International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 7862-7872

https://doi.org/10.70517/ijhsa463673

Analysis of scientific and technological innovation talent development strategy of power grid enterprises based on structural equation modeling

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Abstract In recent years, power grid enterprises have faced the contradiction between talent shortage and the demand for science and technology innovation. This study analyzes the factors influencing the development of scientific and technological innovation talents in power grid enterprises using structural equation modeling (SEM). The study constructed a model based on the framework of "education input-practice input-talent output efficiency", and explored the influence of family education, school education, social education, theoretical innovation, practical innovation and other factors on the effectiveness of talent development. Through the statistical analysis of the data from 400 questionnaires, the results show that school education has a significant impact on the development of scientific and technological innovation talents, with a path coefficient of 0.27 ($p<0.05$); The indirect effect of social education on talent output efficiency is the most significant, with a path coefficient of 0.53; the direct effect of practical innovation on talent output efficiency is 0.334. The conclusion shows that grid enterprises need to strengthen the interaction between school education and social education, and increase the input of practical innovation to enhance the cultivation efficiency of scientific and technological innovation talents. At the same time, family education plays a fundamental role in it and affects the effect of school education and social education. Therefore, power grid enterprises should adopt diversified talent introduction and cultivation strategies in different fields to optimize the existing talent development system.

Index Terms power grid enterprises, scientific and technological innovation, talent development, structural equation modeling, educational input, practical innovation

I. Introduction

With the rapid development of information technology and the construction of smart grid, the promotion of new energy and the acceleration of energy transition, electric power enterprises are facing new challenges and opportunities [1], [2]. Whether it is the construction of smart grid or the effective implementation of the development strategy of power grid enterprises, a large number of high-quality, professional and high-quality talents are needed as a solid intellectual guarantee and talent support [3]-[5]. In the process of building a world-class power grid enterprise with excellent competitiveness, scientific and technological innovation talent is a key point that needs to be broken through [6], [7]. Under such a new situation, the development strategy of scientific and technological innovation talents in power grid enterprises is particularly important [8]. As a multivariate statistical analysis technique, structural equation modeling provides support for analyzing the development strategy of scientific and technological innovation talents in power grid enterprises [9], [10].

Structural equation modeling is a statistical analysis technique based on the existing causal theory, with the corresponding system of linear equations to represent that causal theory, which is aimed at exploring the causal relationship between things and expressing this relationship in the form of causal patterns, path diagrams, etc [11]-[14]. In structural equation modeling, we can propose a particular factor structure and test whether it matches the data [15], [16]. In addition, through structural equation multi-group analysis, we can also understand whether the relationship of the variables within different groups remains constant and whether the means of the factors are significantly different [17]-[19]. And in power grid enterprises, the model can provide an effective method to analyze the development strategy of scientific and technological innovation talents of enterprises, which is of great significance for the innovative development of power grid enterprises [20], [21].

With the transformation of the global energy structure and the rapid development of the power industry, power grid enterprises are facing great challenges and opportunities. Under such a background, scientific and technological innovation has become an important factor to enhance the competitiveness of power grid enterprises. Scientific and technological innovation cannot be separated from high-quality talents, and the cultivation and introduction of innovative talents is the key to enhance the technological strength of enterprises and realize sustainable development. However, power grid enterprises face many difficulties in talent development. First of all, the training of scientific and technological innovation talents has a long cycle, high cost, and the mobility of talents, how to attract and retain these talents has become a problem that many power grid enterprises need to solve. Secondly, the various resources required for talent development, such as funding, education and practice opportunities, are often unbalanced, making it difficult for enterprises to comprehensively improve the innovation ability and practical experience of talents.

From the perspective of education system, talent development of grid enterprises is not only influenced by higher education, but also family education, social education and other external factors play an equally important role. For example, family education can shape an individual's innovative thinking, while school education provides a foundation of specialized knowledge for talents, and social education further enhances the comprehensive ability of talents through social practice and industry exchanges. Therefore, how to reasonably plan and optimize all kinds of educational inputs in this process and form a systematic cultivation mechanism is the key to improve the innovation ability of power grid enterprises.

