Journal of Applied Mathematics and Physics, 2024, 12, 1163-1177
https://www.scirp.org/journal/jamp
ISSN Online: 2327-4379
ISSN Print: 2327-4352

Measurement Research Based on Bayesian Structural Equation Cognitive Model

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How to cite this paper: Fei, S.X., Shi, S.Z., Li, J.X., Zheng, J.L., Yu, X.Y., Huang, Y.F. and Li, X. (2024) Measurement Research Based on Bayesian Structural Equation Cognitive Model. *Journal of Applied Mathematics and Physics*, **12**, 1163-1177.
https://doi.org/10.4236/jamp.2024.124072

Received: March 20, 2024
Accepted: April 21, 2024
Published: April 24, 2024

Abstract

The Bayesian structural equation model integrates the principles of Bayesian statistics, providing a more flexible and comprehensive modeling framework. In exploring complex relationships between variables, handling uncertainty, and dealing with missing data, the Bayesian structural equation model demonstrates unique advantages. Therefore, Bayesian methods are used in this paper to establish a structural equation model of innovative talent cognition, with the measurement of college students' cognition of innovative talent being studied. An in-depth analysis is conducted on the effects of innovative self-efficacy, social resources, innovative personality traits, and school education, aiming to explore the factors influencing college students' innovative talent. The results indicate that innovative self-efficacy plays a key role in perception, social resources are significantly positively correlated with the perception of innovative talents, innovative personality tendencies and school education are positively correlated with the perception of innovative talents, but the impact is not significant.

Keywords

Bayesian Structural Equation Model, Innovative Talents, Measure of Cognition, Innovative Self-Efficacy, Social Resources

1. Introduction

Studying college students' cognition of innovative talent has important practical significance and far-reaching implications for education, talent cultivation, employment, social development, and national scientific and technological development. College students' cognition of innovative talents is not only of great significance in education, personnel training and employment, but also has a profound impact on social development and national science and technology development. By guiding students to pay more attention to their own innovation ability and practical experience, they can improve their competitiveness in the job market, and then promote social innovation and economic development. In addition, training more scientific and technological talents helps to enhance the national scientific and technological innovation capacity, promote the continuous improvement of the national scientific and technological development level, and inject new impetus into the long-term development of the country.

The factors influencing college students' innovation capabilities mainly involve individual factors, environmental factors, and educational factors, as indicated by literature research. Binet and Simon [1] suggested that students with a higher tendency towards innovation are more adept at self-driven, proactive learning, efficiently acquiring knowledge, quickly grasping new concepts and technologies, and applying what they have learned in practice. Maslow [2] and Reinberg [3] believed that innovative talents are typically curious about new things, eager to explore unknown areas, possess strong learning motivation and enduring enthusiasm, are willing to overcome difficulties and setbacks, and persistently pursue personal growth. Wu and Zhu [4] pointed out that college students' innovation capabilities are closely related to personal characteristics, such as gender, city of residence, and students' participation in courses, with engineering students showing significantly higher innovation capabilities than science students. Teachers' teaching methods also have a significant impact on students' innovation capabilities. Luo [5] suggested that environmental factors such as departmental support, teacher guidance, classroom culture, and dormitory atmosphere can either promote or hinder progress. Starting from innovation itself, innovation is domain-specific [6] [7]. Kaufman and Beghetto [8] [9] proposed the 4C model of creativity, which divides creativity into four levels: Mini-C (internal creativity), Little-C (everyday creativity), Pro-C (professional creativity), and Big-C (eminent creativity). This model emphasizes that an individual's innovation capabilities can develop and improve with age and changing environments, and different individuals have varying developmental trajectories. Fianagan *et al.* [10] argued that when formulating educational policies related to cultivating innovative talents, it is crucial to fully consider college students' cognition of innovative talents.

This study on the cognitive measurement of innovative talents among college students based on the Chinese national conditions is mainly conducted. Drawing from Schack's [11] and Kirton's [12] research on creativity and innovative talents, a cognitive model of college students' innovative talents, including innovation self-efficacy, social resources, innovative personality tendency, and five potential factors in school education, is proposed in this paper. By establishing a Bayesian structural equation model, the extent to which each factor influences college students' cognitive perception of innovative talents is determined.

