Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

The role of machine learning techniques in optimising top management interlocking networks for green innovation

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ABSTRACT

Social network structural characteristics of top management (TMT) are important variables that affect the outcome of team functioning, and variability in network structural characteristics leads to variability in TMT performance. This paper analyzes TMT social network structure characteristics based on TMT's social relationship network using machine learning techniques. The top management interlocking network and technological innovation (machine learning technology) are divided into dimensions respectively, and the machine learning technology is used as a mediating variable to establish a model of the mediating effect of machine learning technology between top management interlocking network and green innovation. Statistical analysis of sample data and structural characterization of TMT social relationship networks by machine learning technology are conducted, and regression equations are used to verify the research hypotheses. The test results of the mediating effect of utilized innovation and exploratory innovation covered by the machine learning technology show that the overall regression effect of the model is good (R^2=0.537, R^2=0.579, F-statistical test is significant), i.e., the mediating variables, utilized innovation and exploratory innovation, positively affect the green innovation performance and are significant. Meanwhile, the heterogeneity and size of TMT's social relationship network, as well as relationship strength and relationship quality all have a significant and positive effect on green innovation.

Keywords: mediating effect, regression analysis, correlation analysis, machine learning techniques, top management

1. Introduction

With the rapid development of economic globalization, network and communication and other information technology is changing day by day, which makes the business environment of enterprises become more and more complex, the connotation and extension of the knowledge field that the enterprise operators have to have become very wide, the boundaries between the various knowledge fields have been very blurred, the knowledge of different disciplines cross each other and fusion, and the professional knowledge and skills of the single top management personnel can not ensure that they can The professional knowledge

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Received 01 May 2024; Revised 23 August 2024; Accepted 05 September 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-046

and skills of a single top manager cannot guarantee that he or she can accomplish all the complex tasks faced in the process of enterprise operation, therefore, the top managers of an enterprise work through the form of a team is considered to be a way to improve the strategic leadership ability [1-4]. The way of enterprise management and decision-making by the top management team composed of top executives from different departments and different fields, referred to as TMT, has become the trend of development, and TMT has become the driving force for the sustainable development of the enterprise and the operational unit for maintaining the advantage of the enterprise. Therefore, for modern enterprises, the performance of TMT has also become one of the core factors determining the overall management level and operational efficiency of the enterprise [5-7].

With the further deepening of China's modernization, all kinds of advanced management methods and management experiences from western developed countries have been gradually introduced into the practice of Chinese enterprises. Especially in recent years, Chinese enterprises have realized the promotion effect of TMT operation mode on enterprise performance and actively tried to implement TMT operation mode [8-10]. Overall, the research on TMT in China is still in its infancy, and not many of them can effectively implement team management and give full play to team functions. Current research on TMT performance mainly focuses on the effects of team member characteristics, team structure, and team operation process on performance, and the social network characteristics variable has been neglected by previous research on TMT performance. Since different social network structure characteristics often affect the operation of TMT, it is important to explore the influence of interaction network structure on TMT performance [11-13].

On the other hand, with science and technology innovation as the core element of the new quality productivity will show strong impetus and support for high-quality development, digitalization and greening to accelerate the formation of the new quality productivity to provide an important track to accelerate the release of the value of the data elements has become an urgent task to promote the development of the new quality productivity [14-15]. However, this process can not be separated from the managers directly applied to the daily production and operation activities of enterprises, in order to give full play to the enabling role of the digital economy on the decision-making behavior of enterprises, but also need to be processed by the top management of the enterprise to enhance the commodity value and value of use of data elements, and ultimately incorporated into the decision-making system to improve the program [16-17]. This echoes the barriers to innovation that Chinese enterprises are currently facing, which are the lack of innovative talents, imperfect education and training mechanisms, inability to accurately grasp market information, long payback period and high innovation costs, so enterprises must integrate innovation resources with a more open perspective in the growth process, carry out in-depth cooperation between industry, academia and research institutes, make full use of global resources, and proactively adapt to the current digital transformation and development model to break through the barriers to enterprise innovation. Development mode, break through enterprise innovation barriers, respond to the “help deepen the reform of the science and technology system and talent development system mechanism reform” call [18-20].

In this paper, the top management interlocking network and machine learning technology are divided into five dimensions: network size, network centrality, network heterogeneity, relationship strength and relationship duration. And machine learning technology was used to characterize the structure of top management social relationship network. Machine learning technology was used as a mediating variable and further subdivided into exploitative and exploratory innovations. Based on the interrelationship among top management social relationship network, technological innovation (machine learning technology), and green innovation, research hypotheses are proposed to test the correlation of each variable, and regression models are applied to test the research hypotheses respectively.