This paper analyzes the key factors affecting the development of scientific and technological innovation talents in power grid enterprises, and explores the path to improve the quality of talent training. In order to deeply understand the relationship between these factors, this paper adopts structural equation modeling (SEM) to conduct an empirical study, which reveals the mechanism of action between the factors by analyzing the data in the dimensions of educational input, practical innovation and talent output. The results of the study will provide theoretical support for how power grid enterprises optimize the talent training system in practice.

II. Research design on factors influencing the development of scientific and technological innovation talents

II. A. Selection of factors affecting the development of STI talent

For power grid enterprises, the factors affecting the development of science and technology innovation talents come from various aspects, and the "EFA Quality Improvement Report" released by the United Nations is based on the dimension of process management, and constructs an "input-process-output" assessment of science and technology innovation talent development. The model provides a theoretical basis for the concept and framework of the quality of STI talent development based on process management. The framework refines the process of science and technology innovation talent development into three closely related links of "input, process and output", which provides a clear guidance for the development of science and technology innovation talent.

This paper summarizes that the influencing factors affecting the development of science and technology innovation talents are mainly reflected in the education input, practice input and talent output, and constructs an analysis framework, which is shown in Table 1.

Table 1: Technology innovation talent culture scale

Primary indicator	Secondary indicator
Education input	Family education
	School education
	Social education
Practical input	Theoretical innovation
	Practical innovation
Talent output	Talent output efficiency

II. B. PLS-SEM modeling process

II. B. 1) Introduction to the SEM model

SEM [22] is one of the more widely used multivariate statistical tools at present, which involves two main classifications, covariance-based equation modeling and variance-based equation modeling, also known as equation modeling in the form of principal components. Partial Least Squares (PLS) [23] is a common method for the second category of modeling, which is customarily named PLS-SEM in academia.

By comparison, it can be seen that compared with CB-SEM model, PLS-SEM model has the following five advantages:

(1) The partial least squares method can directly construct the model with source data to complete the relevant calculations. While the covariance method has relatively high requirements, the data must meet the trend of normal

distribution, and if it fails to meet the requirements of normal distribution, the objectivity and authenticity of the estimation results cannot be guaranteed.

(2) The partial least squares method focuses on latent variable scores, such as the satisfaction index, while the covariance method cannot obtain latent variable scores, so both domestic and foreign countries use the PLS method to find the satisfaction.

(3) The constructs assumed by the partial least squares method can include formative indicators.

(4) The partial least squares method is used for small samples, and when the amount of data is small, the traditional multiple regression method may not be able to obtain a stable solution, while the PLS method can effectively deal with such problems.

(5) Favorites of covariance methods usually focus on the biased nature of the partial least squares method and make different arguments against it. Although there is some bias in this method in a normally distributed environment, the impact of this bias is much less than the impact of incorrect errors.

II. B. 2) PLS-SEM build types

There are two types of PLS-SEM conformations, reflective and formative. A closer look at the figure below further reveals that the reflective indicators are highly correlated, with all factors being important components of the conformation. Formative indicators of various factors are also an important part of the average of the common formation of the configuration, can not be exchanged for each other, in principle, the more the better.

Since the sample data in this paper is based on the online and offline questionnaire survey method, it is impossible to ensure that the data is normally distributed, and in order to ensure the accuracy of the results, after various considerations and comprehensive analysis, the article decides to use the more implementable PLS-SEM model for the subsequent empirical research.

II. B. 3) PLS-SEM Calculation Process and Methods

(1) SEM model calculation steps

Figure 1 shows the structural equation model, a closer look can further understand that the SEM model consists of two parts, one is the measurement model, which mainly reveals the composition of potential variables. The second is the structural model, which mainly describes the mechanism of action and the degree of influence among potential variables.

