members cannot only grasp the needs of employees in the innovation process timely, but also provide help for their innovation through their influence.

Nevertheless, the role of online–offline coupling networks may not be sufficiently described merely by the time step of innovation completion. This study also acquired each communication in the innovation process and made statistics on the total communication frequency when the innovation was completed, in which the result is shown in Figure 4.

The number of conversations to be finished reflects the total cost of innovation, in which the number of communication in the online network reflects the cost of communication in itself. Similarly, the number of communication in offline networks demonstrates the cost of innovation. Based on the information presented in Figure 4, the following fact can be derived: as the density ratio of online network to offline network increases, innovation activities depend more heavily on online communication.

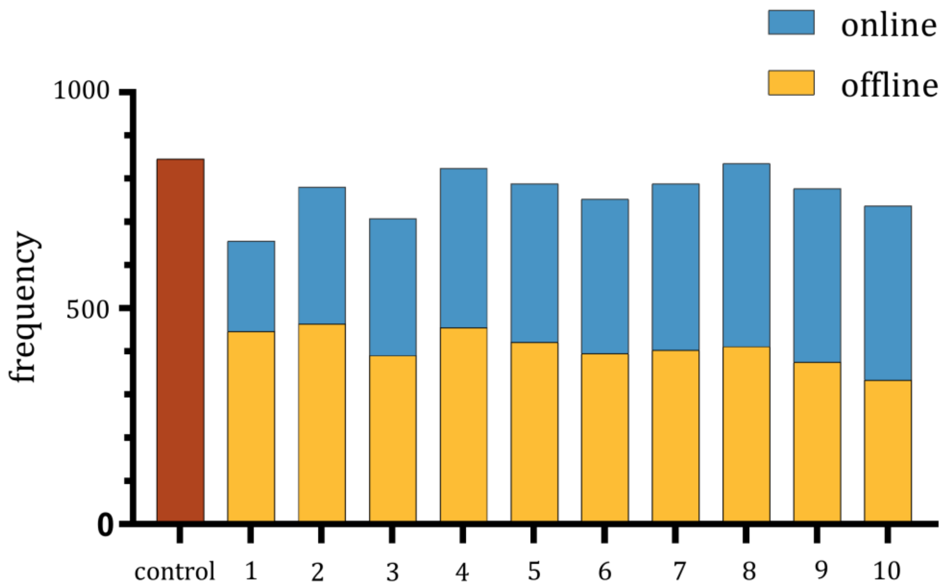

Figure 4. The effect of coupling relationship of double-layer network density on average communication frequency in the innovation process. The first group of data is obtained in an offline single-layer network as the control group.

In the process of knowledge diffusion, subjects cannot communicate with unknown ones. Therefore, the increase in online network density suggests that when the number of subjects in the network is definite, the number of connected edges in the network increases accordingly, thereby increasing the number of adjacent subjects in the network. As online network density increases, the amount of communication through online networks increases during the process of innovation. Combined with the data obtained from the experiment, the trend of total communication frequency when innovation is generated is relatively stable. Therefore, we can understand that as the density ratio of online networks and offline networks continues to increase, more offline communication activities are transferred to online networks.

5. Discussion

Through the analysis of the results of the simulation experiment, this study verifies the impact of online cooperation networks on innovation time. However, as the innovation process is complex and phased, does online cooperation always play a role in promoting it? This study analyzes the innovation process based on the multi-stage innovation theory and hopes to provide suggestions for organizations to explore the use of OSM decisions. Therefore, we follow Perry Smith's idea [53], defining three phases from the beginning to the achievement of innovation as the generation phase, elaboration phase, and championing phase.

In the generation phase, creators generate many different ideas and then self-select one. Importantly, the selected idea is merely a vague idea or core concept to be elaborated upon in future phases. In this phase, it is not the mastery of knowledge that matters, but rather the accumulation of new knowledge. To clearly show the phenomenon that employees communicate through different networks, all the communication within a period is formed as edges, as shown in Figure 5. The edges in the figure are the actual communication between nodes. Communication times are the number of all communications that occur between agents. While individuals are in conversation, they cannot be working on other tasks; communication times in the system reflects the opportunity cost of people's time. An online network structure will provide more chances for subjects to communicate with others. New knowledge enhances the cognitive flexibility of the subject, which enables uncommon associations between conceptually distant ideas.

