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An Empirical Study on the Cultivation of College Students' Computational Thinking in the Context of Deep Learning

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Abstract

In the era of rapid development of information technology, deep learning, as the core driving force in the field of artificial intelligence, is leading profound changes in the education industry. Computational thinking, as a key ability to solve complex problems and design innovative systems, has become one of the important indicators to measure the comprehensive quality of college students. This paper focuses on the cultivation of college students' computational thinking in the context of deep learning, and explores through empirical research how to effectively improve college students' computational thinking ability in the current technological environment, as well as its impact and promotion on the cultivation of college students' computational thinking. By designing and implementing an empirical study targeting students majoring in Electronic Information Engineering at Nanchang Normal University, this study aims to explore the actual effects of deep learning-based teaching models in enhancing college students' computational thinking abilities. Students majoring in Electronic Information Engineering at Nanchang Normal University were selected as the research subjects. A questionnaire survey was conducted, which constructed nine dimensions including decomposition ability, abstract ability, modeling ability, algorithmic thinking, creativity, cooperation ability, iterative optimization, transfer ability and evaluation. These dimensions were found to have significant Pearson correlations at the 0.01 level (two-tailed). Further exploration of gender differences in each dimension revealed that there were significant differences between males and females in terms of decomposition ability, abstract ability, modeling ability, creativity, iterative optimization, transfer ability, and evaluation, with males having significantly higher average scores than females. However, no significant gender differences were observed in algorithmic thinking and cooperation ability. The study points out that deep learning technology provides a new perspective for computational thinking

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education, contributing to the cultivation of students' innovative thinking and autonomous learning abilities. This research provides practical references and theoretical foundations for the teaching reform of electronic majors in universities.

Keywords

Deep Learning, Computational Thinking, Empirical Study, Cultivation

1. Introduction

With the widespread application of big data, cloud computing, artificial intelligence, and other technologies, computational thinking has become a crucial ability indispensable for modern college students. Computational thinking not only requires students to possess the ability to solve complex problems (Cafarella & Vasconcelos, 2024) but also emphasizes logical thinking, algorithm design, system analysis, and data-driven decision-making, among other skills. It serves as an essential tool for them to face complex challenges and achieve innovative breakthroughs in their future careers. However, traditional educational models face numerous challenges in cultivating computational thinking among college students. On the one hand, traditional classroom teaching focuses excessively on the imparting of theoretical knowledge, lacking sufficient practical components to hone students' computational thinking skills. On the other hand, teaching methods are often monotonous, lacking individualization and interaction, making it difficult to stimulate students' learning interests and initiative, leading to unsatisfactory learning outcomes. Consequently, exploring new educational models to more effectively cultivate college students' computational thinking has become an urgent issue in current educational research.

Deep learning is gradually infiltrating various aspects of the educational field, bringing revolutionary changes to traditional teaching models with its powerful data processing capabilities, pattern recognition abilities, and self-learning capabilities. Deep learning can automatically extract useful information from massive amounts of data, discover underlying patterns and rules, and provide scientific foundations for personalized teaching, intelligent evaluation, and the cultivation of complex problem-solving abilities. This study will design and implement a computational thinking cultivation program that integrates deep learning technologies, encompassing curriculum design, teaching resource development, and teaching strategy selection. A certain number of college students will be selected as research subjects for teaching practice. Through questionnaires and other methods, data will be comprehensively collected and analyzed to reveal the specific mechanisms and effects of deep learning in computational thinking cultivation.

Deep learning offers new ideas and methods for the cultivation of computational thinking. Nevertheless, despite its increasingly widespread application in education, how to effectively integrate deep learning with computational thinking cultivation remains an unresolved issue. Traditional educational models tend to emphasize the imparting of knowledge and skill training, neglecting the cultivation of students' thinking and innovative abilities. In contrast, the cultivation of computational thinking requires a greater emphasis on students' subjectivity, practicality, and innovativeness, encouraging them to actively explore, dare to innovate, and continuously enhance their thinking abilities guided by solving practical problems. Therefore, this study will design and implement a computational thinking cultivation program that integrates deep learning technologies, including curriculum design, teaching resource development, and teaching strategy selection. A certain number of college students will be selected as research subjects for teaching practice. Through evaluation methods such as questionnaires, data will be comprehensively collected and analyzed to explore strategies and effects of deep learning-based computational thinking cultivation among college students.

