AI-Driven Dynamic Knowledge Innovation: Social Capital and Cognitive Pathways in Financial Industry Innovation

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Abstract. In this era of artificial intelligence (AI), humanoid systems enhance social capital, and this enhancement promotes knowledge innovation. The intelligent social network (ISN) is a crucial construct in this process. This paper aims to explore the effects of AI on social capital and innovation by constructing various types of social networks and characterizing the entire process of knowledge innovation from a cognitive perspective. This study collected 400 samples from the Xiaoguishan Financial Industrial Park, including data on the centrality of vertical networks, interactive networks, sequential networks, friend networks, advice networks, and ISN of members surveyed using the network nomination method. Members' knowledge innovation was surveyed using cognitive taxonomy and After Action Review (AAR) methods. The gradient descent algorithm was used to iterate and optimize the regression coefficients. The results show that social capital generated by AI has a significantly higher positive impact on innovation than other types of networks, particularly in application, analysis, and remembering in the cognitive taxonomies. This finding contributes to a deeper understanding of AI-driven social capital, facilitating further references to this concept in future research.

Keywords: AI-driven social capital, intelligent social network, dynamic knowledge innovation, cognitive taxonomy, network centrality, gradient descent.

1 Introduction

Mainstream research suggests that social capital stems from the structure and relational embeddedness of networks. Some scholars also argue that social capital arises from cognitive embeddedness. The operation and generation of social capital concretize the community's field entropy theory. The diversity of individual network dimensions arises from differences in community interaction and organizational methods, with personal motivation, relationship circles, positions within groups, and the degree of acceptance of institutions and norms also affecting the multidimensional construction of

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one's network. However, as interaction increases, the diversity of self-network dimensions diminishes while consistency strengthens. This increased consistency in networks leads to blurred boundaries, which hampers further reflection on the operation of social capital, such as the difficulty in attributing a dependent variable to a specific network type, impacting the interpretation and generalization of predictive results. With the integration of intelligent technologies, social capital is present not only in the real world but also in virtual realms. The pathways of social capital generation, based on people and organizations, also encompass the reliance on and trust in anthropomorphic systems [1].

AI-driven social capital is a metaphor for how smart technologies generate and strengthen social capital. First, AI-driven social capital arises from computational networks, which are essentially social networks by nature. Second, many scholars have further elaborated on this explanation, exploring how AI impacts social capital and the mechanisms of embedding intelligent networks [2]. Third, the contribution of AI and virtual technologies to social capital is evident in several ways: the diversity of media connections deepens and expands the networks of individuals and organizations; remote and virtual reality technologies overcome temporal and spatial limitations; AI has established a dependency on humanoid and expert systems [3]. However, the concept of AI-driven social capital has not been adequately introduced in research on the construction of social capital and its role in innovation, and its importance has not been empirically validated in comparison with traditional social capital. More importantly, traditional knowledge management evaluation frameworks rarely investigate or assess AI-driven social capital, with research on innovation communities often focusing more on tools and smart applications.

Evaluating knowledge conversion from the perspective of social networks and AI-driven social capital is beneficial for the construction and management of knowledge networks within innovation communities [4]. This is particularly evident in the following aspects: First, AI-driven social capital derived from computational trust primarily reflects individuals' mastery of computational thinking and numerical control technologies. Second, new forms of social capital continue to demonstrate the support that intelligent applications provide for network embedding. Third, a favorable network position can either generate or control a substantial flow of information, which facilitates the development of new understandings and modes of thinking regarding AI. This paper uses gradient descent algorithms to analyze data collected from formal and informal networks, as well as interactions with anthropomorphic systems within self-networks. The study identifies the factors influencing knowledge conversion and innovation and provides evidence of the impact of AI-driven social capital on knowledge conversion through a comparison of network types.

