

# Empirical Research on the Influencing Factors of Cultivating College Students' Computational Thinking in the "Intelligence+" Era

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## Abstract

With the advent of the "Intelligence+" era, computational thinking, as a crucial ability for solving complex problems and driving innovation, plays a vital role in shaping the career planning and development of university students. This paper aims to explore the relationships between teaching content, teaching methods and means, as well as learning support services, and their impacts on computational thinking ability in the context of the "Intelligence+" era. An empirical study is conducted to reveal the specific mechanisms of these factors. The study targets electronic and information engineering majors at Nanchang Normal University, with questionnaires distributed among them. Through statistical analysis of the survey data, the results show that there is a significant correlation among teaching content, teaching methods and means, learning support services, and computational thinking ability. A predictive model of learning support services' influence on computational thinking ability is constructed, uncovering the specific paths and degrees of impact that learning support services have on cultivating computational thinking among university students. This provides practical guidance and theoretical support for the cultivation of computational thinking among university students.

## Keywords

Computational Thinking, Influencing Factors, Nanchang Normal University, Empirical Research, Cultivation

## 1. Introduction

In the era of "Intelligence+", advanced technologies such as artificial intelligence, big data, and cloud computing have not only profoundly transformed traditional

modes of production and lifestyle but also exerted a significant impact on the field of education. Computational thinking, as a bridge between information technology and problem-solving capabilities in real-world contexts, has emerged as an indispensable core competence for college students in the new era. Computational Thinking has had a significant impact on talent cultivation (Ma, Liu, Li, Fan, & Liang, 2019). Nevertheless, there persist numerous challenges and issues in the cultivation of computational thinking among university students. On the one hand, as technologies continually evolve and upgrade, traditional computer literacy education content and methodologies have struggled to keep pace with the demands of the times. On the other hand, a multitude of factors, including teaching content, teaching methods and means, as well as learning support services, directly or indirectly influence the effectiveness of computational thinking cultivation. Consequently, it is imperative to delve deeply into the influencing factors and their mechanisms of action in the context of the “Intelligence+” era, with regard to the cultivation of computational thinking among university students. This endeavor aims to provide a scientific basis and practical guidance for reforming computer literacy education in higher education institutions.

## **2. Analysis of the Connotation and Influencing Factors of Computational Thinking**

### **2.1. Connotation of Computational Thinking**

Computational thinking involves transforming human instructions into commands recognizable by computers, encompassing a series of thinking activities such as understanding human behavior. It involves problem analysis, abstraction, logical reasoning, and the design of solutions, exhibiting interdisciplinary characteristics. Computational thinking emphasizes core elements such as abstraction, automation, and problem-solving. It is not merely a way of thinking to solve problems but also a comprehensive ability encompassing multiple dimensions, characterized by a problem-oriented and procedural approach.

### **2.2. Analysis of Influencing Factors of Computational Thinking**

#### **2.2.1. Among the Influencing Factors of Computational Thinking, Teaching Content Is a Crucial Aspect**

The relevance of classroom teaching content to the forefront of technological development, its richness and quality, as well as the integration of theory with practice, are directly related to the cultivation and enhancement of students’ computational thinking abilities. With the rapid development of information technology, the teaching content of computational thinking also needs to be continuously updated to reflect the latest technological achievements and application trends. This helps students understand industry frontiers, stimulating their interest in learning and fostering an innovative spirit. Through rich and high-quality teaching content, students can understand and apply computational thinking from multiple angles, enhancing their comprehensive application abilities. The delivery of teaching content

should incorporate abundant practical elements, such as programming projects, problem-solving tasks, and case studies. These practical contents adopt the “project-task-activity” structure, enabling students to complete projects through task design, activity implementation, result testing and other steps, so as to improve their computational thinking ability (Yu & Chen, 2018).

In summary, teaching content plays a significant role among the influencing factors of computational thinking. To effectively cultivate students’ computational thinking abilities, it is necessary to design teaching content that is diverse, appropriately challenging, forward-looking, and interactive. Additionally, teachers should flexibly adjust and optimize the content based on students’ actual situations and computational thinking enhances students’ ability to solve problems (Markandan, Osman, & Halim, 2023).