The structure of this article is arranged as follows: The first part is the introduction, which presents research on the cognitive measurement of innovative talents among college students both domestically and internationally. The second part provides a brief introduction to the theoretical foundations required for this study, including structural equation modeling and Bayesian theory. The third part involves establishing a Bayesian structural equation cognitive model, which reflects the impact of innovation self-efficacy, social resources, innovative personality tendency, and school education on the cognitive perception of innovative talents. The fourth part consists of empirical analysis, which utilizes a Bayesian structural equation model to determine the magnitude of the influencing factors between variables, and conducts a comparative analysis between the Bayesian structural equation model and traditional structural equation models. The fifth part is the conclusion and acknowledgments, which highlight the role of the Bayesian structural equation model in the cognitive measurement of innovative talents among college students.

2. Basic Theory

The model of factors influencing college students' cognitive perception of innovative talents is based on the structural equation model. The structural equation model typically uses Maximum Likelihood (ML) estimation for parameter estimation. When the sample size is too small or there is prior information, the Bayesian method is used in the structural equation model.

2.1. Structural Equation Model

The Structural Equation Model (SEM) is a type of confirmatory multivariate statistical analysis technique, which consists of two parts: the measurement model and the structural model. The measurement model reflects the relationships between latent variables, while the structural model describes the causal relationships between latent variables.

The basic equations of the measurement model can be represented as:

$$\begin{aligned} x &= \mathbf{\Lambda}_x \xi + \delta \\ y &= \mathbf{\Lambda}_y \eta + \varepsilon \end{aligned} \tag{1}$$

where x, y are exogenous and endogenous indicators, respectively, δ, ε represents the measurement error on x, y, $\mathbf{\Lambda}_x$ denotes the relationship between exogenous indicator x and exogenous latent variable ξ, and $\mathbf{\Lambda}_y$ represents the relationship between endogenous indicator y and endogenous latent variable η.

The basic formula of the structural model can be expressed as:

$$\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta \tag{2}$$

where $\mathbf{B}$ represents the relationships between endogenous latent variables, $\mathbf{\Gamma}$ denotes the influence of exogenous variables on endogenous variables, and ζ represents the unexplained portion within the model.

2.2. Maintaining the Integrity of the Specifications

The Bayesian method is a statistical inference method based on Bayes' theorem.

Its basic principle is:

$$\pi(\theta \mid y)=\frac{p(y \mid \theta)\cdot \pi(\theta)}{\int p(y \mid \theta)\cdot \pi(\theta)\mathrm{d}\theta} \tag{3}$$

where $\pi(\theta)$ is the prior distribution, $p(y \mid \theta)=\prod_{i=1}^{n} p(y_i \mid \theta)$ is the likelihood function of the observed data $y=(y_1,\cdots,y_n)$, and $\pi(\theta \mid y)$ is the posterior distribution.

Bayesian inference is performed through the posterior distribution, including point estimation and interval estimation of parameters, as well as prediction of future observations.

3. Bayesian Structural Equation Cognitive Model

3.1. Model Assumption

According to the research on the influencing factors of college students on innovative talents, it can be seen that innovative self-efficacy refers to a person's trust and confidence in his ability to carry out innovative activities. If a person has certain confidence, he is more likely to become an innovative talent. Personal disposition will affect a person's acceptance and interest in new things, new ways of thinking, new action strategies, etc., and have a certain positive impact on becoming an innovative talent. School education plays an important role in the cultivation of innovative talents. Receiving good learning environment and resources can cultivate one's own innovation ability, which has a positive impact on becoming innovative talents. Social resources can give university students the knowledge, skills and opportunities they need to innovate and grow in their fields. The more social resources, the more knowledge college students can learn and the more likely they are to become innovative talents. Therefore, the following assumptions can be made:

H1: Innovation self-efficacy has a positive impact on the formation of innovative talents;

H2: Individual propensity to innovate has a positive influence on the formation of innovative talents;

H3: School resources have a positive impact on the formation of innovative talents;

H4: Social resources have a positive impact on the formation of innovative talents.

3.2. Model Building

This article selects key indicators such as innovative self-efficacy, school education, social resources, and innovative personality tendencies to measure college students' cognitive abilities as innovative talents, denoted as "$\xi=(\xi_1,\xi_2,\xi_3,\xi_4)^{\mathrm{T}}$" The endogenous latent variable for innovative talents is represented as "η". The vector "$\mathbf{x}=(x_1,x_2,\cdots,x_{15})^{\mathrm{T}}$" is composed of exogenous indicators including creative confidence, innovative thinking, creative products, stress resistance, divergent thinking, learning motivation, ambition, learning efficiency, online learning, national policies, social tolerance, innovation competitions, peer assistance, teacher knowledge expansion, and teacher guidance. The variable "$\mathbf{y} = (y_1, y_2)^{\mathrm{T}}$" is composed of endogenous indicators corresponding to participation and innovative outcomes. Table 1 shows the index system of latent and explicit variables used for research. The error vector is represented as "$\mathbf{e}$" and its length varies in different models.