2 Theoretical Foundation and Model Construction

2.1 Cognitive Level Evaluation in Knowledge Management

Knowledge innovation and knowledge conversion are continuous, spiraling processes that can be broadly divided into two stages: tacit knowledge explicitation and explicit knowledge tacitization. Similar to the SECI model, the significance of the (digital) Bloom's taxonomy in the era of intelligent empowerment is more reflected in the construction of digital platforms [5]. Bloom's Taxonomy offers several advantages in evaluating knowledge conversion. First, Bloom's Taxonomy seeks to build competency models by identifying breakthroughs from internal human factors. Second, this evaluation method is well-suited to informal learning, which relies on universal pathways. Third, the Bloom cognitive framework supports social learning. Furthermore, the practical experience of Bloom's Taxonomy in blended learning can serve as a reference for knowledge management. However, evaluations of knowledge conversion from the perspective of cognitive classification rarely focus on innovation communities. More importantly, many evaluations are static and do not emphasize the dynamic nature of the knowledge conversion process.

This study defines knowledge conversion through the enhancement of cognitive levels, which is closely related to knowledge innovation. Therefore, this study employs the AAR (After Action Review) method to survey training and learning personnel.

2.2 Network Types and Functions

From the perspective of group dynamics, different social behaviors and fields collectively produce various social configurations. Different types of social networks not only express individuals' psychological and perceptual aspects through network structure, relational connections, density, scope, accessibility, strength, and frequency but also deeply outline the constraints imposed by institutions, culture, organizational design, and environment [6, 7]. Based on events, positional structure design, reciprocity and interaction modes, and clustering methods, social networks can generally be categorized into vertical networks, sequential networks, interactive networks, friendship networks [8], advice networks [9], and intelligent social networks [10] (see Table 1). If categorized by context, vertical networks, sequential flow networks, and interactive networks are considered formal, while friendship networks, advice networks, and intelligent social networks are informal. However, as mobility and interaction increase, and the similarity between self and others deepens, formal networks tend to become more informal [6]. Furthermore, AI also plays a supplementary and connective role in various types of networks, indirectly demonstrating that AI's penetration leads to a flattening of different network structures and the emergence of consistency [10].

Table 1. Network Types and Their Functions

Types	Functions	Items	References
Vertical network (VN)	It has a normative role in organizational activities. Power does not always reflect centrality, and the distance for information to reach the power center is relatively long, leading to a significant amount of redundant information. Additionally, it has a clear obstructive effect on exploratory innovation	List relevant supervisors and managers Which of your superiors regularly provides you with information resources?	Lv & Zhao,2023; Scott, 2011
Sequential network		To whom will I delegate my work?	

(SN)	Network relationships based on work processes exhibit significant closedness	Who will pass on completed work assignments to me?	
Interactive network (IN)	Consistency Inverted U-shape: Early-stage knowledge exchange increases, while later-stage use of online technology turns the work interactive network into a barrier to knowledge exchange. Inconsistency Inverted U-shape: The network organizational structure has a beneficial impact on employee performance in the early stages but becomes obstructive in the later stages.	Who do I usually work with who needs to interact with each other to get the job done?	
Friendship networks (FN)	It has a strong bidirectional characteristic, with a greater willingness to both send and receive knowledge	Who I know best. Who do I talk to when I am frustrated or chastised at work? Who would I talk to about family and life?	Pillemer & Rothbard, 2018
Advice networks (AD)	It reflects the interaction and collaboration relationships in the innovation process. It is an informal, instrumental network, and advisory relationships also represent, to some extent, network embedding.	Who do I usually ask for advice when I encounter difficulties in my work and study? Who do I usually discuss relevant issues with when dealing with day-to-day business Who will give me advice when things get tough?	Cangialosi et al., 2021
Intelligent social networks (ISN)	It provides digital tools to establish remote and virtual social networks. This relationship is both an extension and a breakthrough of social networks, including not only relationships with humans but also trust relationships with humanoid and expert systems.	media connectivity dimension Behavior of cybercommunities interactions	Yu et al., 2024