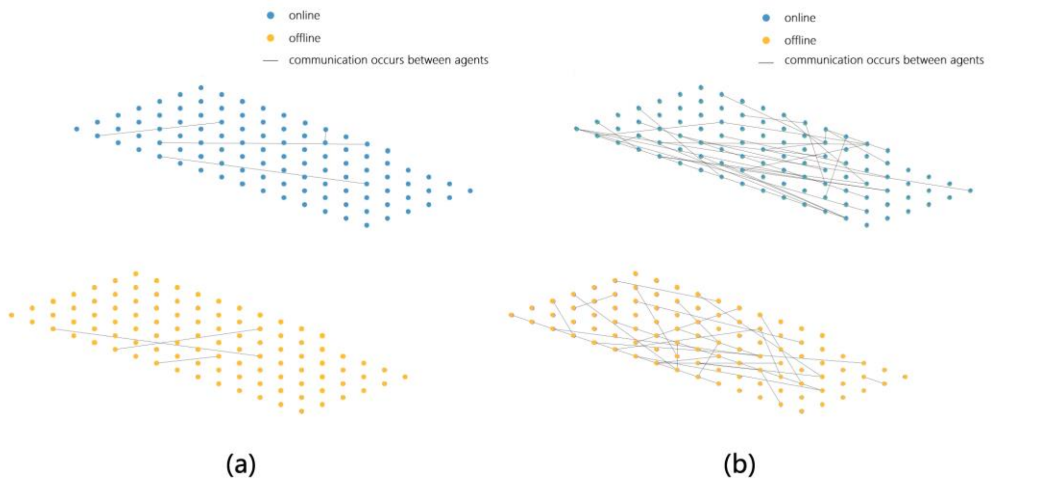

Figure 5. Communication on networks that takes place during a certain period time. (**a**) When t = 1, the total number of communication times in the system (hereinafter we use "the value" to represent the total number of communication times in the system) is 6; (**b**) When t = 4, the value is 34.

In the elaboration phase, creators systematically evaluate a novel idea's potential and then further clarify and develop the idea. Differing from the previous phase, developing the idea needs to enhance the knowledge of different fields. Because of the specialized nature of some of the knowledge, detailed conversations with experts in the field are often required. Meanwhile, creators refine the idea by checking for inconsistencies and making improvements in this phase. On the one hand, creators can communicate with experts face-to-face through offline networks and learn the required knowledge. On the other hand, they can revise their ideas by listening to their opinions widely through online networks. Therefore, in this phase, communication in both networks soared, which is shown in Figure 6.

In the championing phase, given that highly novel ideas have a high risk of rejection, creators aim at obtaining approval to push the idea forward and, consequently, also obtain money, time, or political cover. Strong ties are characterized by norms of reciprocity that facilitate the exchange of favors and mutual support, and individuals through strong ties are motivated to help and support each other's initiatives. Moreover, by contributing strong ties with subjects who own high influence, creators could increase their legitimacy stock and help creators reduce perceived uncertainty by drawing on others' behavioral cues. Offline networks are easier to build strong connections, so it is not difficult to reveal the fact from Figure 7 that communication in offline networks is more significant in this phase.