Combining the above measurements, the structural equation system of the cognitive model is as follows:

$$\begin{aligned} \mathbf{x} &= \mathbf{\Lambda}_x \xi + \mathbf{e} \\ \mathbf{y} &= \mathbf{\Lambda}_y \eta + \mathbf{e} \\ \eta &= \mathbf{\Gamma} \xi + \mathbf{e} \end{aligned} \tag{4}$$

where,

$$\mathbf{\Lambda}_x = \begin{pmatrix} \mathbf{\Lambda}_1 & & & \\ & \mathbf{\Lambda}_2 & & \\ & & \mathbf{\Lambda}_3 & \\ & & & \mathbf{\Lambda}_4 \end{pmatrix}_{15\times 4}, \quad \mathbf{\Lambda}_y = \begin{pmatrix} \lambda_{12} & 0 \\ 0 & \lambda_{13} \end{pmatrix}, \quad \mathbf{\Gamma} = (\gamma_1, \gamma_2, \gamma_3, \gamma_4)$$

Table 1. Indicator system used for research.

Latent variables	Explicit variables
Innovative talent	Engagement
	Innovative results
Creative self-efficacy	Creative finished product
	Creative thinking
	Creative confidence
	Ability to work under pressure
School education	Innovative practice
	Classmate help
	Teacher guidance
	Teacher knowledge development
Social resources	Online learning
	National policy
	Social tolerance
Innovative personality tendency	Motivation to learn
	Aspirational
	Divergent thinking
	Learning efficiency

Here,

$$\mathbf{\Lambda}_1 = \left(\lambda_1, \lambda_2, \lambda_3, \lambda_4\right)^{\mathrm{T}}$$

$$\mathbf{\Lambda}_2 = \left(\lambda_5, \lambda_6, \lambda_7, \lambda_8\right)^{\mathrm{T}}$$

$$\mathbf{\Lambda}_3 = \left(\lambda_9, \lambda_{10}, \lambda_{11}\right)^{\mathrm{T}}$$

$$\mathbf{\Lambda}_4 = \left(\lambda_{14}, \lambda_{15}, \lambda_{16}, \lambda_{17}\right)^{\mathrm{T}}$$

The prior distribution of each parameter is selected as no information prior, that is, uniform distribution: The likelihood function uses normal distribution, which can describe the distribution of actual data well. The model estimation uses Markov Chain Monte Carlo (MCMC) method to estimate the posterior distribution of parameters by constructing a Markov chain and using the convergence property of Markov chain to generate the sample of parameters. The structural equation model of the cognitive model is shown in **Figure 1**.

4. Empirical Analysis

In this section, a questionnaire survey was designed based on the selected indicators. The survey was conducted using Wenjuanxing (a Chinese online survey platform) for online distribution and collection. The data was then subjected to statistical analysis, reliability and validity tests, and finally, a Bayesian structural equation cognitive model was established to analyze the degree of influence of innovative self-efficacy, social resources, innovative personality tendencies, and school education on the cognitive perception of innovative talents.