2.3 Model Construction

This study uses gradient descent algorithms to analyze data on network structures and cognitive classifications. Gradient descent is an optimization algorithm based on machine learning and deep learning, primarily aimed at finding the optimal solution for variable parameters by minimizing the loss function and its partial derivatives. Its advantage in the application of management lies in the precise prediction of input-output relationships to enhance accuracy. Furthermore, the gradient descent method excels in handling large-scale data, improving computational efficiency. Its construction scenarios include linear regression, neural networks, and large-scale datasets. The gradient descent method for linear regression is suitable for ranking the importance of independent variables and predicting parameters. Because it is necessary to handle different types of independent variables (different network types) and dependent variables with hierarchical and sequential logic (cognitive levels in dynamic innovation), this study uses a regression approach to establish a gradient descent training model.

This study uses centrality to represent various types of network structures. The dot centrality (i) of network type X_N (N stands for network type): $deg(i) = \sum_{j,\ i\neq j}^{i} x_{ijq}$ (j for other actors, q for the types of relational connection).

The relative centrality of points (i) in a network of a certain type X_N (see Eq.1):

$$X_{Ni} = \frac{deg(i)}{\frac{1}{n}\sum_{i=1}^{n} deg(i)} \tag{1}$$

Among them, the centrality of the intelligent social network X_{ISN} is formed by the joint construction of human beings, ω_{hunman} is the construction weight of human beings in virtual communities, ω_{AI} is the weight of AI construction, and q_{AI} is the way to establish a relationship with AI: $X_{ISN(i)} = \omega_{human} \cdot \frac{deg(i)}{\frac{1}{n}\sum_{i=1}^{n} deg(i)} + \omega_{AI} \cdot \frac{\sum_{q_{AI}}^{i} x_{iq_{AI}}}{\frac{1}{n}\sum_{i=1}^{n}\sum_{q_{AI}}^{i} x_{iq_{AI}}}$.

Second, establish the regression of relevant knowledge conversion (Y) (see Eq. 2):

$$Y = \beta \cdot X_N + \varepsilon \tag{2}$$

Y is about a dynamic set of Bloom's taxonomy of cognition presented in knowledge conversion, but X_N rather a collection of various network types of centralities, as manifested in:
$$\begin{pmatrix} remember_1 & \cdots & creation_1 \\ \vdots & \ddots & \vdots \\ remember_i & \cdots & creation_i \end{pmatrix} = \begin{pmatrix} 1 & VN_1 & \cdots & ISN_1 \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ 1 & VN_i & \cdots & ISN_i \end{pmatrix} \cdot \begin{pmatrix} \beta_{0_{remember}} & \cdots & \beta_{0_{creation}} \\ \vdots & \ddots & \vdots \\ \beta_{ISN_{remember}} & \cdots & \beta_{ISN_{creation}} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1_{remember}} & \cdots & \varepsilon_{1_{creation}} \\ \vdots & \ddots & \vdots \\ \varepsilon_{m_{remember}} & \cdots & \varepsilon_{m_{creation}} \end{pmatrix}$$
, Third, establish the loss equation (3), $h_\beta(x_i) = \beta \cdot X_N$ is the predicted value, y_i is the actual value, and m is the sample size:

$$J(\beta) = \frac{1}{2m} \cdot \sum_{i=1}^{m} (h_\beta(x_i) - y_i)^2 \tag{3}$$

Establish the equation (4) of gradient descent, where α (learning rate) is the learning rate and $\partial_{J(\beta)}/\partial_\beta$ is the partial derivative of the loss function on the regression coefficient:

$$\beta := \beta - \alpha \frac{\partial_{J(\beta)}}{\partial_\beta} \tag{4}$$

In constructing a model trained on regression coefficients, β is updated at each iteration until $J(\beta)$ converges to a minimum. The number of iterations can be based on the criterion that the loss function $J(\beta)$ is less than the threshold or adjusting based on observing the loss function every 100 iterations. The second approach was chosen in this study, with 1,000 iterations selected. When $J(\beta)$ approaches 0 or the number of iterations is more than 1000, the iteration is stopped and the optimal regression coefficient is obtained. The selection of iterations is based on existing experience and observations, dynamically adjusting the number of iterations to achieve optimal fitting and reduce training time. This approach can refer to Goodfellow et al. [11].