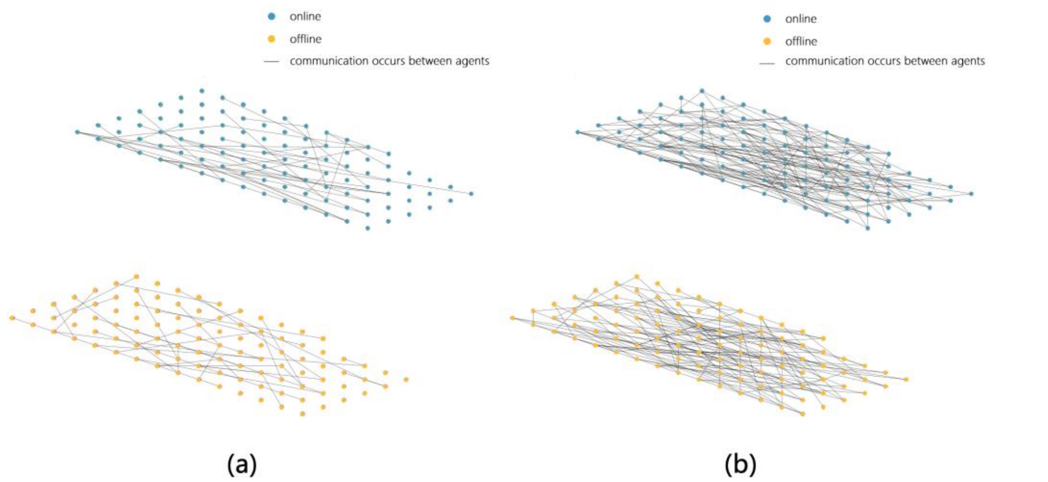

Figure 6. Communication on networks that takes place during a certain period time. (**a**) When t = 5, the value is 57; (**b**) When t = 20, the value is 497.

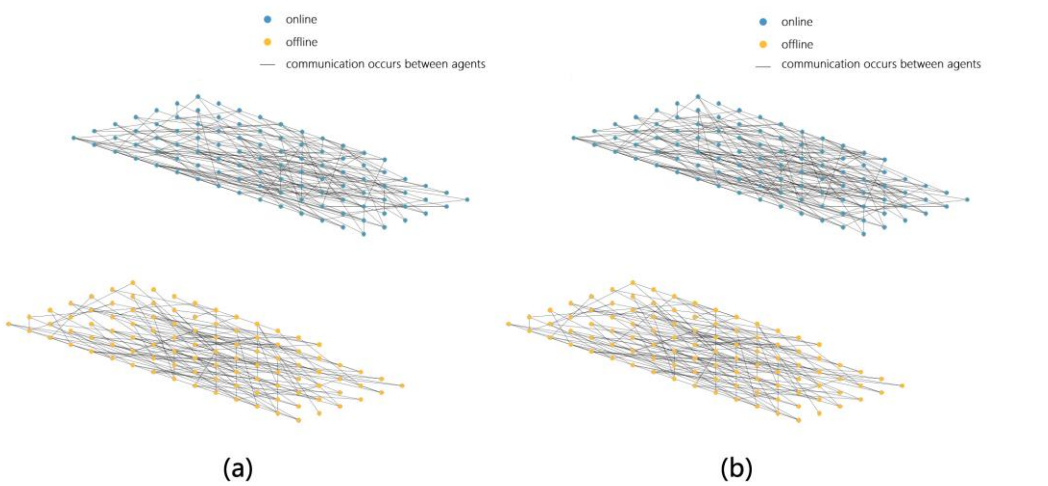

Figure 7. Communication on networks that takes place during a certain period time. (**a**) When t = 21, the value is 512; (**b**) When t = 28, the value is 746, the innovation has been achieved.

6. Conclusions

In this paper, we establish an innovative simulation analysis model on a double-layer coupled network. An online cooperative network differs from offline ones and is characterized by a more flexible structure. By introducing the structure of the online cooperative network, we investigate the impact of the double-layer network relationship on innovation from the perspective of a multi-layer network. Furthermore, we set the selection mechanism to simulate the process of internal knowledge diffusion in the process of innovation. Different from previous studies which merely focused on a specific stage in the innovation process, our proposed recombination mechanism makes the innovation process in the model more complete. Our proposal lays the theoretical foundation in the scope of innovation research from the social network perspective and further extends the meaning of the multi-layer network coupling theory. It is of practical significance to guide enterprises to adjust the structure of their online cooperation network and optimize the internal cooperation relationship.

The online–offline double-layer coupling network with different coupling relations is simulated, and the conclusions are defined as follows.

At the beginning of the innovation process, the generation phase, employees need to contact new knowledge to expand their knowledge reserve and change their cognitive structure. Organizations could shorten the time cost of this stage by increasing the communication between employees by using OSM, such as online meetings. Online meetings offer many advantages such as flexibility, convenience, time, and cost savings, as well as increasing opportunities for communication.