2. Theories Related to Computational Thinking and Deep Learning

2.1. Computational Thinking

Computational thinking, first introduced by Professor Jeannette Wing of MIT in 2006, refers to the mental processes involved in problem-solving, system design, and understanding human behaviors through the application of fundamental concepts of computer science (Brennan & Resnick, 2012). It emphasizes leveraging logic, abstraction, and algorithms to analyze and resolve issues, transcending the conventional physical and temporal perspectives. It is a way of thinking that represents abstract concepts through symbols, using data as the foundation for problem-solving. The core elements of computational thinking encompass abstraction and modeling, automation and algorithm design, data analysis and processing, as well as iteration and optimization. This approach enables individuals to distill critical information from complex problems, construct computational models, devise efficient algorithms, automate problem-solving processes, and reveal patterns and trends hidden within data, thereby providing robust support for decision-making. Throughout the problem-solving journey, continuous experimentation with new methodologies and strategies, as well as adjustments and refinements to algorithms and models, are essential for achieving optimal outcomes.

2.2. Deep Learning

Deep learning utilizes the multi-layered structure of networks to learn and represent abstract features within data, automatically extracting these features from data through continuous learning and practice, thereby enhancing the model's generalization capability. By constructing and training multi-layered neural networks, deep learning achieves data comprehension and interpretation. It is characterized by high automation, robust expressive power, strong adaptability, multi-domain applicability, and scalability. Deep learning models can adapt to diverse tasks and data types, continually improving their performance through iterative training, and have proven to be particularly effective in various fields such as image recognition, natural language processing, and predictive analytics.

3. Research Design

3.1. Survey Design

A questionnaire survey was employed for empirical research, targeting undergraduate students majoring in Electronic Information Engineering at Nanchang Normal University. After designing the survey questionnaire, peer experts were invited to review and validate it, resulting in a final questionnaire comprising 29 measurement items and structuring 9 latent variables. These variables are decomposition ability, abstraction ability, modeling ability, algorithmic thinking, creativity, collaboration ability, iterative optimization, transfer ability, and evaluation ability. The definitions of these nine dimensions are as follows.

Decomposition Ability refers to the capacity to break down complex problems or systems into smaller, more manageable parts or components that are easier to understand (Wing, 2006).

Abstraction Ability is the ability to extract universal laws, essential characteristics, or core elements from specific situations (Shute, Sun, & Asbell-Clarke, 2017).

Modeling Ability refers to the ability to construct mathematical models, physical models, or conceptual models based on actual problems or scenarios.

Algorithmic Thinking is a methodology of solving problems by applying logic and steps (Chuechote, Nokkaew, Phongsasithorn & Laosinchai,2020; Dagli & Tokmak, 2022; Peel & Friedrichsen, 2018).

Creativity is the capacity to generate novel, unique, and valuable ideas, products, or solutions (Kafai, 2016; Runciman, 2011).

Collaboration Ability is the ability to work together with others to achieve common goals (Prabawa, Rosjanuardi, & Nurlaelah,2024).

Iterative Optimization is the process of continuously improving a product or solution through repeated experimentation, feedback, and adjustments (Cafarella & Vasconcelos, 2024).

Transfer Ability refers to the ability to apply knowledge, skills, or experiences gained in one domain or situation to another, different but related, domain or situation.

Evaluation Ability is the capacity to assess things or proposals objectively, comprehensively, and accurately.

Among them, decomposition ability, abstraction ability, modeling ability, algorithmic thinking, creativity, collaboration ability, iterative optimization, and transfer ability each have 3 measurement items, while evaluation contains 5 measurement items, as shown in **Table 1**.

Table 1. Construction of variables.