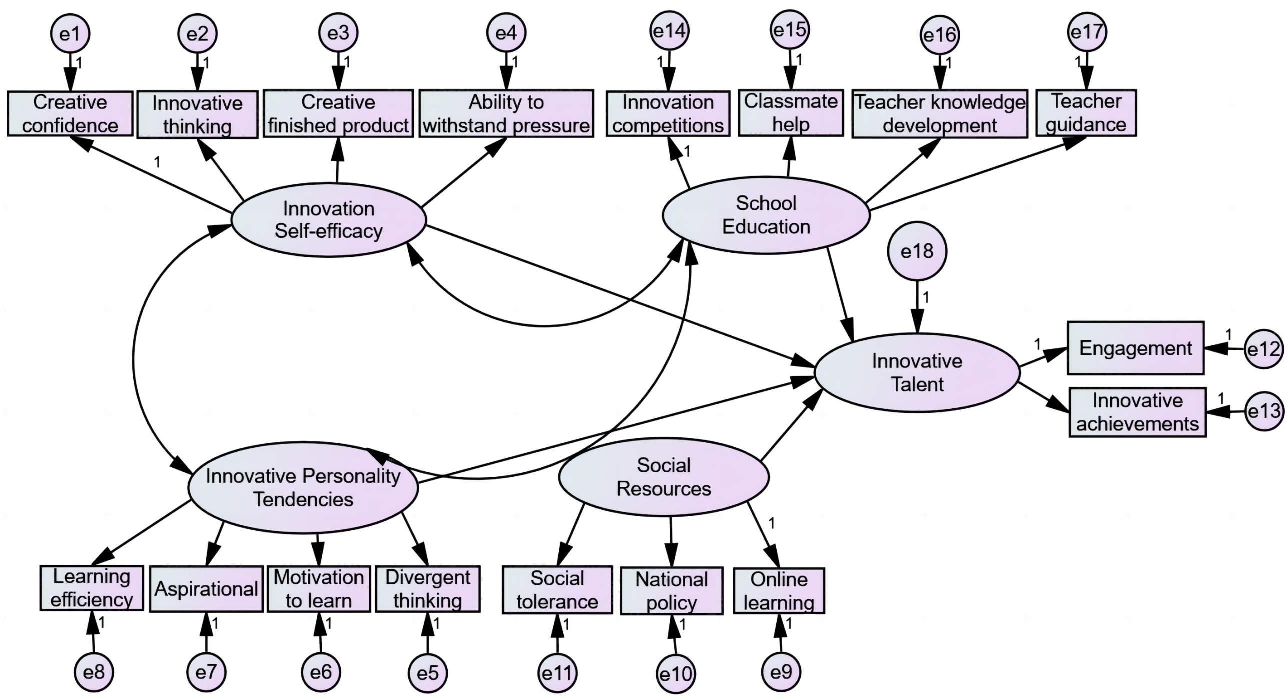

Figure 1. Bayesian structural equation model diagram.

4.1. Questionnaire Survey

Based on the selection of influencing factors, a survey questionnaire on college students' cognitive measurement of innovative talents was developed. In the process of designing the questionnaire, the Likert five-point scale method was used, with responses ranging from "strongly disagree, disagree, neutral, agree, and strongly agree", scored between 1 and 5. The survey questionnaire mainly consisted of three parts: the first part covered basic personal information, and the second part focused on factors influencing whether college students are innovative talents. The survey targeted college students and graduate students from various universities. The questionnaire was primarily distributed through Wenjuanxing, and the collected questionnaire data underwent screening and data preprocessing, resulting in 387 valid questionnaires. Table 2 and Figure 2 show the basic personal information collected in the questionnaire.

Male and female students each accounted for around 50% of the respondents in the questionnaire survey, with a relatively even distribution of numbers,

Table 2. Questionnaire retrieval information table.

Name	Options	Frequency	Percentage
Gender	Male	183	47.29%
	Female	204	52.71%
Grade	Freshman/junior college year 1	55	14.21%
	Sophomore year/junior year 2	113	29.2%
	Junior year/junior college year 3	173	44.7%
	Senior	30	7.75%
	Graduate students	16	4.13%