2. Top management social networks and technological innovation

2.1. High-level management interlock network

2.1.1. Top Management Team (TMT). This paper proposes to describe and measure top management teams (TMT) in terms of team composition, team process and team structure. Team composition and team structure mainly refer to the biographical characteristics (including age, education, seniority, etc.) and authority structure of top management team members. The functioning process of the top management team, on the other hand, includes behaviors such as coordination, communication, conflict management, leadership, and motivation among team members. The demographic characteristics and interaction processes of team members directly affect top-level decision-making, which in turn affects organizational performance and strategic choices.

Corporate TMT evolves by considering the corporate top management team as a living organism, which takes on life characteristics. Corporate TMT is like all living organisms. It has a structure similar to that of a living system at all levels, such as cells and genes, and also possesses its own vitality, mode of movement, life span limit and life trajectory.

Life characteristics of TMT:

1) Metabolism

2) Stress

3) Tight organization and high degree of orderliness

2.1.2. Top management social networks:

1) The TMT's intra-organizational network consists of his connections with other members of the organization, including other members of the top management team, managers of functional departments and branch offices, and even employees in general. The more members of the organization the TMT knows (i.e., the stronger the structural embeddedness) and the more familiar he is with them (i.e., the stronger the associational embeddedness), the deeper the TMT's degree of embeddedness in the organization.

Thus even when TMTs are selected from the same organization, the degree of embeddedness varies greatly from TMT to TMT. Generally speaking, the longer the TMT has worked in the organization, the more functional departments he/she has worked in, the more diversified the management work he/she has done, and the more opportunities he/she has to interact with members of the organization, the more conducive it is for the TMT to expand his/her internal social network. That is, the more the individual's internal organizational network is strengthened.

2) Through the TMT's external social network, the organization is able to obtain a greater amount and quality of information, and is able to cross organizational boundaries accordingly.

TMT's external social network consists of individuals outside the organization who are connected to TMT. These individuals hold information that is valuable to the organization. Typically, these individuals include outside directors, suppliers, customers, competitors, and people in financial institutions, alliance organizations, government agencies, and trade organizations. TMT's stronger external social network means that there are a larger number of members outside the organization who are connected to TMT (i.e., higher structural embeddedness). And the TMT maintains strong ties with them (i.e., higher associative embeddedness).

2.2. Machine Learning Techniques in Social Network Analysis

2.2.1. Social networks. A social network is a type of complex network used to model the interactions of people in an association organization. A social network consists of individuals or groups and the various relationships that exist between them. These relationships include, for example, friendships, commenting and tracking relationships between bloggers, and collaborative tagging relationships between users in tagging systems [21].

Social networks are usually represented by visual “graphs”. Nodes in the graph represent actors, and links in the graph represent relationships between actors.

In addition to the properties of the nodes and links themselves, the structural features of the social network are often used as data processing objects. Social network analysis often uses the following structural features:

1) Network density: describes the level of linking of network nodes and is generally defined as the number of edges (or their proportion of the maximum possible number of edges) in a graph (subgraph).
2) Centrality: measures the structural importance of a node. A few commonly used centrality measures are, degree, compactness and mesomorphism.
3) Structural Equivalence and Structural Hole.
4) Characteristic path length: describes the general distance between two nodes.
5) Clustering coefficient: the ratio of the number of edges between nodes to the number of all possible edges among all neighboring nodes of a given node.

2.2.2. Application of machine learning techniques in social network analysis. Traditional machine learning deals with data instances. These data instances can often be represented by a vector containing multiple attribute values and satisfying the assumption of independent homogeneous distribution.

In contrast, nodes in social network data are not simply statistically independent sampling points; there are connections between nodes. Therefore, using machine learning techniques, the relationships between data instances need to be considered. This brings new challenges to traditional machine learning and gives rise to an emerging research direction called link mining. By analyzing links, richer and more accurate information about instances can be obtained.

The structural properties of social networks, such as the degree of nodes, connectivity, etc., provide important help in the analysis. There are also some complex patterns in social networks, such as subgraphs (which can be understood as associations or groups). How to obtain information about these complex patterns also presents new tasks for machine learning. The following is an introduction to the structural features of social networks.

Social relationships in a social network can be categorized as directed or undirected, and the connection strength between these relationships is also different, which means that the “edges” in a social network have weights.

Unlike an undirected social network, in a directed complete graph with M node, there are at most $M(M-1)$ edges, so according to the definition of network density, the formula (1) for calculating the density of a directed social network can be obtained as shown below:

$$Denstiy = \frac{m}{M(M-1)} \tag{1}$$

In the above equation, m is the actual number of links between all the nodes in the network.