Different from the previous stage, when an idea is initially determined, extensive knowledge is no longer important, and more precise and profound knowledge becomes necessary. Face-to-face communication will be very helpful; while OSM solves the circumstances of absence, online communication has the same effect on knowledge enhancement.

The championing phase aimed at obtaining approval to push the idea forward. OSM is no longer beneficial for obtaining relevant support. Instead, offline communication might obtain influence and legitimacy. Influence is fundamental to protecting ideas from encroachment and criticism, removing obstacles to their acceptance, and persuading relevant decision-makers to provide their approval and resources for implementation. In this phase, organizations should promote offline communication instead of using OSM.

OSM is not always effective, but tighter networks do facilitate innovation. It is worth noting that the closeness of online cooperative networks is not always better; the redundancy of tight networks might reduce the efficiency of innovation. Under the network scale simulated in this study, the optimal double-layer network density coupling relationship does not represent all networks, because this coupling relationship may change with the scale of networks.

This study proves the promoting effect of online cooperative networks on innovation and explores the mechanism of the relationship between online cooperative network and offline cooperative network density on innovation. The conclusions of this study facilitate a better understanding of the coupling relationship in double-layer networks. The model adopted in this study simulates the internal cooperative relationship of contemporary enterprises well, and the online cooperative network extended by this model may have further application in social structures.

Despite the above findings, our future interest will be focusing on collecting real signed social network data to verify the effectiveness of several main conclusions obtained in this study and other vital network structure indexes. The proposed model may also be adaptive to other dynamic problems, involving, but not limited to, knowledge diffusion in asymmetrical networks, and innovation in the case of inconsistent efficiency of knowledge transmission.

Author Contributions: Conceptualization, J.H., W.Z., J.W. and S.L.; methodology, J.W.; formal analysis, J.H.; data curation, W.Z.; writing—original draft preparation, W.Z.; writing—review and editing, W.Z., J.W. and S.L.; visualization, J.W.; supervision, J.H.; funding acquisition, J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 72074139.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Acknowledgments: The authors would like to thank the anonymous referees as well as the editors.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Ramon Saura, J.; Palacios-Marques, D.; Ribeiro-Soriano, D. Exploring the Boundaries of Open Innovation: Evidence from Social Media Mining. *Technovation* **2023**, *119*, 102447. [CrossRef]
2. Fulk, J.; Yuan, Y.C. Location, Motivation, and Social Capitalization via Enterprise Social Networking. *J. Comput.-Mediat. Commun.* **2013**, *19*, 20–37. [CrossRef]
3. Cheng, C.C.J.; Shiu, E.C. How to Enhance SMEs Customer Involvement Using Social Media: The Role of Social CRM. *Int. Small Bus. J.-Res. Entrep.* **2019**, *37*, 22–42. [CrossRef]