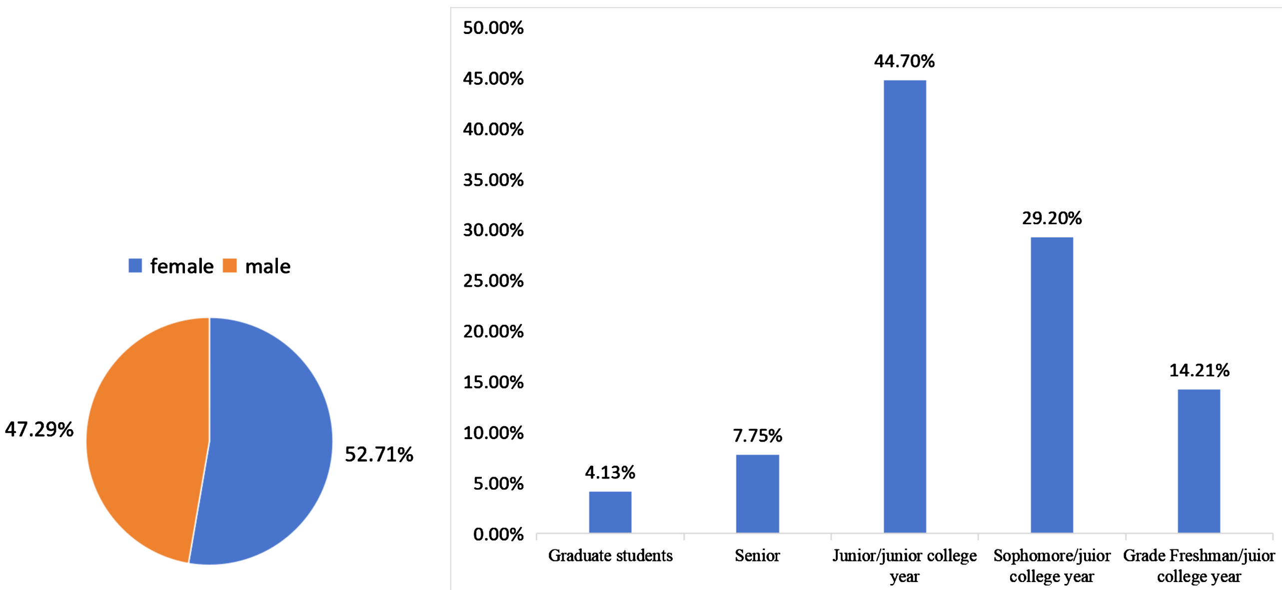

Figure 2. Ratio of male to female (left) and distribution histogram of each grade (right).

allowing for separate structural equation modeling analyses. Among students in their third year or the equivalent of a three-year college program, the percentage reached 44.7%, as indicated in Table 2 of the questionnaire retrieval information. However, there is a limited amount of data for fourth-year students and graduate students, which can be expanded through resampling methods for subsequent structural equation modeling analysis, as shown in Questionnaire retrieval information in Table 2. Next, we will first conduct a structural equation modeling analysis on the overall situation to observe the general trend of the data.

4.2. Reliability and Validity Test

Reliability testing, also known as consistency testing, is used to examine the internal consistency of various dimensions of the survey questionnaire. The Cronbach's alpha coefficient is typically used for observation. If the Cronbach's alpha coefficient of the latent variables is greater than 0.6, it indicates internal consistency in the data. In this study, SPSS was used to conduct reliability testing on the collected data. The specific reliability test data is presented in Table 3.

From Table 3, it is evident that the Cronbach's alpha coefficients for the exogenous latent variables, endogenous latent variables, and the overall data all exceed 0.6, indicating that the dimensions of each variable demonstrate internal consistency and good reliability. This suggests that the questionnaire design is reasonable and the data collection is effective.

Validity testing is primarily used to examine the effectiveness, accuracy, and rationality of the questionnaire design. When the KMO (Kaiser-Meyer-Olkin) statistic is above 0.7, the factor analysis is considered to be effective. If the significance in the Bartlett's test of sphericity is less than 0.01, it indicates conformity to the standard. The KMO and Bartlett's test data are presented in Table 4.

Table 3.Reliability test data.

	Cronbach's alpha coefficient	Number of terms
Overall	0.846	18
Creative self-efficacy	0.784	4
Creative personality tendency	0.716	4
Schooling	0.666	5
Social resources	0.617	3
Innovative talent	0.710	2

Table 4. KMO and Bartlett's test data.

KMO sampling appropriate quantity number		0.870
Bartlett's test of sphericity	Approximate Chi-square	18867.742
	Degrees of freedom	120
	Saliency	0.000

It can be observed that the KMO statistic value is 0.870, which is greater than 0.7, and the significance in the Bartlett's test of sphericity is less than 0.01, indicating effective factor analysis in **Table 4**.

4.3. Result Analysis of Bayesian Structural Equation Cognitive Model

The Bayesian structural equation cognitive model was constructed using AMOS software. When setting up the model, one observed variable for each latent variable was arbitrarily set as a fixed parameter of 1. The prior distribution for each parameter was set as a uniform distribution with a lower limit of and an upper limit of for Bayesian estimation. After iteration, the model convergence index CS = 1.001, indicating that the parameters have converged. In the model adaptation index, the posterior predictive p = 0.15, which is between 0.05 and 0.95, indicates that the posterior predictive P is well adapted to the model.

4.3.1. Path Coefficient Analysis

The non-standard path coefficients obtained from the Bayesian structural equation model are presented in **Table 5**. The table provides Bayesian non-standard path coefficients and SE (Standard Error), where Bayesian non-standard path coefficients are typically used to compare the influence between different variables. If the path coefficient is large and significant, it indicates a strong correlation between the variables; conversely, a smaller path coefficient suggests a weaker correlation between the observed variables and the latent variables. SE represents the uncertainty of the estimated path coefficients.

From data in **Table 5**, it can be seen that the observed variables have a positive impact on the latent variables. Regarding the influence between latent variables, social resources directly influence innovative talents with a Bayesian non-standard path coefficient of 0.425. The impact of school education on innovative talents is relatively small, with a path coefficient of 0.041. The influence of innovative personality traits on innovative talents is relatively small, with a path coefficient of 0.055. Innovative self-efficacy has a significant positive impact on innovative talents, with a path coefficient of 0.535. The standard errors are all less than 0.02, indicating very low uncertainty in the path coefficients. Therefore, the model hypothesis is verified, and H1, H2, H3 and H4 hypotheses are valid.