For the average distance between nodes in a directed social network, it can be calculated by Dijkstra's algorithm. Where after calculating the shortest distance between pairs of nodes, it can be based on Eq:

$$L = \frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M} d_{ij} \tag{2}$$

To compute the average distance in a directed social network and then compute the cohesion of the network based on the average distance.

In a directed graph, the in-degree of a node is defined as the number of ties that terminate at a particular node, using that node as the arrow. The out-degree is the number of ties that start at a node with that node as the end of the arrow. In a directed social network, if the out-degree and in-degree of node X are x_1 and x_2, respectively, then the relative centrality of node X is calculated as shown in equation (3) below:

$$C_{RD}(x) = (x_1 + x_2)/(2n-2) \tag{3}$$

where n is the number of nodes.

The formula for calculating the absolute mediator centrality degree of a directed social network is the same as that of an undirected social network, except that the shortest path in it is calculated differently from that of an undirected social network. The shortest path length between nodes in a directed network can be calculated by Dijkstra's algorithm.

Relative mediator centrality is also used when studying social networks without using scale, and the formula (4) for calculating relative mediator centrality for directed networks is shown below:

$$C_{RBi} = C_{ABi}/C_{\max} = C_{ABi}/(n-1)(n-2) \tag{4}$$

Where $C_{\max}$ denotes the maximum possible value of mediated centrality degree and n is the number of nodes.

When analyzing the proximity centrality degree in a directed social network, there exists a sender proximity centrality degree and a receiver proximity centrality degree. The formula (5) for the outgoing proximity centrality degree is shown below:

$$C_{Co}(x_i) = \left[\sum_{j=1}^{n} d(x_i, x_j)\right]^{-1} \tag{5}$$

where $\sum_{j=1}^{n} d(x_i, x_j)$ is the sum of the shortest distances between node x_i and all its "attention" nodes x_j.

$$C_{Cl}(x_i) = \left[\sum_{j=1}^{n} d(x_i, x_j)\right]^{-1} \tag{6}$$

where $\sum_{j=1}^{n} d(x_i, x_j)$ is the sum of the shortest distances between node x_i and all its "fan" nodes x_j.

The meaning of the above two equations is that the proximity centrality of a node is the reciprocal of the sum of the distances of the shortest paths of that node from other nodes in the network. The smaller the value of proximity centrality, the more it is at the core. The current applications of machine learning in social network analysis are described below in turn, mainly in terms of node ranking, link-based classification, and link prediction.

In a social network, the likelihood that two people who initially share a common friend will become friends later increases. This principle is also known as ternary closure.

Ternary closure and embeddedness characterize the three-edged relationship between three nodes in a network, and although it may not be applicable to all connected-edged situations on large-scale complex networks, as an effective abstraction of the laws of reality often provides a reference basis for the study of link prediction. Link prediction, in a nutshell, is to infer the hidden edges in a network from the known information in the network. Prediction of edges between two nodes includes both prediction of unknown edges (i.e., lost edges) and prediction of future edges.

According to the ternary closure principle, in network G, node a and node b may be neighbors if they have a common neighbor a. It is also possible that node c and node b are also neighbors, which makes abc the three points interconnected to form a closed triangle. Node similarity is often a generalization of the above ternary closure principle. In a general network, the more common neighbors two nodes have with each other then the more similar these two nodes are. The basic node similarity metric based on the same number of neighbors is defined as follows:

$$s_{xy} = |\Gamma(x) \cap \Gamma(y)| \tag{7}$$

where $\Gamma(x)$ represents the set of neighbor nodes of node x.

In fact, the definition of similarity will be more precise if the neighbors are subdivided and different weights are assigned to different common neighbors. For example, the Adamic-Adar metric and Resource Allocation metric based on common neighbor statistics. The basic idea of the AA metric is that common neighbors with small degrees contribute more to the similarity than common neighbors with large degrees, and AA assigns a weight to each common neighbor node individually based on the node's degree, which is equal to one of the logarithms of the node's degree. The specific definition is as follows:

$$s_{xy} = \sum_{n \in \Gamma(x) \cap \Gamma(y)} \frac{1}{\log k(n)} \tag{8}$$

Where $k(n)$ represents the degree of node n. And RA based on resource allocation, consider two nodes x and y which are not directly connected in the network, from x can pass some resources to y. And in this process, their common neighbors become the medium of passing. Assuming that each medium has one unit of resource and distributes the resource equally to all its neighbors, the number of resources that y can receive is defined as the similarity degree of nodes x and y. RA obtains a similarity formula similar to AA:

$$s_{xy} = \sum_{n \in \Gamma(x) \cap \Gamma(y)} \frac{1}{k(n)} \tag{9}$$

Both AA and RA weaken the weights of large-degree common neighbor nodes. The prediction accuracies of AA and RA are close to each other when the average degree of the network is small. However, as the average degree of the network increases, the gap between the prediction accuracies increases. Experiments show that RA performs better in networks with larger average degree. In addition to assigning different weights to common neighbor nodes. The relative number of common neighbors of two nodes x, y can also be considered. Many variants of the basic similarity metric can be generated by using different normalization operations.