### **2.2.2. Among the Many Influencing Factors in Cultivating Computational Thinking, Teaching Methods and Means Are Also Significant**

Choosing appropriate and efficiently utilizing teaching methods is a crucial path to promoting the development of students’ computational thinking. On one hand, teaching methods such as “learning by doing” and “project-based learning” are also widely adopted in computational thinking education (Xue & Liu, 2021). By guiding students to participate in and complete specific projects, it deeply embeds the cultivation of computational thinking into practice. This model not only emphasizes hands-on practice but also focuses on enhancing teamwork and problem-solving abilities simultaneously, laying a solid foundation for the all-round development of students’ computational thinking. On the other hand, the flipped classroom, as a disruptive traditional teaching model, redefines the allocation of learning time and space, granting students greater autonomy in learning. Students pre-learn new knowledge through activities such as video lectures and material reading before class, while the classroom becomes a space for deepening understanding, practical application, and interactive discussions. The teacher’s role transforms into a guide and facilitator, focused on answering questions, promoting intellectual exchanges, and further stimulating students’ computational thinking potential. This teaching model not only improves learning efficiency but also significantly enhances students’ innovation and self-directed learning abilities.

In summary, the diversification and optimization of teaching methodologies and approaches provide strong support for students to comprehensively grasp computational thinking knowledge and skills. They not only facilitate deep understanding of knowledge and effective mastery of skills but also subtly cultivate students’ comprehensive application abilities and innovative thinking, opening up broad prospects for the further development of computational thinking education.

### **2.2.3. Among the Influencing Factors of Computational Thinking, Learning Support Services Have Emerged as a Critical Dimension That Cannot Be Overlooked**

Faced with various challenges and difficulties encountered by students in learning

computational thinking, implementing timely and effective learning guidance strategies is particularly crucial. These strategies encompass personalized instructional tutoring (such as one-on-one guidance from teachers or counselors), collaborative learning models (like cooperative interactions within study groups), and the application of digital learning support platforms (e.g., online Q&A systems). By implementing precise learning guidance programs, the learning outcomes of students can be significantly enhanced. Furthermore, fostering a dynamic learning community environment is also vital, providing students with a comprehensive platform for exchanging ideas, sharing knowledge, and collaboratively solving problems. In this interactive environment, students can not only deepen their understanding and application of computational thinking but also make substantial progress in developing their teamwork and communication skills.

In summary, learning support services occupy a central position in the multifactorial model of computational thinking development. To comprehensively promote the leap in students' computational thinking abilities, educational institutions should strive to strengthen the construction and management of learning support service systems, including offering customized learning guidance programs, building instant learning feedback mechanisms, and cultivating an interactive learning community environment, thereby providing students with comprehensive and multi-layered support services.

### 3. Research Design

#### 3.1. Design of the Survey Questionnaire

This study selected 215 students majoring in Electronic Information Engineering from Nanchang Normal University as the research subjects, and a questionnaire survey was employed as the research method. First, the research literature on computational thinking was reviewed. Guided by the theoretical framework, a preliminary questionnaire was designed and distributed to several teachers and students with rich experience in the field of electronic and information engineering education for trial completion and feedback. Based on the trial completion feedback and revision suggestions, the questionnaire was revised and polished for many times, and finally a formal questionnaire was formed. Following the design requirements of the Likert scale, numbers 1 to 5 were used to sequentially represent “strongly disagree,” “disagree,” “neutral,” “agree,” and “strongly agree.” The survey questionnaire comprised 14 measurement items, structuring four latent variables: teaching content, teaching methods and means, learning support services, and computational thinking abilities, as depicted in **Table 1**. The formation mechanism of an indicator system is a systematic and complex process that requires researchers to fully consider various aspects, including theoretical frameworks, literature reviews, variable identification and definition, indicator system construction, expert consultation and revision, pre-testing and adjustment, as well as formal use and validation.