By introducing prior knowledge and adjusting the structure of the model, Bayes method can more flexibly deal with the complex relations and uncertainties among variables, including direct and indirect effects, nonlinear relations, etc., which can better capture the complex relations between variables and describe the degree of uncertainty of parameters through a posterior distribution. This helps to more fully understand the model's results and takes into account uncertainties, making inferences more reliable and accurate.

4.3.2. Analysis of the Degree of Influence

1) Significant Impact of Innovative Self-efficacy on Innovative Talents

The significant impact of innovative self-efficacy on innovative talents is due

Table 5. Path coefficients.

Path			SE	Bayesian nonstandard path coefficients
Innovative talent	<---	Creative self-efficacy	0.017	0.535
Innovative talent	<---	School education	0.007	0.041
Innovative talent	<---	Creative personality tendency	0.015	0.055
Innovative talent	<---	Social resources	0.008	0.425
Stress resistance	<---	Creative self-efficacy	-	1.000
Creative finished products	<---	Creative self-efficacy	0.007	1.188
Think creatively	<---	Creative self-efficacy	0.008	1.243
Creative confidence	<---	Creative self-efficacy	0.009	1.258
Innovation competition	<---	School education	-	1.000
Classmate help	<---	School education	0.006	1.111
Teacher Knowledge expansion	<---	School education	0.006	0.642
Teacher guidance	<---	School education	0.006	1.325
Motivation learn	<---	Creative personality tendency	-	1.000
Aspirational	<---	Creative personality tendency	0.004	0.977
Learning efficiency	<---	Creative personality tendency	0.004	0.880
Divergent thinking	<---	Creative personality tendency	0.003	0.558
Online learning	<---	Social resources	-	1.000
National policy	<---	Social resources	0.018	1.587
Social tolerance	<---	Social resources	0.007	0.883
Innovative achievements	<---	Innovative talent.	-	1.000
Participation	<---	Innovative talent	0.004	0.690

to its important role in multiple aspects. Firstly, the confidence and perceived ability of innovative self-efficacy not only stimulate individuals' enthusiasm and motivation for innovative activities, but also enhance their ability to cope with challenges and difficulties. Secondly, innovative self-efficacy further shapes the foundation for individuals to become innovative talents by influencing their learning and development paths. In summary, innovative self-efficacy plays an important role in stimulating individual innovation, guiding innovative behavior, and shaping innovative capabilities, providing necessary support and guarantees for individuals to become talents with innovative potential and strength.

2) Significant Impact of Social Resources on Innovative Talents

The significant impact of social resources on innovative talents is due to the important influence of social resources on individuals' innovative abilities and achievements in multiple aspects. Firstly, social resources provide broad external support and assistance for innovative talents. Through communication and collaboration with others, innovative talents can acquire more information and resources, expanding the scope and possibilities of innovation. Secondly, social resources provide a wider development platform and opportunities for innovative talents. With the support of social resources, innovative talents can more easily access innovative projects and opportunities, participating in challenging and forward-looking projects, thereby enhancing their own innovative abilities and levels. In conclusion, social resources provide important guarantees and support for individuals to become talents with innovative capabilities and potential.

3) Insignificant Impact of School Education on Innovative Talents

Regarding the relatively small and insignificant impact of school education on innovative talents, this paper analyzes the reasons as follows:

a) School education is largely constrained by standardized and regulated curricula, which cannot effectively cultivate students' innovative abilities.

b) Schools typically evaluate students' academic performance and abilities through examinations, leading students to focus more on exam skills rather than the cultivation of innovative abilities.

c) Innovation often requires the integration of knowledge and methods from multiple disciplines.

4) Insignificant Impact of Innovative Personality Traits on Innovative Talents

In this study, the impact of innovative personality traits on innovative talents is very small, primarily due to the following reasons:

a) Individual differences: Each person's innovative personality is unique and influenced by individual differences.

b) Environmental factors: The development and expression of innovative personality traits are also influenced by environmental factors.

4.4. Comparative Analysis of Bayesian and Traditional Structural Equation Models

In social science research, structural equation modeling has been widely used to explore and analyze relationships between variables. Traditional structural equation models typically use methods such as maximum likelihood estimation from a frequentist perspective to estimate parameters. However, in recent years, Bayesian structural equation modeling has gradually gained attention as an emerging statistical modeling method. Based on Bayesian theory, the Bayesian approach offers unique advantages in parameter estimation compared to traditional methods. One important aspect is that Bayesian methods can provide more flexible and accurate estimates of path coefficients, as shown in **Table 6**, including some non-standard path coefficients from both methods.