Paths are an important component of a network, and whether two nodes in a network are related to each other is largely determined by the paths between these two nodes. Therefore, path information is also often used to calculate the similarity between nodes. There are three main types of path-based similarity metrics:
1) LP metrics. On the basis of common neighbors, in addition to considering the first-order neighbors, the information of second-order neighbors is also considered to portray the degree of node similarity.LP considers the number of paths between two points with path lengths of 2 and 3, and the more paths there are, the greater the degree of similarity:

$$s_{xy} = \left(A^2\right)_{xy} + \alpha\left(A^3\right)_{xy} \tag{10}$$

where α is the attenuation factor.
2) Katz metric, a more general form of the LP metric, which takes into account all lengths of paths in the network and the shorter the path, the greater the contribution to similarity:

$$\begin{aligned} s_{xy} &= \sum_{i=1}^{+\infty} \beta^i \left(A^i\right)_{xy} \\ &= \left(I - \beta A\right)^{-1} \beta A \left(I - (\beta A)^{+\infty}\right)_{xy} \\ &= \left(\left(I - \beta A\right)^{-1} - I\right)_{xy} \end{aligned} \tag{11}$$

where β is used as the attenuation factor of the weights, I is the unit matrix, and A is the adjacency matrix of the network. Since the optimal value of β can only be obtained through a large number of experimental verifications, the method has some limitations.

3) LHN-II metric, which is a generalization of Katz similarity metric. Unlike in Katz where the matrix coefficient β is constant, in LHN-II β is related to the expected value of $\left(A^n\right)_{xy}$:

$$s_{xy} = 2m\lambda_1 D^{-1}\left(I - \frac{\alpha}{\lambda_1}A\right)^{-1} D^{-1} \tag{12}$$

where D is the degree matrix, λ_1 is the maximum eigenvalue of the adjacency matrix A, and α is an adjustable parameter.

In general, path information-based similarity metrics tend to be more accurate due to the fact that they utilize more information than metrics based on the number of common neighbors, and accordingly, the computation consumes more resources. Among the three path information-based similarity metrics, LP has a better overall performance and lower computational complexity than Katz and LHN-II, and thus is more suitable for application to link prediction on large-scale networks.

2.3. *Theoretical modeling and hypothesis formulation*

2.3.1. Theoretical modeling. In this paper, the social relationship network of top management is divided into five dimensions, namely, network size, network centrality, network heterogeneity, relationship strength, and relationship longevity.

Innovation performance and operation performance are used to examine the green innovation of top management.

The independent variable in this paper is top management social relationship network, which includes five dimensions, namely X1 network size, X2 network centrality, X3 network heterogeneity, X4 relationship strength, and X5 relationship durability. Among them, X1 network size, X2 network centrality, X3 network heterogeneity three dimensions describe the structural characteristics of the social relationship network, X4 relationship strength, X5 relationship durability, two dimensions describe the relationship characteristics of the social relationship network.

The dependent variable of this paper is green innovation.

The mediating variable in this paper is technological innovation/machine learning technology, including two dimensions, Z1 utilizational innovation, Z2 exploratory innovation.

2.3.2. Formulation of hypotheses:

1) The hypothesis of the relationship between TMT interlocking networks and green innovation. It has been concluded that green innovation increases with the increase of network size of TMT social relationship network, and TMT network size has a positive effect on green innovation. The breadth of the network represents the size of the network, and the strength of the network represents the strength of the relationship between the members of the network. It can be seen that network size and relationship strength have a positive effect on green innovation. In summary, combining the research results respectively proves that the independent variables of this paper, the five dimensions of the top management social relationship network, i.e., network size, network centrality, network heterogeneity, relationship strength, and relationship longevity, all have a positive impact on the green innovation of enterprises.

Combined with related research on the effects of network location centrality, linkage strength, and network size on organizational learning, it is then concluded that it has a positive impact on green technology innovation performance. In summary, the previous research results respectively proved that the five dimensions of this paper's independent variable-TMT social relationship network, i.e., network size, network centrality, network heterogeneity, linkage strength, and linkage longevity, all have positive impacts on the green innovation performance of enterprises. Based on the above analysis, this paper proposes the following hypotheses:

Hypothesis H1: Top management social relationship network has a positive impact on green innovation.

Hypothesis H1a: Top management social relationship network size has a positive effect on green innovation.

