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The Intelligent Upgrade Path of Moral Education in Higher Education through Flipped Classrooms: A Study on the Computational Thinking Cultivation Model in Housing Policy Ethics Education

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Abstract Computational thinking is an extension of an individual's problem-solving skills and can foster creativity and critical thinking. To promote the cultivation of talent in housing policy ethics education, this article takes a housing policy ethics education course as an example and provides a detailed design of a flipped classroom for moral education, covering aspects such as teaching resource development, teaching preparation, pre-class learning, in-class learning, and formative assessment. It then introduces large-scale networked teaching platforms, specialized teaching resources, and self-directed learning models to propose a design framework for cultivating computational thinking among college students, and elaborates on the specific process design for fostering students' computational thinking. In the independent samples t-test analysis of the post-test total scores for computational thinking, the α value for the two post-test groups was 0.352 (greater than 0.05), and the P value was 0.005 (less than 0.01). This indicates that there is a significant difference in the post-test scores of computational thinking between the two classes, suggesting that the experimental class's adoption of the methods outlined in this paper is more effective in cultivating students' computational thinking than the control class. Practice has proven that, compared to traditional classrooms, flipped classroom teaching can effectively improve teaching quality and is conducive to cultivating students' computational thinking abilities.

Index Terms flipped classroom, housing policy ethics education, computational thinking, cultivation model

I. Introduction

Modern education is no longer confined to traditional teaching methods but is increasingly exploring more effective educational approaches [1], [2]. The flipped classroom, as a novel and effective teaching method, has been widely adopted in many schools [3]. The flipped classroom breaks away from the traditional teacher-centered, student-listening model, using class time for discussion, practice, and problem-solving to enhance students' core competencies [4], [5]. However, the current application of flipped classrooms in China faces the issue of "emphasizing form over substance," with only a small number of universities achieving deep interaction, particularly in university moral education, where "deep interaction" remains elusive [6]-[8].

In the past, traditional strategies for moral education typically involved delivering moral education content through moral lectures, class meetings, and attending lectures [9], [10]. This educational approach was quite effective for a long time but is now insufficient to meet the needs of contemporary society [11], [12]. Due to the rapid development of modern society and factors such as social benefits, many students are facing moral education issues, making school moral education work increasingly important [13]-[15]. Therefore, the intelligent upgrading of flipped classrooms in university moral education is of great significance for improving the effectiveness of moral education. However, the application of technology in education must also adhere to certain ethical constraints; otherwise, it may have the opposite effect [16]-[18]. Taking housing policy ethics education as an example, the current curriculum content of real estate-related majors in Chinese universities is dominated by "technology" and severely lacks an 'ethics' module, resulting in housing policy education that lacks consideration for human factors, which contradicts the original intent of "moral education" [19]-[22].

This article first provides a detailed design for the construction of teaching resources, teaching preparation, pre-class learning, in-class learning, and formative assessment in the implementation of flipped classroom teaching in university moral education, along with specific and feasible implementation plans, thereby proposing an intelligent upgrade path for flipped classroom teaching in university moral education. It then explores the design of a new teaching model guided by computational thinking, investigating specific pathways for enhancing college students' computational thinking abilities under the new flipped classroom model for moral education. Finally, the article conducts an experimental study on two parallel classes at a certain university, using computational thinking questions and a computational perspective scale to quantitatively evaluate students' computational thinking abilities and computational perspectives, thereby verifying the feasibility and effectiveness of the computational thinking cultivation proposed in this paper for housing policy ethics education.

II. Method

II. A. Smart Upgrading Pathways for Moral Education Flipped Classrooms in Higher Education Institutions

Small-scale restricted online courses (SPOCs) are a product of combining MOOCs with classroom instruction and serve as a powerful tool for implementing flipped classroom teaching. This paper conducts a practical study on a flipped classroom blended teaching model based on SPOCs. First, a housing policy ethics education course was established on the MOOC platform "iCourse," providing students with the necessary resources and environment to transition from superficial learning to deep learning. The SPOC platform allows for the creation of personalized learning processes, meeting students' individualized learning needs. Then, through the construction of a teaching resource expansion platform, the design of learning task sheets, the use of teaching auxiliary software, and formative assessments, the classroom is flipped [23]. The design and implementation scheme for blended teaching based on the flipped classroom is shown in Figure 1. The following sections provide a detailed introduction to the five aspects of the scheme: teaching resource construction, teaching preparation, pre-class learning, in-class learning, and formative assessments.