**Table 1.** Construction of latent variables and measurement variables.

Latent Variable	Measurement Variable
Teaching Content (TC)	Course content keeps up with the cutting-edge development of science and technology (TC1)
	The content of classroom teaching is rich and high-quality (TC2)
	The course emphasizes the close integration of theory and practice (TC3)
Teaching Methods and Means (TMM)	The school often adopts teaching methods such as flipped classrooms and project-based learning (TMM1)
	The teacher actively interacts with students in class and gives timely feedback (TMM2)
	Fully utilize information technology tools such as online platforms and simulation software in teaching (TMM3)
Learning Support Services (LSS)	The guidance and counseling provided by the tutor system in the school are helpful to learning (LSS1)
	Learning communities such as study groups in the school are active (LSS2)
	The school provides sufficient psychological and emotional support for students to cope with the challenges in learning (LSS3)
Computational Thinking Abilities (CTA)	I am good at breaking down complex problems into a series of simple and manageable sub-problems, and abstracting key information from them (CTA1)
	I am able to design concise and effective algorithms to solve practical problems, and understand the logic behind the algorithms (CTA2)
	When solving computational problems, I am accustomed to evaluating the advantages and disadvantages of different solutions and making reasonable choices (CTA3)
	I am good at using innovative thinking to find non-traditional solutions to problems and am willing to try new methods (CTA4)
	I am able to effectively cooperate with team members and clearly communicate my ideas and solutions (CTA5)

### 3.2. Analysis of Basic Characteristics of the Sample

The questionnaires were distributed and data collected through the online platform Wenjuanxing. A total of 151 questionnaires were distributed online, with 141 questionnaires recovered and all of them valid, resulting in a recovery rate of 93.38% and an effectiveness rate of 100%. The basic characteristics of the survey respondents consist of four parts: gender, hometown, grade, and family economic status (annual income). The basic characteristics are as follows:

**Gender characteristics:** The frequency of male respondents is 91, accounting for 64.54%; while the frequency of female respondents is 50, accounting for 35.46%. Less than 40% of the respondents are female university students, while more than 60% are male.

**Hometown characteristics:** The frequency of respondents from rural areas is

100, accounting for 70.92%; from towns, 30, accounting for 21.28%; and from cities, 11, accounting for 7.8%. Over 70% of the respondents are from rural areas.

Grade characteristics: The frequency of sophomores is 60, accounting for 42.55%; and juniors, 81, accounting for 57.45%.

Family economic status (annual income) characteristics: The frequency of respondents with an annual income of over 500,000 yuan is 2, accounting for 1.42%; from 100,000 to 500,000 yuan, 20, accounting for 14.18%; from 50,000 to 100,000 yuan, 59, accounting for 41.84%; from 20,000 to 50,000 yuan, 43, accounting for 30.50%; and less than 20,000 yuan, 17, accounting for 12.06%. The basic characteristics of the survey respondents are shown in **Table 2**.

**Table 2.** Basic characteristics of survey respondents.

Feature	Option	Frequency	Percentage
Gender	Male	91	64.54%
	Female	50	35.46%
Hometown	rural areas	100	70.92%
	Town	30	21.28%
	City	11	7.8%
Grade	Freshman	0	0%
	Sophomore	60	42.55%
	Junior	81	57.45%
	Senior	0	0%
Family economic status (annual income)	Over 500,000 yuan	2	1.42%
	Between 100,000 and 500,000 yuan	20	14.18%
	Between 50,000 and 100,000 yuan	59	41.84%
	Between 20,000 and 50,000 yuan	43	30.50%
	less than 20,000 yuan	17	12.1%

### 3.3. Analysis of the Reliability and Validity of the Scale

As indicated in **Table 3**, the Cronbach's  $\alpha$  values for all four latent variables are greater than 0.85, and the Corrected Item-Total Correlation (CITC) values are all above 0.6. This suggests that the scale exhibits good reliability. Furthermore, the standardized factor loadings of all measurement items are greater than 0.5 and significant. The Composite Reliability (CR) values for the four dimensions—teaching content, teaching methods and means, learning support services, and computational thinking ability—are all above 0.7, while the Average Variance Extracted (AVE) values are all above 0.5. Therefore, the scale demonstrates good convergent validity.