Hypothesis H1b: Top management social relationship network centrality has a positive effect on green innovation.

Hypothesis H1c: Top management social relationship network heterogeneity has a positive effect on green innovation.

Hypothesis H1d: top management social relationship network relationship strength has a positive effect on green innovation.

Hypothesis H1e: Relationship longevity of top management social relationship network has a positive effect on green innovation.

2) The relationship between technological innovation (machine learning technology) and green innovation hypothesis. The competitive advantage of enterprises originates from technological innovation. The technological innovation (machine learning technology) described in this paper contains two aspects, exploratory innovation and utilization innovation.

The essence of utilizational innovation is to further expand and deepen the existing knowledge and technology of the enterprise, to tap the potential of the original resources, to reduce the unnecessary waste of resources, and to ensure the survival of the current enterprise, and the utilizational innovation of the enterprise will ultimately affect the innovation performance of the enterprise.

In summary, this paper puts forward the hypothesis:

Hypothesis 2a: Utilizational innovation has a significant positive impact on green innovation.

Hypothesis 2b: Exploratory innovation has a significant positive impact on green innovation.

3) Hypotheses of the mediating role of technological innovation (machine learning technology) in the relationship between TMT social relationship networks and green innovation:

Hypothesis Ⅰ: The mediating role analysis hypothesis of exploitative innovation. From the point of view of the heterogeneity of TMT social relationship network, the heterogeneity of TMT social relationship network makes it possible for TMT to obtain key information related to the existing knowledge structure of the enterprise from these heterogeneous network resources, which in a way the more conducive to the in-depth excavation and development of the existing technology, thus promoting the utilization innovation. Network heterogeneity will make TMTs seek more resources and promote TMTs to fully exploit existing skills, which ultimately promotes utilizational innovation and thus influences green innovation.

In summary, utilizability innovation has a mediating role between TMT's social relationship network and green innovation.

Hypothesis II: Analytical hypotheses for the mediating role of exploratory innovation. Generally enterprises carry out exploratory innovation in order to obtain non-redundant technological innovation information knowledge resources. The richer the knowledge technological innovation resources acquired by TMT through network relationships, the stronger the competitive advantage of the enterprise. The heterogeneity of the TMT social network relationships provides enterprises with access to more technological knowledge information channels, which helps to improve the performance of TMT.

In terms of the impact of TMT social relationship network size, TMTs with larger relationship network size have access to more information knowledge technology. As well as expanding the effective channels to use complementary innovation knowledge and skill resources among TMTs, thus facilitating TMTs to carry out exploratory innovation for green innovation.

In summary, exploratory innovation will have a mediating role between TMT social relationship networks and green innovation.

Based on the above, the following hypotheses are proposed:

Hypothesis 3a: Exploitative innovation mediates between TMT social relationship networks and green innovation.

Hypothesis 3b: Exploratory innovation mediates between TMT social relationship networks and green innovation.

3. Empirical test of TMT social network and green innovation

3.1. Sample description

The data of the enterprises related to the research was collected by distributing questionnaires. The research object of this paper is corporate TMT, taking into account the difficulty of research on top managers. And there is also a certain subjective influence of top managers' evaluation of their own personality traits, so the questionnaire in this paper adopts a more flexible design, which can be filled out by top managers based on their understanding of themselves and the company, as well as by corporate executives and other relevant personnel based on their own understanding of top managers and the company.

In the study, the following channels were chosen to be used:

With the help of the school-enterprise cooperation project undertaken, we went to the enterprises to interview and distribute questionnaires to the executives, R&D personnel, HR department and other related personnel, 50 questionnaires were distributed and 46 were returned, totaling 46 valid questionnaires.

The questionnaires were distributed and recovered through management consulting companies, and 35 valid questionnaires were recovered.

Through the help of classmates, family members, friends and students working in the enterprise, let them utilize the questionnaire star platform to distribute questionnaires to the enterprise executives, technical research and development, human resources management and other related personnel. As well as to know the top management through wechat, qq and other ways to send questionnaire star link. Through the questionnaire star a total of 105 points to retrieve the questionnaire, valid questionnaires 101. A total of 182 valid questionnaires were obtained, 16 senior management teams, all used as analysis samples, basically in line with the requirements of theoretical research on effective questionnaires.

Through the pre-test, the validity and reliability of each question item of the relevant research variables passed the test. From the statistical data, it can be seen that the absolute value of skewness of all sample data is less than 2, and the absolute value of kurtosis is less than 4, showing a normal distribution, which meets the requirements of the study.