3 Data Analysis

3.1 Data Survey

As the foundation of this research, we collected relevant data from Xiaoguishan in Wuhan. The survey was conducted between 2021 and 2023. Xiaoguishan Financial and Cultural Park is an industry park themed around finance, encompassing industries such as design, financial services, consulting, investment, culture, and data services. The number of valid samples collected in this study is 400.

3.2 Data Analysis

Using the gradient descent algorithm based on regression coefficients, we derived the impact of various network centralities on memory, understanding, application, analysis, evaluation, and creation in the knowledge conversion process. In the gradient descent model, the learning rate is set at 0.01, determined through multiple trials. A learning rate too large can cause convergence difficulties, while a rate too small results in slow iteration speeds. As illustrated in Figure 1, the training set reaches a steady state after 200 iterations, with an error below 2.8, indicating a good fit for the training set.

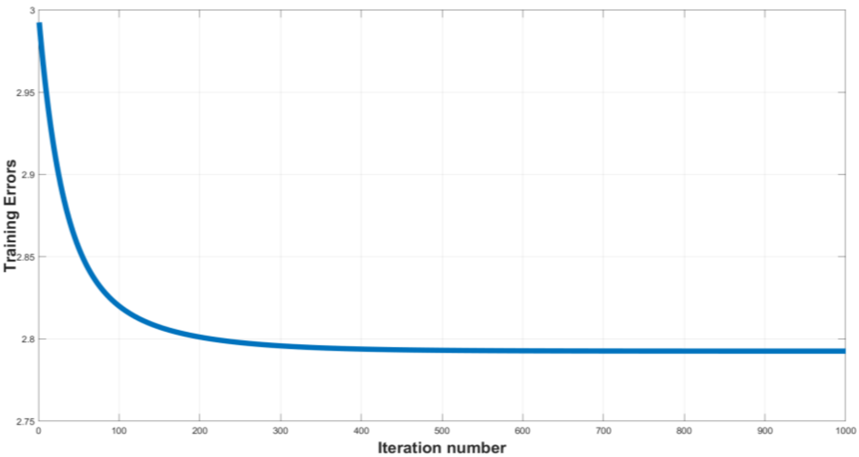

Fig. 1. Error Plot-Gradient Descent

Figure 2 illustrates the optimal regression coefficients. It can be observed that vertical networks have a relatively small and often negative impact on all dependent variables, particularly on memory and creation. This suggests that hierarchical organizational networks have a minimal effect on various cognitive aspects of knowledge innovation. A similar trend is seen in work interaction networks and sequential networks, although the sequential network shows a notably strong impact on evaluation. In contrast, friend networks, advice networks, and ISN have a more substantial influence on the dependent variables, especially the ISN.