**Table 3.** Reliability and validity test of the scale.

Latent Variable	Measurement Variable	Mean	Standard Deviation	Factor Loading	Cronbach's $\alpha$	Composite Reliability (CR)	Average Variance Extracted (AVE)	Corrected Item-Total Correlation (CITC)
Teaching Content (TC)	Course content keeps up with the cutting-edge development of science and technology (TC1)	3.60	0.828	0.698	0.940	0.7765	0.5369	0.664
	The content of classroom teaching is rich and high-quality (TC2)	3.75	0.863	0.758				0.720
	The course emphasizes the close integration of theory and practice (TC3)	3.74	0.832	0.741				0.696
Teaching Methods and Means (TMM)	The school often adopts teaching methods such as flipped classrooms and project-based learning (TMM1)	3.56	0.889	0.742	0.870	0.8132	0.5923	0.696
	The teacher actively interacts with students in class and gives timely feedback (TMM2)	3.87	0.821	0.786				0.733
	Fully utilize information technology tools such as online platforms and simulation software in teaching (TMM3)	3.87	0.839	0.780				0.731
Learning Support Services (LSS)	The guidance and counseling provided by the tutor system in the school are helpful to learning (LSS1)	3.83	0.862	0.830	0.923	0.8597	0.6714	0.789
	Learning communities such as study groups in the school are active (LSS2)	3.65	0.949	0.821				0.772
	The school provides sufficient psychological and emotional support for students to cope with the challenges in learning (LSS3)	3.77	0.875	0.807				0.754
Computational Thinking Abilities (CTA)	I am good at breaking down complex problems into a series of simple and manageable sub-problems, and abstracting key information from them (CTA1)	3.58	0.829	0.738	0.920	0.8637	0.5591	0.687
	I am able to design concise and effective algorithms to solve practical problems, and understand the logic behind the algorithms (CTA2)	3.57	0.864	0.747				0.695
	When solving computational problems, I am accustomed to evaluating the advantages and disadvantages of different solutions and making reasonable choices (CTA3)	3.50	0.789	0.782				0.744
	I am good at using innovative thinking to find non-traditional solutions to problems and am willing to try new methods (CTA4)	3.48	0.798	0.716				0.667
	I am able to effectively cooperate with team members and clearly communicate my ideas and solutions (CTA5)	3.55	0.806	0.754				0.708

## 4. Analysis of Survey Data

### 4.1. Correlation Analysis

As can be seen from **Table 4**, teaching content (TC) and Teaching Methods and Means (TMM) are significantly correlated at the 0.01 level (two-tailed) with a correlation coefficient of 0.729, indicating a strong positive correlation between the two. Teaching Content (TC) and Learning Support Services (LSS) are also significantly correlated at the 0.01 level (two-tailed) with a correlation coefficient of 0.567, suggesting a moderately strong positive correlation. Teaching Content (TC) and Computational Thinking Ability (CTA) are significantly correlated at the 0.01 level (two-tailed) with a correlation coefficient of 0.450, demonstrating a moderately strong positive correlation.

Moreover, Teaching Methods and Means (TMM) and Learning Support Services (LSS) are significantly correlated at the 0.01 level (two-tailed) with a correlation coefficient of 0.733, indicating a strong positive correlation. Teaching Methods and Means (TMM) and Computational Thinking Ability (CTA) are also significantly correlated at the 0.01 level (two-tailed) with a correlation coefficient of 0.605, suggesting a moderately strong positive correlation. Lastly, Learning Support Services (LSS) and Computational Thinking Ability (CTA) are significantly correlated at the 0.01 level (two-tailed) with a correlation coefficient of 0.727, revealing a strong positive correlation between the two.

**Table 4.** Correlation among factors.

	Teaching Content (TC)	Teaching Methods and Means (TMM)	Learning Support Services (LSS)	Computational Thinking Ability (CTA)
Teaching Content (TC)	1			
Teaching Methods and Means (TMM)	0.729**	1		
Learning Support Services (LSS)	0.567**	0.733**	1	
Computational Thinking Ability (CTA)	0.450**	0.605**	0.727**	1

Note: \*\*. are significantly correlated at the 0.01 level (two-tailed).