The results of the combined descriptive statistics of the entries of each research variable are shown in Table 1. The sample mean values of the relevant indicators are all above 3, the absolute value of skewness of all data is less than 2, the absolute value of kurtosis is less than 4, basically in line with the normal distribution, and it is initially judged that the design of the questionnaire and the data collected, etc. are reasonable and can be further analyzed in depth.

Table 1. The entries of each study variable describe the statistical results

Variable	Numbering	Dimension	Mean	Standard deviation	Variable mean
Green innovation	Y	Green innovation	4.231	1.362	4.522
TMT social network	X1	Network size	3.265	1.247	3.749
	X2	Network center	3.984	1.032	
	X3	Network heterogeneity	4.102	1.045	
	X4	Relationship strength	3.865	1.669	
	X5	Relationship duration	4.003	1.704	

Technical innovation (machine learning technology)	Z1	Usability innovation	3.811	1.542	3.983
	Z2	Exploratory innovation	3.756	1.119	

3.2. TMT Social Network Calculation

Based on the collected questionnaires, the data from the social network part were inputted into Ucinet 6 for windows software to calculate five indicators for each of the 16 teams, i.e., X1 Network Size, X2 Network Centrality, X3 Network Heterogeneity, X4 Relationship Strength, and X5 Relationship Durability.

The calculated values were entered into SPSS 22.0 statistical software as the indicators of social network structural properties, which were statistically analyzed with the variables of green innovation performance. The statistics of the indicators of social network structural properties are shown in Figure 1. The mean value of X1 (network size) of the sample TMT social network is 0.535 and the maximum value is 0.75.

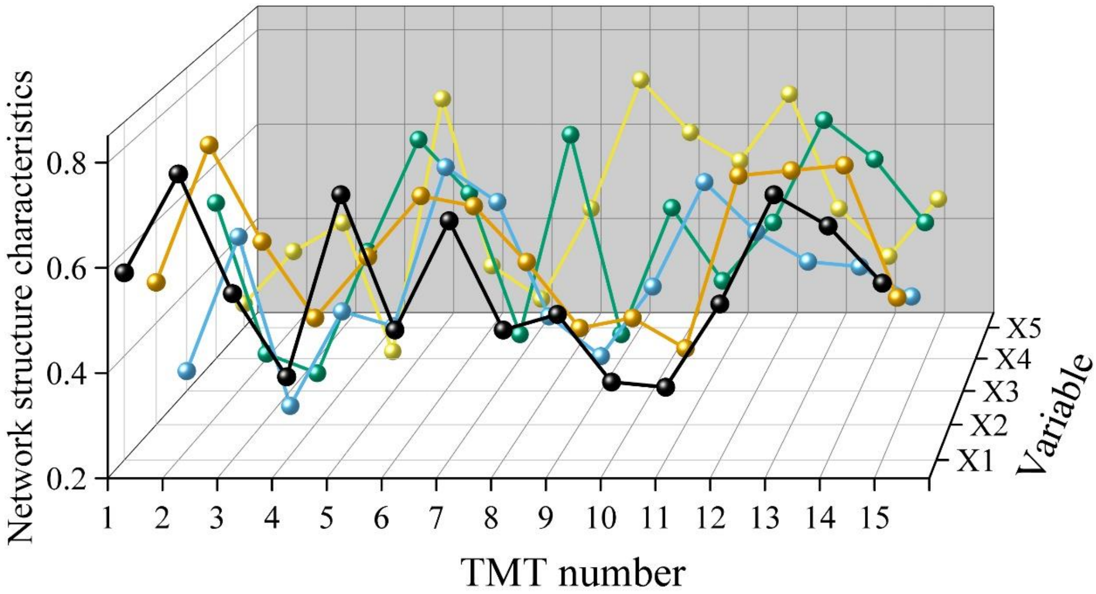

Fig. 1. Statistics of social network structure characteristics

3.3. Correlation analysis

In this section, hierarchical regression analysis and dominance analysis will be used to verify the proposed hypotheses. Hierarchical regression analysis is used to test the impact of TMT social network on innovation performance and operational performance, and dominance analysis is used to explore the magnitude of the impact of TMT social network on green innovation.

SPSS 22.0 was used to do Person correlation analysis on the variables in the model, and the analysis of the correlation coefficients of the variables is shown in Table 2.

The social relationship network of top management as an independent variable, such as network size, network centrality, network heterogeneity, relationship strength, relationship longevity, and all the variables of green innovation as a dependent variable are correlated two by two and significantly correlated. This indicates that there exists a high degree of rationality in the model and hypotheses of this paper, and this result is basically consistent with the hypotheses presented in the previous paper.

The correlation coefficient between the network size of top management social relationship network and the operational performance of green innovation is 0.507, $P<0.01$, which shows that the network size of top management social relationship network is significantly and positively correlated with the operational performance dimension.