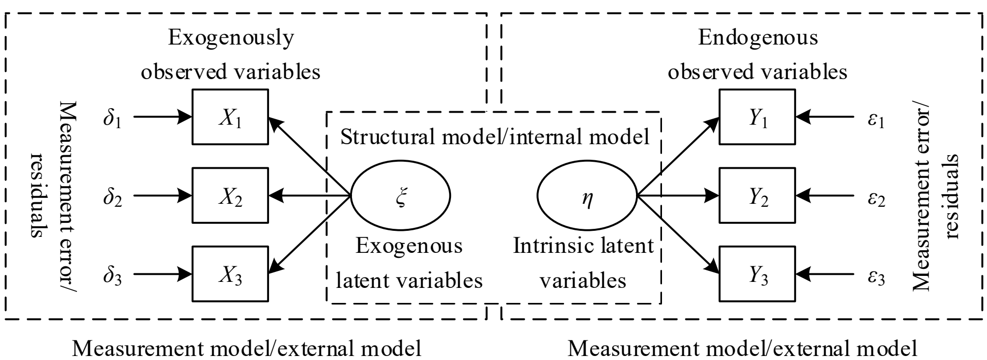

Figure 1: Diagram of the structural equation model

ξ as explanatory variable, specifically defined as equation (1). η as the outcome variable, specifically defined as equation (2). The variable η is able to be explained by other factors and is therefore called endogenous latent variable. The variable ξ as a variable affecting η is then called exogenous latent variable. Latent and observed variables put together are called constructs.

$$x = \Lambda_x \xi + \delta \tag{1}$$

$$y = \Lambda_y \eta + \varepsilon \tag{2}$$

where x = vector of exogenous observed variables, y = vector of endogenous observed variables.

Factor loading matrix of $\Lambda_x = x$ on ξ [24].

Factor loading matrix of $\Lambda_y = y$ on η.

δ, ε = measurement error vector.

The following equation (3) is a typical structural model of SEM, which visualizes the interaction between ξ and η.

$$\eta = \beta_\eta + \Gamma\xi + \zeta \tag{3}$$

where ξ = vector of exogenous latent variables, η =vector of endogenous latent variables, β = regression path coefficient of the effect between different η, Regression path coefficient of the effect of $\Gamma = \xi$ on η, ζ = model measurement residuals.

Combine the equations of the measurement model with the equations of the structural model to find the best solution, which is the structural equation model.

(2) PLS-SEM model calculation steps

In the parameter estimation of PLS, the relationship between observed variables and latent variables is called the external model, while the relationship between latent variables and potential variables is called the internal model. In the external model part, since different variables have different causal relationships, PLS proposes two distinct assumptions, one is that the variation of the observed variables depends entirely on the latent variables, which is known as the reflective model, and its calculation procedure can be referred to the above equations (1) and (2). The second is that the variation of the latent variables depends entirely on the observed variables, the so-called formative model.

$$\xi = \Pi x + v \tag{4}$$

where ξ = exogenous latent variables, x = vector of exogenous observed variables, Weight matrix of $\Pi = x$ on ξ, v =vector of measurement errors.

The realization process is as follows:

a) Standardize the values of the observed variables (ξ for exogenous latent variables, η for endogenous latent variables)

$$x_{ij} = \frac{x_{ij} - \overline{x_j}}{\sqrt{\operatorname{var} x_j}} \tag{5}$$

$$y_{ij} = \frac{y_{ij} - \overline{y_j}}{\sqrt{\operatorname{var} y_j}} \tag{6}$$

where, i = sample size of observations, j = number of observed variables, $\overline{x_j} = \xi$ Mean value of potential variable j observed variable, $\overline{y_j} = \eta$ Mean of potential variable j observation variable, $varx_j = \xi$ Variance of potential variable j observation variable, $vary_j = \eta$ Variance of potential variable j observation variable.

b) Principal component analysis using regression

$$t_1 = E_0 w_1 \tag{7}$$

$$u_1 = F_0 c_1 \tag{8}$$

where $t_1 = \xi$ extracted principal components, $u_1 = \eta$ extracted principal components, E_0 = Matrix after standardization of the observation variable x_{ij}, F_0 = Matrix after standardization of the observation variable y_{ij}, w_1 =Unit vector, first axis of E_0, $\|w_1\| = 1$, u_1 = unit vector, first axis of F_0, $\| u_1 \| = 1$.