4. De Zubielqui, G.C.; Jones, J. How and When Social Media Affects Innovation in Start-Ups. A Moderated Mediation Model. *Ind. Mark. Manag.* **2020**, *85*, 209–220. [CrossRef]
5. Wang, G.; Zhang, W.; Zeng, R. WeChat Use Intensity and Social Support: The Moderating Effect of Motivators for WeChat Use. *Comput. Hum. Behav.* **2019**, *91*, 244–251. [CrossRef]
6. Ali-Hassan, H.; Nevo, D.; Wade, M. Linking Dimensions of Social Media Use to Job Performance: The Role of Social Capital. *J. Strateg. Inf. Syst.* **2015**, *24*, 65–89. [CrossRef]
7. Karakayali, N.; Kilic, A. More Network Conscious Than Ever? Challenges, Strategies, and Analytic Labor of Users in the Facebook Environment: More Network Conscious Than Ever. *J. Comput.-Mediat. Commun.* **2013**, *18*, 61–79. [CrossRef]
8. Wang, W.; Liang, Q.; Mahto, R.; Deng, W.; Zhang, S.X. Entrepreneurial Entry: The Role of Social Media. *Technol. Forecast. Soc. Chang.* **2020**, *161*, 120337. [CrossRef]
9. Coleman, J.S. Social Capital in the Creation of Human Capital. *Am. J. Sociol.* **1988**, *94*, S95–S120. [CrossRef]
10. Hua, L.; Yang, Z.; Shao, J. Impact of Network Density on the Efficiency of Innovation Networks: An Agent-Based Simulation Study. *PLoS ONE* **2022**, *17*, e0270087. [CrossRef]
11. Havakhor, T.; Soror, A.A.; Sabherwal, R. Diffusion of Knowledge in Social Media Networks: Effects of Reputation Mechanisms and Distribution of Knowledge Roles. *Inf. Syst. J.* **2018**, *28*, 104–141. [CrossRef]
12. Perry-Smith, J.E.; Mannucci, P.V. From Creativity to Innovation: The Social Network Drivers of the Four Phases of the Idea Journey. *Acad. Manag. Rev.* **2017**, *42*, 53–79. [CrossRef]
13. Chan, T.H.; Liu, H.; Keck, S.; Tang, W. When Do Teams Generate Valuable Inventions? The Moderating Role of Invention Integrality on the Effects of Expertise Similarity, Network Cohesion, and Gender Diversity. *Prod. Oper. Manag.* **2023**, *32*, 1760–1777. [CrossRef]
14. Almaatouq, A.; Noriega-Campero, A.; Alotaibi, A.; Krafft, P.M.; Moussaid, M.; Pentland, A. Adaptive Social Networks Promote the Wisdom of Crowds. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 11379–11386. [CrossRef] [PubMed]
15. Mustafa, S.; Zhang, W.; Naveed, M.M. How to Mend the Dormant User in Q&A Communities? A Social Cognitive Theory-Based Study of Consistent Geeks of StackOverflow. *Behav. Inf. Technol.* **2023**, 1–20. [CrossRef]
16. Dong, Y.; Zha, Q.; Zhang, H.; Kou, G.; Fujita, H.; Chiclana, F.; Herrera-Viedma, E. Consensus Reaching in Social Network Group Decision Making: Research Paradigms and Challenges. *Knowl.-Based Syst.* **2018**, *162*, 3–13. [CrossRef]
17. Chong, A.Y.L.; Lacka, E.; Boying, L.; Chan, H.K. The Role of Social Media in Enhancing Guanxi and Perceived Effectiveness of E-Commerce Institutional Mechanisms in Online Marketplace. *Inf. Manag.* **2018**, *55*, 621–632. [CrossRef]
18. Pollet, T.V.; Roberts, S.G.B.; Dunbar, R.I.M. Use of Social Network Sites and Instant Messaging Does Not Lead to Increased Offline Social Network Size, or to Emotionally Closer Relationships with Offline Network Members. *Cyberpsychol. Behav. Soc. Netw.* **2011**, *14*, 253–258. [CrossRef]