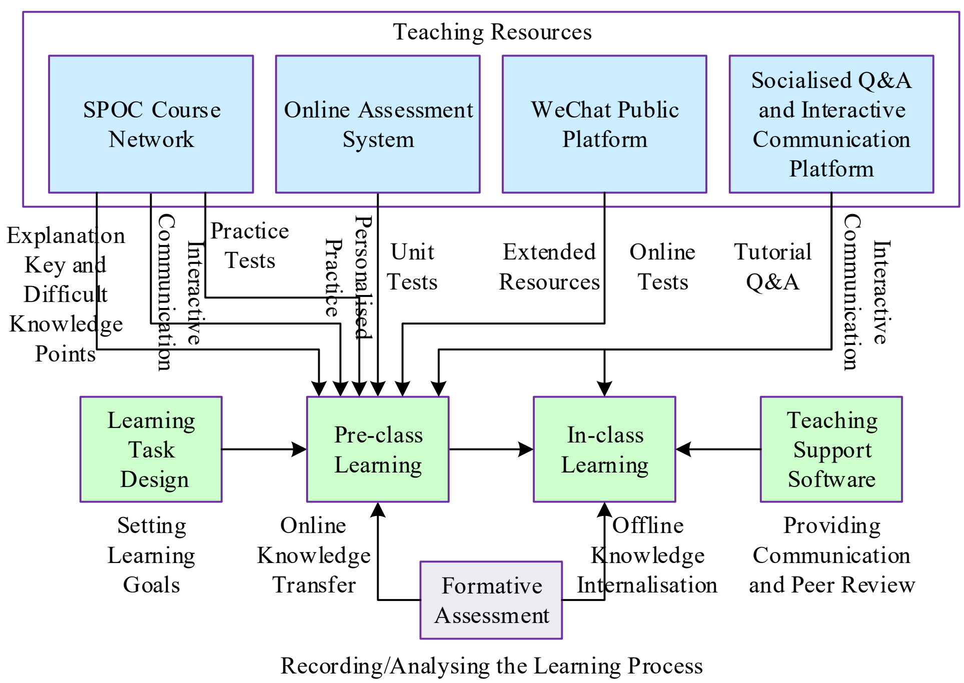

Figure 1: Design and implementation of hybrid teaching based on flipped classroom

II. A. 1) Teaching Resource Development

The development of teaching resources is the foundation for implementing flipped classroom teaching in higher education institutions. This article proposes a four-in-one O2O teaching resource platform, which primarily consists of four components: an SPOC course website, an online assessment system, a WeChat public platform, and a socialized Q&A and interactive communication platform. Some course content is sourced from MOOCs, which provide abundant teaching resources. Based on the characteristics of our students, we carefully select MOOC resources and adapt the selected content to better align with our students' learning habits. Additionally, each chapter includes three supplementary components: "knowledge expansion," "virtual experiments," and "software applications."

II. A. 2) Teaching Preparation

Flipped classroom teaching requires students to complete new content independently before class. Students' acceptance and understanding of new knowledge is inseparable from teachers' preparation for teaching. Adequate preparation for teaching directly determines the success or failure of a flipped classroom. Teaching preparation mainly includes four aspects: teaching design, teaching content, practice tests and Q&A. In the process of teaching design, we have developed a detailed pre-class learning task list to help students further clarify the learning goals, requirements and methods, and provide theoretical guidance for students to carry out personalized learning. In terms of teaching content, MOOC teaching videos with sufficient breadth and depth are carefully selected, and the content of the videos is both advanced and time-sensitive. In addition, in the course team has produced and accumulated a number of excellent operation videos with teachers as the first person to give lectures, which can be used by students for online and offline independent learning. During practice tests and Q&A sessions, the SPOC course offers online quizzes, group discussions, and Q&A sessions. The group discussions are mainly practiced, applied and inquiry-based, which are interesting and inspiring, and can guide students to actively use computational thinking to solve problems. The Q&A session is an effective way to provide timely feedback and solve students' problems, and enhance the interaction between teachers and students. Teachers should be actively and fully prepared for the various questions that may arise during the Q&A session before class.

II. A. 3) Pre-class learning

Pre-class learning refers to students engaging in online learning prior to class using materials and platforms provided on the course website, in accordance with the requirements outlined in the learning task sheet. The advantage of online learning lies in its flexibility, as students can learn anytime and anywhere. By integrating emerging technologies such as virtual 3D, online learning can also present knowledge in a three-dimensional and vivid manner to learners, making the learning process more independent, organized, and engaging. To facilitate students' self-assessment of their pre-class learning outcomes, the online assessment system provides a wealth of practice questions for students to conduct comprehensive self-assessments. During the pre-class learning process, the learning task sheet helps students further clarify the objectives, requirements, and methods of learning, providing synchronous guidance and playing a positive role in promoting pre-class learning. Additionally, a clear knowledge map has been designed to help students better grasp the structure of new knowledge and guide them in exploratory thinking.