### 4.2. Regression Analysis

As indicated in **Table 5**, the F-value is 53.699, and the P-value is 0.000, suggesting that at least one of Teaching Content (TC), Teaching Methods and Means (TMM), and Learning Support Services (LSS) has an impact on Computational Thinking Ability (CTA). The  $R^2$  value is 0.540, indicating that Teaching Content (TC), Teaching Methods and Means (TMM), and Learning Support Services (LSS) can explain 54% of the variations in Computational Thinking Ability (CTA). The D-W value of 1.708 indicates no autocorrelation among the factors, and the VIF values are between 2 and 3, less than 5, suggesting no multicollinearity. According

to the significance results, the P-values for Teaching Content (TC) and Teaching Methods and Means (TMM) are both greater than 0.05, indicating that their regression coefficients are not significant. To establish a better predictive model, a re-modeling process was conducted, yielding the model as shown in **Table 6**. The regression model is presented in Equation (1).

$$\text{Computational Thinking Ability (CTA)} = 1.207 + 0.621 * \text{Learning Support Services (LSS)} \quad (1)$$

**Table 5.** Summary of model coefficient indicators.

Variable	Unstandardized Coefficients		Standardized Coefficients	t-value	Significance	VIF
	B	Standard Error	Beta			
Constant	1.040	0.223	-	4.660	0.000	-
Teaching Content (TC)	-0.021	0.076	-0.023	-0.270	0.787	2.147
Teaching Methods and Means (TMM)	0.160	0.097	0.170	1.651	0.101	3.150
Learning Support Services (LSS)	0.526	0.073	0.616	7.212	0.000	2.175
R-squared			0.540			
Adjusted R-squared			0.530			
D-W Value			1.708			
F-value			53.699			
P-value			0.000			

**Table 6.** Model coefficients of stepwise regression<sup>a</sup>.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Standard Error	Beta			Tolerance	VIF
1	Constant	1.207	0.191		6.326	0.000	
	LSS	0.621	0.050	0.727	12.499	0.000	1.000 1.000

<sup>a</sup>. Dependent variable: CTA.

## 5. Research Findings and Analysis

Based on the research findings, it can be concluded that Teaching Content (TC), Teaching Methods and Means (TMM), Learning Support Services (LSS), and Computational Thinking Ability (CTA) are significantly correlated with each other at the 0.01 level (two-tailed). The TC, TMM, and LSS jointly account for 54% of the variation in CTA, enabling the construction of a predictive model for CTA changes through LSS. Through LSS, such as online learning resources, personalized tutoring, and learning communities, learners can gain diverse learning experiences and feedback. By analyzing these learning behavior data, we can

closely integrate LSS with the enhancement of CTA, providing crucial insights for predicting changes in CTA. This transformation from “experience-based teaching” to “data-driven teaching” allows for the provision of personalized teaching suggestions and interventions, thereby enhancing the pertinence and effectiveness of teaching and offering a scientific basis for educational practices.

### **Funded Project**

This research is a staged achievement of the Jiangxi Provincial Higher Education Teaching Reform Research Project titled “The Cultivation Mode and Practice of Computational Thinking for Undergraduates Majoring in Electronic Information Engineering in ‘Intelligence+ Era’ Application-Oriented Colleges” (Project Number: JXJG-21-23-6). This research project has introduced a novel computational thinking cultivation model specifically for undergraduate students majoring in Electronic Information Engineering. This model is utilized to quantitatively assess the improvement in students’ computational thinking abilities, thereby offering both theoretical foundations and practical guidance for the cultivation of computational thinking among undergraduate students in the field of Electronic Information Engineering. This research is supported by the Science and Technology Project of Jiangxi Provincial Department of Education, titled “Research on Garbage Classification and Detection Based on Deep Learning R-CNN” (Project Number: GJJ212612). This project possesses theoretical innovation and practical feasibility, which is conducive to enhancing the comprehensive quality and innovative ability of students. This research is supported by the research project of Jiangxi Provincial Higher Education Society, titled “Precision Evaluation and Personalized Learning Research Driven by Educational Big Data” (Project Number: ZX2-C-001). This project attaches great importance to precision evaluation and personalized learning, and conducts in-depth exploration of the various complex factors that influence the cultivation of computational thinking skills in higher education.

### **Conflicts of Interest**

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

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