Table 2. Analysis of variable correlation coefficients

	X1	X2	X3	X4	X5	Y	Z1	Z2
X1	1							
X2	0.524*	1						
X3	0.477*	0.419*	1					
X4	0.569*	0.632*	0.525*	1				
X5	0.614*	0.758*	0.699*	0.589*	1			
Y	0.507*	0.547*	0.653*	0.512*	0.634*	1		
Z1	0.529	0.725	0.753	0.546	0.633	0.648	1	
Z2	0.635	0.719	0.699	0.642	0.582	0.621	0.705	1

3.4. *Regression analysis and hypothesis testing*

3.4.1. Examination of the relationship between TMT social networks on green innovation. The regression results of TMT social relationship network on green innovation are shown in Table 3.

In the first step, the effect of control variables on green innovation is examined, and the results show that there is a significant positive correlation between total corporate assets and green innovation, and the larger the size, the better the green innovation accordingly.

The second step is to add the top management team mean characteristics variable to measure the impact of top management team mean characteristics on green innovation under the condition of controlling the size of top management team. From the results of regression analysis, $F = 2.809$, $p<0.01$, indicating that the top management team mean characteristics have a significant correlation with green innovation. Top management team size, age and green innovation change in the same direction, top management team tenure, education level and green innovation change in the opposite direction, both failed the significance test.

In the third step, the social network characteristic variable of top management team was added. Model 1 passed the F-test at the $p<0.001$ significant level, indicating that the constructed model is valid. And the goodness-of-fit of model 1 adjusted increased, indicating that only considering the mean characteristics of the top management team could not provide useful suggestions for improving green innovation. And the model 1 constructed in this paper not only passes the significance test, but the regression analysis results also show that the network size, network centrality, network heterogeneity, relationship strength, and relationship longevity of the top management team are all significantly and positively correlated with green innovation, and the hypotheses H1a, H1b, H1c, H1d, and H1e are supported, and the hypothesis H1 is established.

Table 3. The return of the TMT social network to green innovation

Model 1	Hierarchical regression					
	β	t	β	t	β	t
Enterprise size	0.285	4.663***	0.245	3.216**	0.243	4.509**
Team size	-	-	0.038	0.505	-0.024	-0.075
Team age	-	-	0.092	2.113	0.106	1.968
Team term	-	-	-0.046	-0.369	-0.078	-1.475
Team education	-	-	-0.044	-0.402	0.036	0.896
Network size	-	-	-	-	0.092	2.504
Network center	-	-	-	-	0.117	3.325*
Network heterogeneity	-	-	-	-	0.075	0.931
Relationship strength	-	-	-	-	0.199	2.365*
Relationship duration	-	-	-	-	0.246	3.246**
Model R^2	0.054		0.041		0.092	
Adjusted R^2	0.059		0.035		0.065	

P value	0.001	0.008	0.000
F value	25.634**	2.809**	3.776***

3.4.2. Testing the relationship between technological innovation and green innovation. In order to test hypothesis 2, this paper applied the statistical analysis software SPSS 22.0 to regression analysis of relevant variables. The regression analysis of technological innovation (machine learning technology) and green innovation is shown in Table 4.

The coefficients of the regression equation between technological innovation (machine learning technology) and green innovation are positive and significant at different levels under the control conditions of the size of the top management team and "history". The coefficients of the regression equation for model 1 (exploitative innovation) and model 2 (exploratory innovation) are 0.415 and 0.496, respectively; therefore, hypothesis H2 is supported and verified by the data.

Table 4. The regression analysis of technological innovation and green innovation

	Green innovation	
	Model 1	Model 2
Top management team size	-0.125	-0.049
History	0.086	0.052
Usability innovation	0.415***	-
Exploratory innovation	-	0.496***
F	0.933	6.317
Adjusted R^2	-0.001	0.129
P value	0.003	0.002
F value	2.156**	3.077**

3.4.3. Test for mediating effects of technological innovation. Through the analysis of the previous data, the TMT social network has a significant impact on the enhancement of green innovation, but this enhancement may also be affected by other factors. According to the theoretical analysis and hypothesis of this study, there exists the analytical paradigm of "structure-behavior-performance", and this part will test the mediating effect of behavior in two dimensions of technological innovation.

The first step is to establish the regression analysis between the independent variable and the dependent variable, and test whether the regression coefficient is significant.

In the second step, the regression analysis of the independent variable with the mediator variable and the mediator variable with the dependent variable is established to test the significance of the regression coefficients.

In the third step, regression analyses were established between the independent variable, the mediator variable and the dependent variable, and the regression coefficients were partially mediated if the regression coefficients of the independent variable on the dependent variable were significant (and the coefficients were decreasing), and fully mediated if they were not significant.