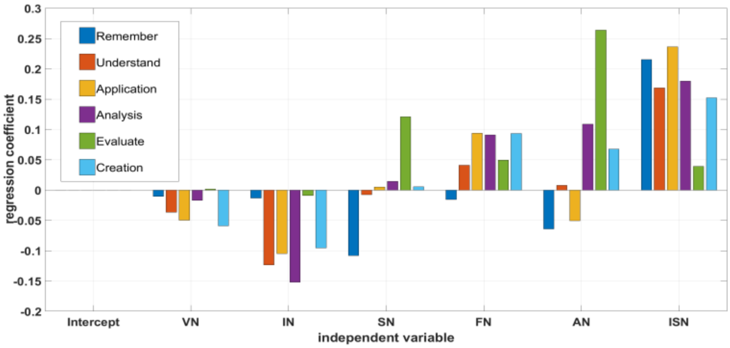

Fig. 2. Optimal Regression Coefficient

From Figure 2, it is evident that AI (or ISN) significantly impacts application, analysis, memory, understanding, and creativity within the knowledge innovation process. The social capital generated by the advice network (AD) is mainly reflected in its evaluative behaviors towards knowledge. AS same as AD, the friends network influences other cognitive behaviors, except for memory, but their impact is less pronounced than that of ISN (see Fig. 3.). The sequential network in the workplace, which is more formal, primarily affects evaluation and commentary. Vertical and interactive networks do not exhibit a significant impact on cognition within the knowledge innovation process.

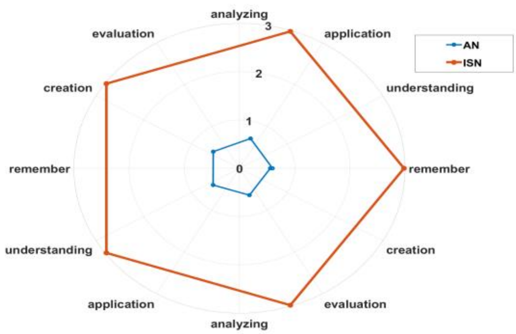

Fig. 3. Advice Networks vs. Intelligent Social Networks

4 Conclusions

In this study, we utilized the gradient descent algorithm to evaluate the impact of various network centrality on different cognitive levels within the knowledge conversion process. Our aim was to identify the differences that demonstrate AI's significant influence on knowledge innovation through social capital. The findings indicate that AI-driven social capital plays a crucial role across all cognitive levels of knowledge conversion, significantly enhancing the knowledge innovation process. This finding provides new insights for both academia and practitioners, aiding in a deeper understanding of the significance and mechanism of AI-driven social capital within innovation networks, particularly addressing the issue of its insufficient incorporation in related research [12].

By integrating cognitive levels with the social network paradigm, this paper establishes a dynamic model of knowledge conversion, arguing that AI's positive output toward knowledge innovation in Society 5.0 must align with appropriate cognitive levels. Building upon previous research [13], this study further combines the social network paradigm to develop a dynamic evaluation of knowledge innovation based on cognitive classification. This approach facilitates a deeper assessment of the relationship between different types of social capital and knowledge innovation. Moreover, by closely examining the interconnections among structural capital, relational capital, and human capital, this paper posits that A is the driving force behind technological transformation and knowledge innovation [14], and further identifies the reasons from a cognitive classification perspective. Finally, through iterative calculation of regression coefficients using gradient descent, it was found that the way AI-driven social capital impacts knowledge innovation is markedly different from traditional methods. The significant influence of AI-driven social capital on knowledge innovation is evident in its enhancement effects on application, analysis, memory, understanding, and creativity. This is significantly different from other informal network types, such as the instrumental advice network, which primarily influences knowledge collaboration through evaluation and commentary. However, AI's effect on facilitating commentary is relatively low (below average). These findings indicate that the mechanism of AI-driven social capital's impact on knowledge innovation requires differentiated research.

This study contributes by filling the gap in the existing literature regarding AI-driven Social Capital and further elucidates the mechanism by which AI-driven Social Capital impacts knowledge innovation. A limitation of this study is that the sample is solely derived from the Wuhan Xiaoguishan Financial Park, and the characteristics of this specific region may limit the generalizability of the findings. Future research should expand the sample scope to verify the universality of the results. Looking ahead, future research should incorporate control variables, covariates, and moderators to gain a more comprehensive understanding of AI's impact on knowledge collaboration, sharing, and innovation. This is essential for two primary reasons: first, the current study did not account for factors such as demographics, motivation, and psychology; second, it is crucial to explore the relationships between AI and various cognitive levels, including application, analysis, memory, understanding, and creativity. These connections reveal unique pathways for AI-driven knowledge innovation.

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