To extract accurate and valid principal components, the following requirements must be followed:

First maximize the information covered in the observed variables.

$$\operatorname{var}(t_1) \to \max \tag{9}$$

$$\operatorname{var}(u_1) \to \max \tag{10}$$

Secondly the correlation between the principal components needs to be at the highest level.

$$r(t_1, u_1) \to \max \tag{11}$$

The above two processes are executed repeatedly, and the m th round extracts the components of the remaining information after ξ has been interpreted by t_1, and the extraction can be stopped as long as the marginal contribution of component t_m is not significant.

c) Iterative analysis

Since the main objective of parameter evaluation is to maximize the residual impact, the fitted values of the model for the two sets of observed variables should maximize the explanation of the relationship between ξ and η.

II. C. Questionnaire design and data collection

Based on the previous related research, this paper compiled the “Questionnaire of Influencing Factors on the Development of Science and Technology Innovation Talents”, and chose a total of 20 experts in 12 different disciplines except cross-cutting fields to carry out two rounds of back-to-back validation of the questionnaire. The distribution of titles was 8 for senior titles and 12 for deputy senior titles. After validation, the questionnaire was designed on the basis of 6 questions related to secondary influencing factors, and the final questionnaire included 36 questions.

With the help of WeChat app “Questionnaire Star”, the survey questionnaire was prepared, and multiple rounds of mobilization and questionnaire distribution were organized for state-owned or state-controlled power grid enterprises, foreign-funded or Sino-foreign joint venture power grid enterprises, private power grid enterprises, colleges and universities, scientific research institutes, hospitals, etc., through various channels such as governmental departments, colleges and universities, management committees, associations and societies, scientific research institutes and other units. Distribution.

III. Analysis of findings based on structural equation modeling

III. A. Data verification

III. A. 1) Reliability test

In this paper, Cronbach's Alpha was used to estimate the reliability of the questionnaire data, which was used to judge the internal consistency of the items.The threshold value of Cronbach's Alpha is usually set at 0.7, and higher than this value, it can be judged that the scale items are set reasonably. The results of the reliability test are shown in Table 2, and the reliability values of each factor are greater than 0.7 by SPSS, indicating that the items of each factor have good internal consistency.

Table 2: Reliability test

Factor	Topic number	Cronbach’s Alpha
Family education	5	0.754
School education	7	0.726
Social education	5	0.739
Theoretical innovation	6	0.846
Practical innovation	7	0.899
Talent output efficiency	6	0.952

III. A. 2) Validity tests

SPSS was used to calculate the KMO value of the questionnaire and the significance value of Bartlett's test, and the results obtained are shown in Table 3. It can be seen that the KMO value is 0.915, which is close to 1. The significance value of P<0.01 in the Bartlett's test indicates that the data structure validity is good and can be analyzed by factor analysis.

Table 3: Validity test

KMO sampling availability number		0.915
Bartlett test	Approximate card	13516.541
	Freedom	1099
	Significance	0.000

III. A. 3) Validation factor analysis

By synthesizing the actual questionnaire data and the influencing factors analyzed in the previous section after argumentation, the scale questions can be initially divided into six factors: family education, school education, social education, theoretical innovation, practical innovation, and talent output efficiency, and the validation factor analysis was conducted on the six factors set, and the results are shown in Table 4. Note:*P<0.1, **P<0.05, ***P<0.01.

All six factors satisfy most of the standardized loading coefficients of the question items are more than 0.6, which can be regarded as having sufficient variance explained performance, and each variable can be shown on the same factor. Average common factor variance extracted (*AVE*) is a statistic used in statistics to test the internal consistency of structural variables. Combined reliability (C.R.) reflects whether all the questions in each latent variable consistently explain that latent variable. An *AVE* above 0.5 or a C.R. above 0.7 indicates high convergent validity, and only one of them needs to be looked at. The C.R. values of all six factors reached 0.7, among which the C.R. value of talent output efficiency was the highest, 0.984, and the extraction of the measures within the factors was better, indicating a more excellent discriminant validity. Summarizing the above analysis, it can be concluded that the questionnaire has excellent structural validity, and the division into six factors is reasonable, with excellent differentiation and reliability.