Latent Variable	Measurement Variable
Decomposition Ability (DA)	I am able to break down complex systems into multiple smaller systems. (DA1)
	I am able to clarify the logical sequence between multiple small systems. (DA2)
	I am able to establish connections between multiple small systems. (DA3)
Abstract Ability (AA)	I am able to identify crucial relationships or conditions within complex systems. (AA1)
	I am able to find common patterns across different systems. (AA2)
	I am able to extract useful information from the known conditions of the system. (AA3)
Modeling Ability (MA)	I am able to clarify my problem-solving approach by drawing block diagrams or other methods. (MA1)
	I am able to represent the system model using mathematical formulas. (MA2)
	I am able to establish system models using different transformation domains. (MA3)
Algorithmic Thinking (AT)	I am accustomed to finding the steps to solve a problem step by step. (AT1)
	I usually try to find effective ways to solve problems. (AT2)
	I am able to eliminate unnecessary steps when solving problems. (AT3)
Creativity (CT)	I approach problems from different angles to generate multiple ideas. (CT1)
	When encountering a problem, I look for details that are usually overlooked. (CT2)
	When doing something, I try to come up with as many solutions as possible. (CT3)
Cooperation Ability (CA)	I enjoy collaborating with others to solve problems. (CA1)
	I am able to carefully understand others' approaches to solving problems. (CA2)
	I actively communicate with others about our respective approaches to solving problems. (CA3)
Iterative Optimization (IO)	I am able to independently complete iterative optimizations and carefully document the iteration process. (IO1)
	I am aware of the need to debug solutions, but I require continuous support and suggestions during this process. (IO2)
	I possess the awareness to iteratively optimize solutions. (IO3)
Transfer Ability (TA)	I am able to apply the experience and methodologies I have learned to independently solve new problems or problems in other contexts. (TA1)
	After the teacher poses a new problem, I am able to recall and apply the experience and methodologies I have learned to solve it. (TA2)
	I am able to utilize various methods to solve new problems or problems in other contexts. (TA3)

Continued

Evaluate Ability (EA)	I tend to find the correct method to solve a problem. (EA1)
	I usually strive to come up with the best solution for a problem. (EA2)
	I usually try to find the most effective solution to a problem. (EA3)
	I usually come up with quick solutions to problems. (EA4)
	I am very satisfied with the cultivation of my computational thinking skills. (EA5)

3.2. Analysis of Basic Characteristics of Samples

Questionnaires were distributed via the Wenjuanxing platform. A total of 110 questionnaires were sent out, with 104 questionnaires returned and all 104 were valid, resulting in an effectiveness rate of 100%. The basic characteristics of the samples are comprised of four parts: gender, hometown, grade, and family economic status (annual income). The basic characteristics are as follows:

1) Gender characteristics: The frequency of males is 76, accounting for 73.08%; the frequency of females is 28, accounting for 26.92%. Among the respondents, males account for over 70%, while females account for nearly 30%.

2) Hometown characteristics: The frequency of those from rural areas is 77, accounting for 74.04%; the frequency of those from urban areas is 27, accounting for 25.96%. The majority of respondents come from rural areas.

3) Grade characteristics: The frequency of freshmen is 1, accounting for 0.96%; sophomores, 53, accounting for 50.96%; juniors, 49, accounting for 47.12%; seniors, 1, accounting for 0.96%. The respondents are mainly sophomores and juniors, almost evenly split.

4) Family economic status (annual income) characteristics: The frequency of those with an annual income exceeding 500,000 yuan is 1, accounting for 0.96%; between 100,000 and 500,000 yuan, 15, accounting for 14.42%; between 50,000 and 100,000 yuan, 41, accounting for 39.42%; between 20,000 and 50,000 yuan, 29, accounting for 27.88%; and below 20,000 yuan, 18, accounting for 17.31%. The largest proportion is those with an annual income between 50,000 and 100,000 yuan, accounting for nearly 40%, followed by those with an annual income between 20,000 and 50,000 yuan, accounting for nearly 30%. In other words, those with an annual income between 20,000 and 100,000 yuan account for nearly 70% (**Table 2**).

Table 2. Basic characteristics of the samples.

Item	Options	Frequency	Percentage (%)
Gender	Male	76	73.08%
	Female	28	26.92%
Hometown	Rural	77	74.04%
	Urban	27	25.96%

Continued

Grade	Freshman	1	0.96%
	Sophomore	53	50.96%
	Junior	49	47.12%
	Senior	1	0.96%
Family economic status (annual income)	Over 500,000 yuan	1	0.96%
	Between 100,000 and 500,000 yuan	15	14.42%
	Between 50,000 and 100,000 yuan	41	39.42%
	Between 20,000 and 50,000 yuan	29	27.88%
	Below 20,000 yuan	18	17.31%

3.3. Reliability and Validity Analysis

As can be seen from Table 3, the Cronbach's α values of the nine dimensions of the scale, namely decomposition ability, abstract ability, modeling ability, algorithmic thinking, creativity, cooperation ability, iterative optimization, transfer ability, and evaluate, are all above 0.88, indicating good internal consistency. Additionally, the Corrected Item-Total Correlation (CITC) values are all greater than 0.6, suggesting a high correlation among the items. The standardized factor loadings are all above 0.6, the Composite Reliability (CR) values are all greater than 0.7, and the Average Variance Extracted (AVE) values are all above 0.5. Therefore, the scale demonstrates good convergent validity.