The path coefficients of creative self-confidence, innovative thinking, and creative outcomes on innovative self-efficacy increased by 0.016, 0.017, and 0.014 respectively. The path coefficient of innovative self-efficacy on innovative talent increased by 0.034. The path coefficients of national policies and social tolerance on social resources increased by 0.103 and 0.031 respectively. The path coefficient

Table 6. Comparison of partial path coefficients between Bayesian and traditional structural equation models.

Path			Nonstandard path coefficient	Bayesian nonstandard path coefficient
Innovative talent	<---	Innovation self-efficacy	0.501	0.535
Creative confidence	<---	Innovation self-efficacy	1.242	1.258
Innovative thinking	<---	Innovation self-efficacy	1.226	1.243
Creative product	<---	Innovation self-efficacy	1.174	1.188
National policy	<---	Social resources	1.484	1.587
Social tolerance	<---	Social resources	0.852	0.883
Teacher guidance	<---	School education	1.305	1.325
Degree of participation	<---	innovative talent	0.556	0.690

of teacher guidance on school education increased by 0.02. The participation level of innovative talent increased by 0.134, as shown in **Table 5**. These changes in path coefficients quantify the advantages of Bayesian models over traditional models in parameter estimation, clearly demonstrating the impact of the Bayesian method on model results. The Bayesian method allows the incorporation of prior knowledge in the parameter estimation process, handles uncertainty more flexibly, and provides more accurate parameter estimates. Therefore, compared to traditional frequentist methods, Bayesian methods often yield more precise and accurate results in path coefficient estimation.

By using Bayesian methods, some challenges in structural equation models can be effectively solved. Especially in the case of small sample size, Bayesian method realizes more accurate parameter estimation by introducing prior knowledge, which is no longer limited to point estimation, but can obtain the posterior distribution of parameters for inference, thus enhancing the reliability of model results. In addition, Bayesian methods enable parameter estimation without the need for interpolation data, and can even deal with missing values in the data, enabling complete data analysis. However, it should be noted that when Bayesian structural equation models are inferred using Monte Carlo simulation, it may lead to high computational complexity, especially in the case of more variables or more complex models, which may require a lot of time and computational resources.

4.5. Model Testing

The Bayesian method model is used for analysis, before the parameter test, the prior information is first added to the sample, and then the posterior distribution of the parameters is calculated using Bayes' theorem, and the result of parameter convergence is shown through the correlation parameter graph.

Prior information was added to the sample to set parameters. The following only shows the prior results of innovative talent, innovative self-efficacy and innovative personality tendency, as shown in **Figure 3**. With the increase of sampling times, the model converges gradually. After iteration, the convergence index CS of the model is 1.001, indicating that the parameters have converged.

The posterior distribution of the model parameters is analyzed, including the results of innovation self-efficacy, innovation personality tendency and innovation talent. By observing the parameter estimation diagram in **Figure 4**, it can be clearly seen that the parameters have no obvious up-and-down oscillation or random drift, indicating that the parameters have converged. In addition, the autocorrelation graph in **Figure 5** shows that the autocorrelation values near lag100 approach 0, which further verifies the convergence of Bayesian estimation parameters. Therefore, the convergence of the Bayesian structural equation model

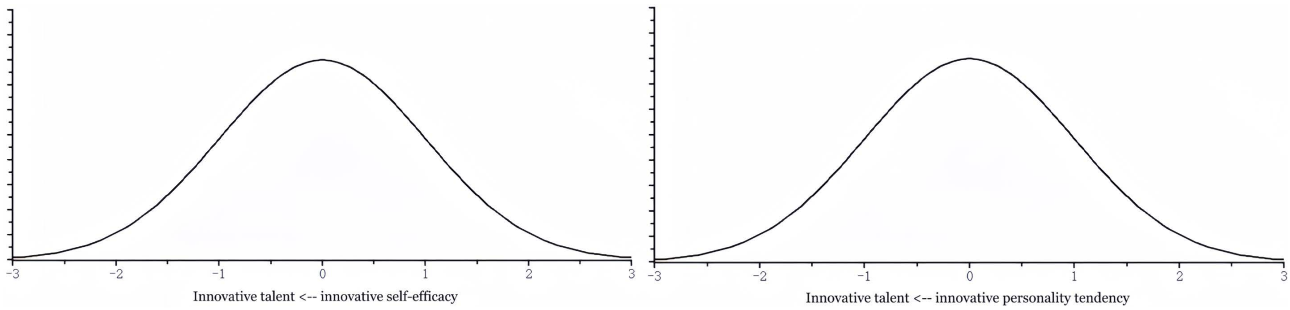

Figure 3. Innovative talent <--- innovative self-efficacy (left), innovative talent <--- innovative personality tendency (right). Note: The vertical axis represents the variation in prior information, which can be used to compare the prior differences between different variables.