Table 4: Validation factor analysis results

Factor	Item	Factor load	*z*	*S.E.*	*P*	*AVE*	*C.R.*
Family education	1	0.195	3.546	0.154	0.000***	0.356	0.733
	2	0.561	8.451	0.124	0.000***		
	3	0.544	8.125	0.154	0.000***		
	4	0.812	11.564	0.154	0.000***		
	5	0.836	11.599	0.156	0.000***		
School education	1	0.845	8.456	0.356	0.000***	0.256	0.705
	2	0.841	8.123	0.384	0.000***		
	3	0.822	8.021	0.354	0.000***		
	4	0.456	4.512	0.369	0.000***		
	5	0.293	2.562	0.268	0.000***		
	6	0.489	4.612	0.246	0.000***		
	7	0.516	5.698	0.369	0.000***		
Social education	1	0.845	8.978	0.045	0.000***	0.411	0.765
	2	0.812	8.562	0.059	0.000***		
	3	0.594	5.954	0.068	0.000***		
	4	0.568	5.641	0.069	0.000***		
	5	0.598	5.999	0.049	0.000***		
Theoretical innovation	1	0.421	4.562	0.078	0.000***	0.511	0.874
	2	0.219	2.569	0.098	0.000***		
	3	0.022	0.229	0.056	0.000***		
	4	0.056	0.598	0.098	0.000***		
	5	0.481	4.698	0.094	0.000***		
	6	0.745	7.895	0.055	0.000***		
Practical innovation	1	0.651	7.214	0.076	0.000***	0.481	0.912
	2	0.669	7.945	0.056	0.000***		
	3	0.451	4.698	0.057	0.000***		
	4	0.265	2.865	0.059	0.000***		
	5	0.651	7.541	0.091	0.000***		
	6	0.235	2.398	0.095	0.000***		
	7	0.689	7.954	0.096	0.000***		
Talent output efficiency	1	0.235	2.398	0.119	0.000***	0.766	0.984
	2	0.911	12.165	0.115	0.000***		
	3	0.265	2.641	0.131	0.000***		
	4	0.845	10.493	0.135	0.000***		
	5	0.956	12.544	0.136	0.000***		
	6	0.325	3.540	0.125	0.000***		

III. B. Results of structural equation modeling

The preliminary structural equation model of China's science and technology innovation talent cultivation was established using AMOS17.0, as shown in Figure 2. The preliminary structural equation model contains 6 latent variables. In order to ensure the scientific validity of the model, 36 residual terms are introduced, numbered from e1 to e36, and the correlation coefficients between the residual terms and the observed variables are 1. The results obtained from the structural equation model are as follows: ① Eight paths are significant at the 5% level, which are valid paths. 4 paths are not significant at the 5% level. ② Initial fitting index χ^2/df =4.884<5, but the root mean square of the approximation error is 0.099, which is greater than 0.05, the model fit is of average goodness of fit, and the fitting indexes NFI =0.805, TLI =0.772, CFI =0.715, all three of which fail to meet the minimum criteria for the model to be valid (NFI > 0.90, TLI > 0.9, and CFI > 0.9). Due to the existence of insignificant correlation paths and the unsatisfactory goodness of fit of the initial structural equation model, in order to make the model more reasonable, this paper corrects the initial model to explore the paths and optimization.