19. Schötteler, S.; Laumer, S.; Schuhbauer, H. Consequences of Enterprise Social Media Network Positions for Employees: A Literature Review and Research Agenda. *Bus. Inf. Syst. Eng.* **2023**, *65*, 425–440. [CrossRef]
20. Pee, L.G. Affordances for Sharing Domain-Specific and Complex Knowledge on Enterprise Social Media. *Int. J. Inf. Manag.* **2018**, *43*, 25–37. [CrossRef]
21. Leonardi, P.M. Social Media, Knowledge Sharing, and Innovation: Toward a Theory of Communication Visibility. *Inf. Syst. Res.* **2014**, *25*, 796–816. [CrossRef]
22. Pillet, J.-C.; Carillo, K.D.A. Email-Free Collaboration: An Exploratory Study on the Formation of New Work Habits among Knowledge Workers. *Int. J. Inf. Manag.* **2016**, *36*, 113–125. [CrossRef]
23. Martín-Rojas, R.; Garrido-Moreno, A.; García-Morales, V.J. Social Media Use, Corporate Entrepreneurship and Organizational Resilience: A Recipe for SMEs Success in a Post-Covid Scenario. *Technol. Forecast. Soc. Chang.* **2023**, *190*, 122421. [CrossRef]
24. McAfee, A.P. Enterprise 2.0: The Dawn of Emergent Collaboration. *IEEE Eng. Manag. Rev.* **2006**, *34*, 38. [CrossRef]
25. Leonardi, P.M.; Huysman, M.; Steinfield, C. Enterprise Social Media: Definition, History, and Prospects for the Study of Social Technologies in Organizations. *J. Comput.-Mediat. Commun.* **2013**, *19*, 1–19. [CrossRef]
26. Moqbel, M.; Kock, N. Unveiling the Dark Side of Social Networking Sites: Personal and Work-Related Consequences of Social Networking Site Addiction. *Inf. Manag.* **2018**, *55*, 109–119. [CrossRef]
27. Bretschneider, S.; Parker, M. Organization Formalization, Sector and Social Media: Does Increased Standardization of Policy Broaden and Deepen Social Media Use in Organizations? *Gov. Inf. Q.* **2016**, *33*, 614–628. [CrossRef]
28. Hsu, M.-H.; Chang, C.-M. Examining Interpersonal Trust as a Facilitator and Uncertainty as an Inhibitor of Intra-Organisational Knowledge Sharing: Interpersonal Trust and Uncertainty. *Inf. Syst. J.* **2014**, *24*, 119–142. [CrossRef]
29. Aalbers, R.H.L.; Dolfsma, W.; Leenders, R.T.A.J. Vertical and Horizontal Cross-Ties: Benefits of Cross-Hierarchy and Cross-Unit Ties for Innovative Projects: Vertical and Horizontal Cross-Ties. *J. Prod. Innov. Manag.* **2016**, *33*, 141–153. [CrossRef]
30. Cao, B.; Han, S.; Jin, Z. Modeling of Knowledge Transmission by Considering the Level of Forgetfulness in Complex Networks. *Phys. A* **2016**, *451*, 277–287. [CrossRef]
31. Qiao, T.; Shan, W.; Zhang, M.; Liu, C. How to Facilitate Knowledge Diffusion in Complex Networks: The Roles of Network Structure, Knowledge Role Distribution and Selection Rule. *Int. J. Inf. Manag.* **2019**, *47*, 152–167. [CrossRef]
32. Deichmann, D.; Moser, C.; Birkholz, J.M.; Nerghes, A.; Groenewegen, P.; Wang, S. Ideas with Impact: How Connectivity Shapes Idea Diffusion. *Res. Policy* **2020**, *49*, 103881. [CrossRef]