According to this step, the mediating effect of exploratory innovation and utilized innovation are tested separately.

1) Test of mediating effect of utilizing innovation. The test of the mediating role of utilized innovations is shown in Table 5, from the results. Model 2 examines the regression effect of the explanatory variables on the explanatory variables, and the results show that the overall regression effect of the model is good (R^2 =0.537, F-statistical test is significant), and the heterogeneity and size of TMT's social relationship network, as well as the relationship strength and relationship quality, have a significant positive effect on green innovation. In summary in testing the mediating effect of utilized innovation, the tests of heterogeneity, relationship quality, and relationship strength and relationship quality all pass, and hypothesis H3a holds.

Table 5. Use of the mediation effect of sexual innovation

Model	Model 1	Model 2	Model 3	Model 4	Model 5
				Green innovation	Usability innovation
TMT categories	0.25	0.06	0.16	-0.46	-0.039
TMT scale	0.239***	0.152*	0.312**	0.175*	-0.008
TMT life span	0.005	-0.063	-0.018	-0.003	0.024
Heterogeneity	-	0.215***	-	0.136**	0.324***
Scale	-	0.298***	-	0.247	0.266***
Relationship strength	-	0.247***	-	0.314***	0.213**
Relation quality	-	0.457***	-	0.349***	0.379***
Usability innovation	-	-	0.596***	0.372**	-
Statistic	-	-	-	-	-
R^2	0.326	0.721	0.489	0.659	0.524
Adjusted R^2	0.231	0.714	0.362	0.673	0.506
F Value	22.365***	60.789***	58.903***	56.774***	54.273***
ΔR^2	-	0.537	0.397	0.512	-

2) Mediating effect of exploratory innovation. In order to verify the mediating effect of exploratory innovation on TMT's social relationship network and green innovation, the same methods and steps described above are taken.

The test of the mediating role of exploratory innovation is shown in Table 6. From the test results of Model 3, the influence relationship between the mediating variable and the explanatory variables $R^2 =$ 0.579, the F statistical test is significant, the regression analysis of the model is good, and $\beta = 0.528$, p<0.001, the mediating variable exploratory innovation positively affects the green innovation performance and is significant. Hypothesis H3b is valid.

Table 6. The intermediary effect of exploratory innovation

Model	Model 1	Model 2	Model 3	Model 4	Model 5
				Green innovation	Usability innovation
TMT categories	0.25	0.06	0.038	-0.29	-0.076
TMT scale	0.239***	0.163*	0.285**	0.147*	0.061
TMT life span	0.005	-0.054	0.036	0.005	-0.08
Heterogeneity	-	0.215***	-	0.175**	0.241***
Scale	-	0.298***	-	0.248	0.365**
Relationship strength	-	0.247***	-	0.307**	0.279**
Relation quality	-	0.457***	-	0.325***	0.441***
Usability innovation	-	-	0.528***	0.371**	-
Statistic	-	-	-	-	-
R^2	0.326	0.669	0.579	0.669	0.548
Adjusted R^2	0.231	0.703	0.652	0.645	0.517
F Value	22.365***	61.556***	57.114***	55.373***	52.019***
ΔR^2	-	0.537	0.421	0.648	-

4. Conclusion

This paper analyzes the composition of high-level management interlocking network, takes high-level management interlocking network, green innovation, and machine learning technology as model variables respectively, designs research hypotheses, carries out descriptive analyses of all variables, and conducts regression analyses to test the research hypotheses.

The specific characteristics of the top management interlocking network are expressed as network size, network centrality, network heterogeneity, relationship strength, and relationship longevity. In the regression test, the variable of social relationship network characteristics of top management team was added. Model 1 passes the F test at the $p<0.001$ significant level, indicating that the constructed model is valid and the model fit is good. That is, the network size, network centrality, network heterogeneity, relationship strength, and relationship longevity of the top management team are all significantly and positively related to green innovation, and hypothesis H1 is valid.

The technological innovation represented by machine learning technology includes exploratory innovation and utilization innovation, and the regression coefficient is upward, and technological innovation has a significant positive correlation with green innovation. On this basis, the mediating effect test of technological innovation is carried out. From the results of the model test, it can be seen that between the mediating variables and the explanatory variables, the F statistical test is significant, and the regression analysis of the model is good. That is, the mediating variables exploratory innovation and utilization innovation positively affect green innovation performance and are significant. Hypothesis H3 is established.

Acknowledgements

1) Academic funding project for Research Foundation of Education Bureau of Hunan Province in 2022 under Grant No.22B0901.
2) Academic funding project for the General Program of Natural Science Foundation of Changsha in 2022 under Grant No. kq2208005.

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