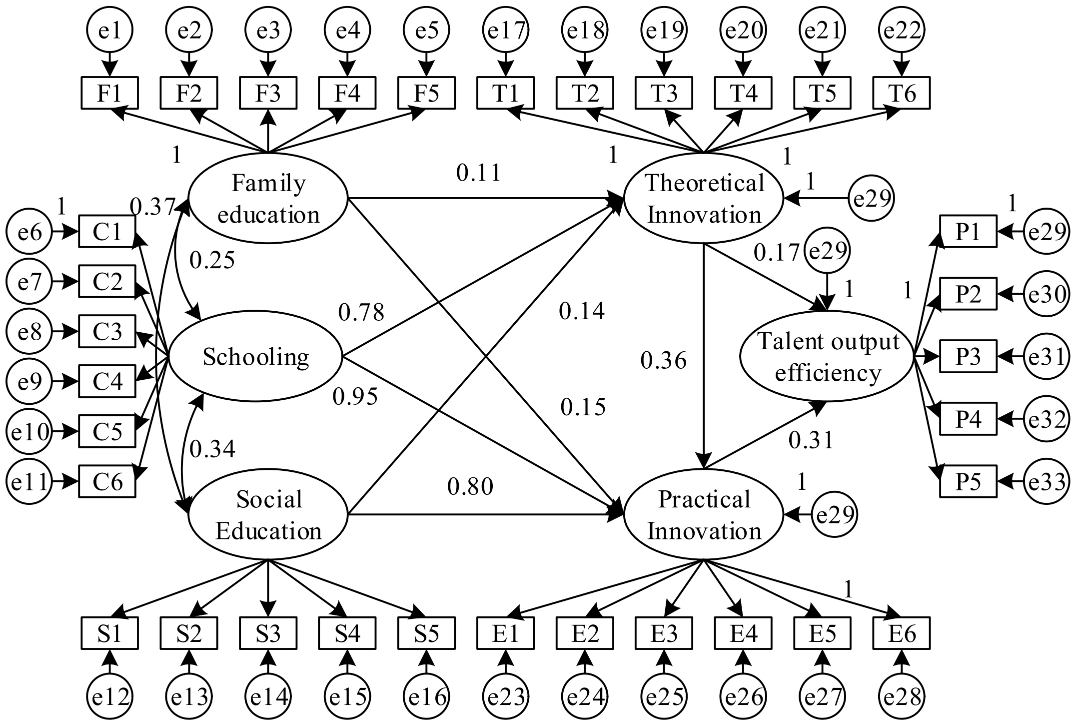

Figure 2: Model of initial structural equation

III. C. Modification and determination of the model

Considering the possibility of omitted correlations between the corresponding residuals of the indicator variables, the addition of residual paths was first explored. When the model fit is significantly improved by adding the residual correlation, this correlation is retained. In this paper, we adopt the commonly used improvement criterion in existing studies, i.e., MI>4. After adding the covariance relationship between the residuals, the model fit is improved, and the fitting results of the modified structural equation model are shown in Table 5. Note:*** denotes significant at the 0.05 level, Estimate is the standardized path coefficient estimate, Goodness of fit indices: χ^2 =80 (p>0.05 does not reach the significant level), χ^2/df =2.262, $RM-SEA$ =0.043, NFI = 0.904, TLI = 0.906, CFI = 0.905. Same below.

The fitting degree of the modified model was significantly improved, and its absolute fitting index and relative fitting index reached the ideal level. From the perspective of path test, there are still four paths in the modified model that do not reach the significant level, namely "family education → theoretical innovation", "social education → theoretical innovation", "family education → practical innovation", "theoretical innovation → talent output efficiency", and their significant coefficients are 0.125, 0.185, 0.164 and 0.129, respectively. The above invalid paths are deleted, and the subsequent path and effect analysis is based on the remaining valid paths. According to the results, the model of scientific and technological innovation talent development is simplified, and the simplified structural equation path is shown in Figure 3.