33. Goclowska, M.A.; Ritter, S.M.; Elliot, A.J.; Baas, M. Novelty Seeking Is Linked to Openness and Extraversion, and Can Lead to Greater Creative Performance. *J. Pers.* **2019**, *87*, 252–266. [CrossRef]
34. Mueller, J.; Melwani, S.; Loewenstein, J.; Deal, J.J. Reframing the Decision-Makers' Dilemma: Towards a Social Context Model of Creative Idea Recognition. *Acad. Manag. J.* **2018**, *61*, 94–110. [CrossRef]
35. Ter Wal, A.L.J.; Alexy, O.; Block, J.; Sandner, P.G. The Best of Both Worlds: The Benefits of Open-Specialized and Closed-Diverse Syndication Networks for New Ventures' Success. *Adm. Sci. Q.* **2016**, *61*, 393–432. [CrossRef]
36. Kwayu, S.; Lal, B.; Abubakre, M. Enhancing Organisational Competitiveness Via Social Media—A Strategy as Practice Perspective. *Inf. Syst. Front.* **2018**, *20*, 439–456. [CrossRef]
37. Phan, T.Q.; Airoldi, E.M. A Natural Experiment of Social Network Formation and Dynamics. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 6595–6600. [CrossRef] [PubMed]
38. Lavie, D.; Rosenkopf, L. Balancing Exploration and Exploitation in Alliance Formation. *Acad. Manag. J.* **2006**, *49*, 797–818. [CrossRef]
39. Burt, R.S. Structural Holes and Good Ideas. *Am. J. Sociol.* **2004**, *110*, 349–399. [CrossRef]
40. Scaringella, L.; Miles, R.E.; Yann, T. Customers Involvement and Firm Absorptive Capacity in Radical Innovation: The Case of Technological Spin-Offs. *Technol. Forecast. Soc. Chang.* **2017**, *120*, 144–162. [CrossRef]
41. Argyres, N.; Rios, L.A.; Silverman, B.S. Organizational Change and the Dynamics of Innovation: Formal R&D Structure and Intrafirm Inventor Networks. *Strateg. Manag. J.* **2020**, *41*, 2015–2049. [CrossRef]
42. Gunasekaran, A.; Papadopoulos, T.; Dubey, R.; Wamba, S.F.; Childe, S.J.; Hazen, B.; Akter, S. Big Data and Predictive Analytics for Supply Chain and Organizational Performance. *J. Bus. Res.* **2017**, *70*, 308–317. [CrossRef]
43. Butler, B.S. Membership Size, Communication Activity, and Sustainability: A Resource-Based Model of Online Social Structures. *Inf. Syst. Res.* **2001**, *12*, 346–362. [CrossRef]
44. Cennamo, C.; Ozalp, H.; Kretschmer, T. Platform Architecture and Quality Trade-Offs of Multihoming Complements. *Inf. Syst. Res.* **2018**, *29*, 461–478. [CrossRef]
45. Von Briel, F.; Schneider, C.; Lowry, P.B. Absorbing Knowledge from and with External Partners: The Role of Social Integration Mechanisms: Absorbing Knowledge from and with External Partners. *Decis. Sci.* **2019**, *50*, 7–45. [CrossRef]
46. Bernstein, B.; Singh, P.J. An Integrated Innovation Process Model Based on Practices of Australian Biotechnology Firms. *Technovation* **2006**, *26*, 561–572. [CrossRef]
47. Roper, S.; Du, J.; Love, J.H. Modelling the Innovation Value Chain. *Res. Policy* **2008**, *37*, 961–977. [CrossRef]
48. Chen, K.; Guan, J. Mapping the Innovation Production Process from Accumulative Advantage to Economic Outcomes: A Path Modeling Approach. *Technovation* **2011**, *31*, 336–346. [CrossRef]
49. Guidolin, M.; Manfredi, P. Innovation Diffusion Processes: Concepts, Models, and Predictions. *Annu. Rev. Stat. Appl.* **2023**, *10*, 451–473. [CrossRef]
50. Liu, C.; Liu, X. Research on Knowledge Transfer Behaviour in Cooperative Innovation and Simulation. *Econ. Res.-Ekon. Istraživanja* **2019**, *32*, 1219–1236. [CrossRef]
51. McKelvey, B. Toward a Complexity Science of Entrepreneurship. *J. Bus. Ventur.* **2004**, *19*, 313–341. [CrossRef]
52. Held, F.P.; Wilkinson, I.F.; Marks, R.E.; Young, L. Agent-Based Modelling, a New Kind of Research. *Australas. Mark. J.* **2014**, *22*, 4–14. [CrossRef]
53. Wang, Z.; Zhang, M.; Sun, H.; Zhu, G. Effects of Standardization and Innovation on Mass Customization: An Empirical Investigation. *Technovation* **2016**, *48–49*, 79–86. [CrossRef]
54. Dou, R.; Zong, C.; Nan, G. Multi-Stage Interactive Genetic Algorithm for Collaborative Product Customization. *Knowl.-Based Syst.* **2016**, *92*, 43–54. [CrossRef]
55. Opara, V.; Spangsdorf, S.; Ryan, M.K. Reflecting on the Use of Google Docs for Online Interviews: Innovation in Qualitative Data Collection. *Qual. Res.* **2023**, *23*, 561–578. [CrossRef]
56. March, J.G. Exploration and Exploitation in Organizational Learning. *Organ. Sci.* **1991**, *2*, 71–87. [CrossRef]
57. Levinthal, D.A.; March, J.G. The Myopia of Learning. *Strat. Mgmt. J.* **1993**, *14*, 95–112. [CrossRef]
58. Shiau, W.-L.; Dwivedi, Y.K.; Yang, H.S. Co-Citation and Cluster Analyses of Extant Literature on Social Networks. *Int. J. Inf. Manag.* **2017**, *37*, 390–399. [CrossRef]
59. Wang, Q.-H. Research and Development of Distributed Constraint Satisfaction Problems. *J. Softw.* **2006**, *17*, 2029. [CrossRef]
60. Chakravarty, S.; Dogan, K.; Tomlinson, N. A Hedonic Study of Network Effects in the Market for Word Processing Software. *Decis. Support Syst.* **2006**, *41*, 747–763. [CrossRef]