Table 3. Reliability and validity test.

Latent Variable	Measurement Variable	Mean	Standard Deviation	Factor Loading	Cronbach's α	CR	AVE	CITC
DA	DA1	3.19	0.915	0.661	0.938	0.7748	0.5353	0.645
	DA2	3.15	0.845	0.766				0.758
	DA3	3.06	0.912	0.763				0.753
AA	AA1	3.11	0.858	0.835	0.919	0.8788	0.7074	0.827
	AA2	3.12	0.828	0.853				0.845
	AA3	3.20	0.817	0.835				0.824
MA	MA1	3.13	0.935	0.718	0.890	0.8139	0.5937	0.703
	MA2	3.06	0.912	0.802				0.791
	MA3	2.90	0.830	0.789				0.776
AT	AT1	3.44	0.857	0.833	0.913	0.8625	0.6765	0.818
	AT2	3.52	0.870	0.835				0.819
	AT3	3.38	0.896	0.799				0.782
CT	CT1	3.44	0.798	0.834	0.887	0.8554	0.6636	0.819
	CT2	3.30	0.811	0.825				0.810
	CT3	3.42	0.821	0.784				0.766

Continued

CA	CA1	3.45	0.799	0.720	0.886	0.8195	0.6028	0.697
	CA2	3.55	0.787	0.818				0.799
	CA3	3.49	0.859	0.788				0.765
IO	IO1	3.30	0.858	0.841	0.895	0.8911	0.7317	0.826
	IO2	3.43	0.773	0.856				0.840
	IO3	3.32	0.792	0.869				0.854
TA	TA1	3.36	0.812	0.846	0.934	0.8822	0.7141	0.830
	TA2	3.43	0.810	0.838				0.819
	TA3	3.39	0.769	0.851				0.835
EA	EA1	3.49	0.812	0.810	0.923	0.9102	0.67	0.790
	EA2	3.28	0.756	0.853				0.837
	EA3	3.40	0.770	0.847				0.830
	EA4	3.33	0.756	0.811				0.791
	EA5	3.38	0.827	0.769				0.749

4. Analysis of Survey Data

4.1. Correlation and Regression Analysis

According to Table 4, there is a significant Pearson correlation at the 0.01 level (bilateral) between decomposition ability, abstract ability, modeling ability, algorithmic thinking, creativity, cooperation ability, iterative optimization, transfer ability, and evaluation. The correlation coefficient ranges from 0.800 to 1.000, indicating a high correlation; from 0.600 to 0.799, indicating a strong correlation; and from 0.400 to 0.599, indicating a moderate correlation. According to Table 5, R^2 is 83.9%, indicating that the model has a good degree of explanation. In the ANOVA analysis, F is 61.801, P is less than 0.01, indicating that the model is statistically significant.

Table 4. Correlation.

	DA	AA	MA	AT	CT	CA	IO	TA	EA
DA	1								
AA	0.859**	1							
MA	0.698**	0.807**	1						
AT	0.597**	0.756**	0.758**	1					
CT	0.637**	0.800**	0.711**	0.844**	1				
CA	0.506**	0.671**	0.638**	0.764**	0.775**	1			
IO	0.649**	0.800**	0.774**	0.814**	0.819**	0.835**	1		
TA	0.630**	0.756**	0.697**	0.756**	0.760**	0.796**	0.890**	1	
EA	0.642**	0.797**	0.724**	0.803**	0.830**	0.829**	0.875**	0.843**	1

Notes:**. Significant correlation at the 0.01 level (bilateral).

Table 5. Regression results.

Dependent variable	Independent variable	Unstandardized coefficient		Standardized coefficient	t	p	R^2	Adjusted R^2	F
		B	Standard error	Trial version					
EA	(Constant)	0.271	0.148		1.830	0.070	0.839	0.825	61.801**
	DA	−0.010	0.068	−0.013	−0.152	0.879			
	AA	0.159	0.103	0.180	1.550	0.124			
	MA	−0.008	0.066	−0.010	−0.126	0.900			
	AT	0.054	0.076	0.063	0.713	0.478			
	CT	0.147	0.087	0.157	1.695	0.093			
	CA	0.209	0.076	0.224	2.733	0.007			
	IO	0.205	0.110	0.219	1.864	0.065			
	TA	0.166	0.086	0.181	1.915	0.058			

* $p < 0.05$, ** $p < 0.01$.