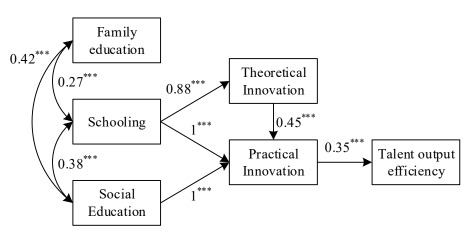

Figure 3: Simplifies the structure equation path

Table 5: The modified structure equation model is fitted

Path			Estimate	*S.E.*	*C.R.*	*P*
School education	←	Family education	0.268	0.050	6.729	***
Social education	←	School education	0.381	0.039	7.798	***
Social education	←	Family education	0.420	0.074	5.824	***
Theoretical innovation	←	Family education	0.140	0.104	1.274	0.125
Theoretical innovation	←	School education	0.885	0.068	13.062	***
Theoretical innovation	←	Social education	0.170	0.113	1.509	0.185
Practical innovation	←	Theoretical innovation	0.444	0.046	9.366	***
Practical innovation	←	Family education	0.207	0.122	1.675	0.164
Practical innovation	←	School education	1.009	0.088	12.024	***
Practical innovation	←	Social education	1.005	0.076	13.510	***
Talent output efficiency	←	Practical innovation	0.334	0.071	4.503	***
Talent output efficiency	←	Theoretical innovation	0.207	0.178	1.181	0.129
F1	←	Family education	1.000			
F2	←	Family education	0.844	0.116	7.388	***
F3	←	Family education	1.030	0.116	9.530	***
F4	←	Family education	1.026	0.157	6.546	***
F5	←	Family education	1.212	0.119	10.035	***
T1	←	Theoretical innovation	1.000			
T2	←	Theoretical innovation	0.882	0.079	10.728	***
T3	←	Theoretical innovation	0.918	0.090	10.402	***
T4	←	Theoretical innovation	1.389	0.092	14.827	***
T5	←	Theoretical innovation	1.164	0.098	12.054	***
E6	←	Practical innovation	1.000			
E5	←	Practical innovation	1.555	0.095	16.794	***
E4	←	Practical innovation	1.132	0.094	11.702	***
E3	←	Practical innovation	1.488	0.098	15.767	***
E2	←	Practical innovation	0.859	0.082	10.219	***
E1	←	Practical innovation	1.423	0.094	15.224	***
P1	←	Talent output efficiency	1.000			
P2	←	Talent output efficiency	1.136	0.089	12.724	***
P3	←	Talent output efficiency	1.092	0.097	11.647	***
P4	←	Talent output efficiency	0.954	0.090	10.592	***
P5	←	Talent output efficiency	0.908	0.088	9.608	***
C3	←	School education	1.000			
C2	←	School education	1.023	0.119	9.799	***
C1	←	School education	0.951	0.101	10.139	***
S3	←	Social education	1.000			
S2	←	Social education	1.166	0.104	11.448	***
S1	←	Social education	0.978	0.092	10.289	***
S4	←	Family education	0.949	0.112	8.459	***
S4	←	School education	1.237	0.104	12.141	***
S5	←	School education	0.886	0.085	9.850	***
S4	←	Social education	1.489	0.092	16.730	***
S5	←	Social education	1.232	0.091	13.123	***
T6	←	Theoretical innovation	0.996	0.076	11.156	***

III. D. Model Interpretation and Effects Analysis

The role of structural equation modeling is to explain the structural relationships among the latent variables, between the latent variables and the observed variables, and among the observed variables, which are represented by the path coefficients (loading coefficients) that result from the modeling operations. According to the simplified path diagram, the effects between the latent variables are shown in Table 6.

Family education has a significant effect on school education and social education, but has no significant effect on both practical input and talent output efficiency. Family education has a direct positive effect on school education, the impact coefficient is 0.27, which is significant at the 5% level, and it has not only a direct positive effect on social education but also an indirect effect, the impact coefficients are 0.42 and 0.11 respectively, which are both significant at the 5% level, and the total effect is 0.53. However, there is no significant effect of family education on the practical inputs and the outputs of talents. It shows that family education has a significant impact on both school education and social education, and the impact on social education is more significant, with a direct impact. Therefore, we should pay more attention to the basic position of family education in education input, improve the importance of family education to promote the efficiency of social education, so as to promote the development of scientific and technological innovation talents in power grid enterprises.