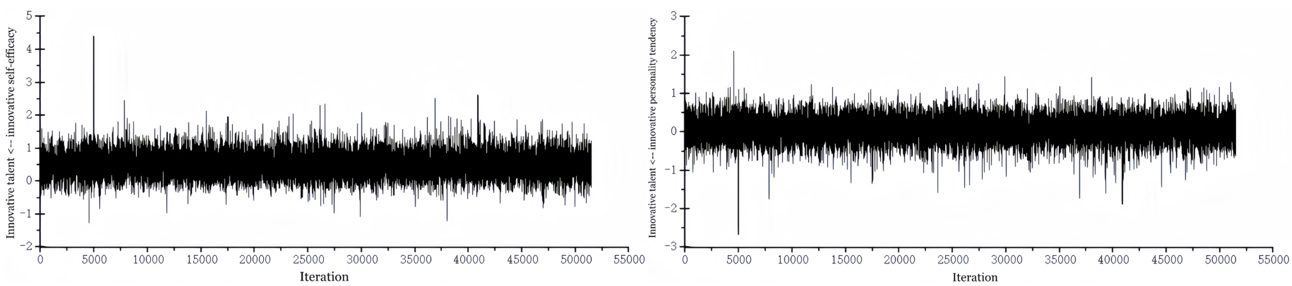

Figure 4. Parameter estimation chart: innovative talent <--- innovative self-efficacy (left), innovative talent <--- innovative personality tendency (right).

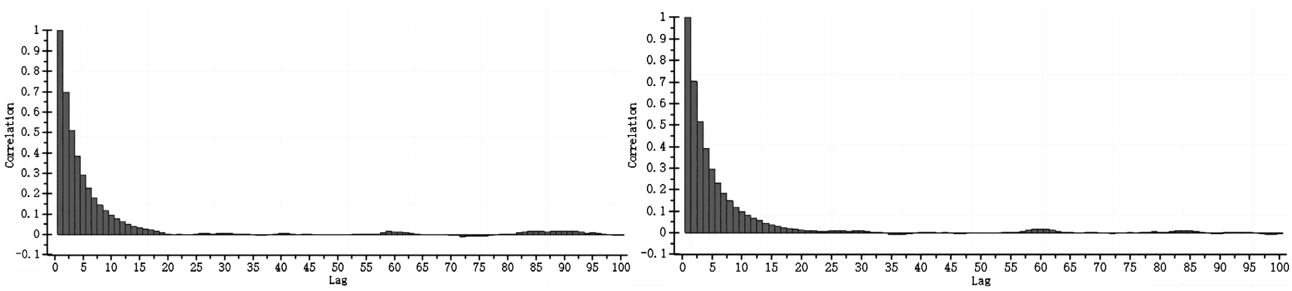

Figure 5. Autocorrelation chart: innovative talent <--- innovative self-efficacy (left), innovative talent <--- innovative personality tendency (right).

indicates that the model parameters gradually stabilize during the sampling iteration process, which ensures the accuracy and stability of parameter estimation.

5. Summary

This study aimed to explore the cognitive level of college students regarding innovative talents. By constructing a Bayesian structural equation model, it delved into the intrinsic relationships of college students in terms of their cognition of innovative talents, selecting innovative self-efficacy, social resources, innovative personality traits, and school education as factors influencing college students' cognitive perception of innovative talents. The results indicated that innovative self-efficacy plays a crucial role in cognition, social resources are significantly positively correlated with the perception of innovative talents, and innovative personality traits and school education are positively correlated but with insignificant impact. This reveals the contribution of these factors to college students' innovative abilities. The research findings not only provide empirical support for understanding college students as innovative talents, but also offer reference points for further improving educational and nurturing programs.

The Bayesian structural equation model demonstrates advantages in parameter estimation compared to traditional structural equation models in the research presented in this article. The Bayesian approach, by incorporating prior knowledge, handles uncertainty more flexibly and provides more accurate parameter estimates, thereby making the model application more reliable.

Acknowledgements

Special thanks to Professor Sanzhi Shi for his careful guidance, the support from the Jilin Province University Student Innovation and Entrepreneurship Training Program (2023206), and the funding from the Jilin Provincial Education Science "14th Five-Year Plan" 2022 General Project Fund (GH22674).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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