4.2. Analysis of Differences

An in-depth analysis of the data in Table 6 allows us to further explore the specific manifestations of gender differences in various abilities. Firstly, the results of the Levene's test for homogeneity of variance ($p > 0.05$) ensure the validity of subsequent t-tests, indicating that the variances of different gender groups in various abilities are equal. This provides a solid foundation for comparing the mean differences between the two groups. Significant differences between genders were observed in decomposition ability, abstract ability, modeling ability, creativity, iterative optimization, transfer ability, and evaluation, with males scoring significantly higher on average than females. This finding may reflect the combined effects of multiple factors. Notably, algorithmic thinking and cooperation ability did not exhibit significant differences between genders, suggesting that in certain cognitive and social skills, males and females may possess similar potential and performance. The lack of gender difference in algorithmic thinking, a crucial ability for solving complex problems, may reflect the universal emphasis placed on logical thinking and problem-solving abilities in modern education, as well as the cultivability of these abilities across genders. Similarly, the insignificant difference in cooperation ability underscores the importance of teamwork and communication skills for all students, regardless of gender.

Table 6. T-test results.

	Gender (Mean ± Standard Deviation)		Levene's Test for Equality of Variances		T-test for Equality of Means	
	Male	Female	F	P	t	P
DA	3.27 ± 0.79	2.76 ± 0.87	0.217	0.642	2.837	0.005
AA	3.24 ± 0.77	2.87 ± 0.74	0.012	0.912	2.216	0.029

Continued

MA	3.14 ± 0.78	2.73 ± 0.83	0.665	0.417	2.393	0.019
AT	3.54 ± 0.78	3.20 ± 0.83	0.042	0.838	1.914	0.058
CT	3.47 ± 0.71	3.15 ± 0.76	0.114	0.737	2.000	0.048
CA	3.54 ± 0.76	3.37 ± 0.66	2.676	0.105	1.075	0.285
IO	3.46 ± 0.75	3.06 ± 0.62	3.523	0.063	2.503	0.014
TA	3.49 ± 0.75	3.14 ± 0.70	1.259	0.264	2.113	0.037
EA	3.48 ± 0.67	3.10 ± 0.65	0.511	0.476	2.547	0.012

5. Conclusion and Suggestions

5.1. Conclusion

Firstly, through the Levene's test for homogeneity of variance, it was confirmed that when comparing the performance of males and females in various abilities, the variances of the data groups were homogeneous (all P-values were greater than 0.05). Subsequently, the results of the t-test revealed significant effects of gender differences on multiple key abilities. Specifically, significant differences were observed between genders in decomposition ability, abstract ability, modeling ability, creativity, iterative optimization, transfer ability, and evaluation, with males consistently scoring higher on average than females in these areas. However, it is noteworthy that algorithmic thinking and cooperation ability did not exhibit statistically significant differences based on gender. This suggests that in terms of algorithmic logical thinking and teamwork collaboration skills, males and females possess similar potential and room for development, and gender is not a decisive factor.

5.2. Suggestions

1) Personalized Education and Training: Given the significant gender differences observed in specific abilities, universities should consider implementing more personalized education and training programs. Tailored curriculum content and learning paths should be designed based on the strengths and weaknesses of males and females in different abilities, promoting the comprehensive development of each learner.

2) Cultivation of Gender Equality Awareness: While the data reveals gender differences in certain abilities, this does not imply that one gender is inherently superior to the other in these abilities. Therefore, efforts should be intensified to promote gender equality awareness through education and advocacy, encouraging males and females to learn from each other, leverage each other's strengths, and mutually improve.

3) Encouraging Cross-Gender Collaboration: In areas where algorithmic thinking and cooperation ability do not exhibit significant gender differences, active promotion of cross-gender collaboration and communication should be pursued. Through inter-gender teamwork, not only can innovative thinking be stimulated,

but also team diversity and inclusiveness can be enhanced, thereby driving the production of higher-quality outcomes.

4) Data-Driven Decision-Making: The integration of deep learning and computational thinking enables in-depth mining and efficient utilization of data to knowledge. Deep learning models, through large-scale data training, can automatically learn and optimize the processing capabilities for complex tasks. A data-driven decision-making process can ensure that students receive fair opportunities and treatment based on their actual abilities.

5) Continuous Monitoring and Evaluation: The relationship between gender and abilities is a complex and dynamically evolving topic. Therefore, it is necessary to continuously monitor and evaluate the manifestation of gender differences across different periods and fields, allowing for timely adjustments to educational strategies to adapt to changing times and demands.

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Conflicts of Interest

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

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