Table 6: The effect of the latent variables

Classification		Family education	School education	Social education	Theoretical innovation	Practical innovation
School education	Direct effect	0.27***				
	Indirect effect					
	Total effect	0.27***				
Social education	Direct effect	0.42***	0.38***			
	Indirect effect	0.11***				
	Total effect	0.53***	0.38***			
Theoretical innovation	Direct effect		0.88***			
	Indirect effect					
	Total effect		0.88***			
Practical innovation	Direct effect		1.00***	1.00***	0.45***	
	Indirect effect		0.37***			
	Total effect		1.37***	1.00***	0.45***	
Talent output efficiency	Direct effect					0.35***
	Indirect effect		0.47***	0.33***	0.16***	
	Total effect		0.47***	0.33***	0.16***	0.35***

IV. Strategies for the development of scientific and technological innovation talents

IV. A. Seize development opportunities and build a talent introduction platform

The synergistic development of power grid enterprises around the world has brought opportunities for the introduction of local scientific and technological innovation talents, and at the same time, it is also a challenge. It is recommended to grasp the development opportunities from the following aspects: strengthening external scientific research cooperation, scientific research cooperation and exchanges with scientific research institutes in developed regions and key well-known enterprises, and increasing the exchange and introduction of talents in technology research and scientific research and innovation. Through the scientific research units stationed, university enrollment, famous enterprises to invest in factories and other channels to expand the scale of the introduction of talent. Introducing and supporting the development of leading enterprises and new industries, especially the development of high-tech industries, industrial development and the introduction of talents are complementary. Through the construction of talent introduction platform, broaden the introduction of talent introduction channels, you can realize the effect of double enhancement of the number and quality of talents.

IV. B. Conduct adequate research and do a good job of talent introduction planning

Government agencies should play an active role in the overall grasp and coordination of the allocation of the introduction of scientific and technological innovation talents. Enterprises, R&D organizations, universities and other institutions should combine their actual needs to formulate talent introduction plans and report them to government agencies for the record. The government can formulate scientific, reasonable and efficient talent introduction planning on a macro level based on the direction of industrial development, the type of talent demand and other factors to realize the optimal allocation of talent. At the same time, it helps government agencies to establish and improve policies for attracting and utilizing talents.

IV. C. Scientific and rational planning, improve the talent policy system

The formulation and improvement of the policy system for the introduction of talents is related to the scale and quality of the introduction of talents. Legal and institutional safeguards should be provided at the political, economic and cultural levels for the introduction, training and utilization of talents. For example, the establishment of special funds for the development of scientific and technological innovation talents ensures the provision of high-quality scientific research platforms on the one hand, and increases the support for the research and development of high-tech projects, and the transformation and promotion of achievements on the other. Set up a relaxed mechanism for the exchange and promotion of scientific and technological talents, so that scientific and technological innovation talents will have greater motivation and more opportunities to choose. Significantly increase the wages and benefits of scientific and technological innovation talents, to attract and retain talents with favorable material living conditions.

V. Conclusion

Through the analysis of structural equation modeling, the study finds that the cultivation of scientific and technological innovation talents in power grid enterprises is significantly influenced by various factors such as educational input, practical innovation and talent output efficiency. School education plays a fundamental role in talent cultivation, and its influence coefficient on scientific and technological innovation talents is 0.27. The influence of social education is particularly prominent, especially in enhancing talent output efficiency, and the path coefficient of social education through indirect effect is 0.53. In terms of practical innovation, the direct influence of practical innovation on talent output efficiency is 0.334, which proves that the practical innovation plays a central role in enhancing the innovative the central role in talent efficiency.

In addition, the study also found that family education plays a bridging role in promoting the role between school education and social education, and although its impact on practical innovation and talent output efficiency is not significant, the positive impact of family education on school education is 0.42.Therefore, when carrying out the cultivation of scientific and technological innovation talents, power grid enterprises should pay more attention to the coordinating role of basic education and social education, and strengthen the practical innovation investment, especially increasing the proportion of practical aspects in the cooperation with universities and research institutions.

Based on the above results, power grid enterprises should strengthen the dual investment in education and practical innovation in their talent development strategy and optimize the talent training system to achieve the comprehensive improvement of scientific and technological innovation capability.

Acknowledgements

Supported by the Management Science and Technology Project: "Research on the Evaluation and Development System of Scientific and Technological Innovation Talents under the Target of New Power System" (1400-202257473A-2-0-ZN) of State Grid Co., Ltd.

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