II. A. 4) Classroom Learning

The task of classroom learning is to internalize knowledge. This process is non-linear and requires diverse forms. How teachers organize high-quality classroom learning is the key to successful flipped classroom teaching. First, it is necessary to construct a complete and clear learning scenario and formulate multiple discussion topics or learning tasks related to teaching. Second, it is necessary to design classroom activities and arrange classroom time reasonably.

II. A. 5) Process-based assessment

During the teaching process, online assessment systems and teaching assistance software are utilized to develop diverse forms of stage-based evaluations tailored to the unique characteristics of learners, enabling comprehensive formative assessments of students. The big data platform meticulously records learners' learning status and outcome data in various formats. Based on this big data, teachers can real-time monitor and assess students' learning abilities, attitudes, and outcomes, continuously adjusting the teaching pace and formulating reasonable tutoring and Q&A plans. Students with weaker learning abilities are given special attention and targeted guidance by teachers, effectively preventing them from being marginalized. Based on big data, students can accurately assess their learning outcomes, promptly adjust their study plans and habits, continuously accumulate personal learning experiences, and enhance their ability for self-directed learning.

II. B. Designing a Computational Thinking Training System for College Students

To effectively enhance the effectiveness of computational thinking education, existing innovative teaching models can be fully leveraged to break through the time and space constraints in the cultivation of computational thinking among college students. This approach enables students to fully benefit from the advantages computational thinking brings to their professional development, thereby promoting their understanding and mastery of computational thinking. To this end, the computational thinking cultivation system for college students should be integrated into their professional development programs, incorporating large-scale networked teaching platforms, specialized teaching resources, and self-directed learning models. This system extends computational thinking cultivation from traditional classrooms to professional learning supported by new teaching models, focusing on the enhancement of computational thinking skills themselves, thereby facilitating the creation of a seamless computational thinking cultivation platform for college students.

The development of network and information technology is creating a favorable generalized learning environment, driving new teaching models toward networked and information-based directions, making knowledge dissemination ubiquitous and available at all times. As students increasingly adopt new teaching models such as MOOCs, micro-courses, and flipped classrooms for computational thinking training, diverse resources and multi-dimensional teaching models will be closely integrated, making computational thinking cultivation more sustainable and effective.

In the college students' computational thinking cultivation system supported by new teaching models, computational thinking cultivation will retain the advantages of traditional classroom-based teaching models while integrating the achievements of information technology development. This represents a transformation of network-based teaching models and drives computational thinking training toward networked, intelligent, and virtualized approaches, evolving from a single-mode system to a composite-mode system. It is evident that the college students' computational thinking cultivation system integrated with new teaching models combines classroom instruction, the internet, and open educational resources into a systematic computational thinking training platform, facilitating the transition from individual training modes to collaborative training modes.

II. C. Designing the process of cultivating students' computational thinking through new teaching models

From the perspectives of cognitive development and learning application needs, the cultivation of computational thinking requires a gradual and systematic process. Under the support of new teaching models, the process of cultivating computational thinking can be divided into interconnected subsystems at different levels and from different directions. These systems are organically integrated to form an effective framework for cultivating computational thinking among college students. The MOOC system is built on a large-scale networked teaching platform, which publishes course resources online. These resources can be either independent computational thinking training courses or computational thinking training modules that complement professional courses [24]. The flipped classroom system encourages learners to post information or express their opinions, and deepens the effectiveness of computational thinking training through on-site exchanges or guidance.

II. C. 1) Online Learning Process Design

When it comes to online resources, you can use a mix of point and surface learning. First, teachers need to develop course resources related to computational thinking training on the platform. Learners register for these courses through the platform, learn and understand the goals, content, and knowledge of computational thinking training, and get a good grasp of the courses as a whole to build up a broad knowledge base. Then, learners can use micro-courses to dig deeper into or practice the parts they find hard to understand or difficult to master.

II. C. 2) Designing the on-site teaching process using the flipped classroom approach

In utilizing the flipped classroom approach to cultivate computational thinking, it is essential to fully leverage the advantages of both in-person classroom instruction and online learning. During in-person learning sessions, instructors employ the flipped classroom model to assess whether students have truly grasped computational thinking concepts and actively guide them in addressing any existing challenges, enabling students to apply these concepts flexibly within their respective fields of study. In the cultivation of computational thinking among college students, the flipped classroom primarily addresses the personalized challenges associated with learning and applying computational thinking. Through in-person discussions and interactions, teachers and students can further enhance the effectiveness of computational thinking training.

II. C. 3) Utilizing Learning Evaluation of Public Services and Community Learning Process Design

In the cultivation of computational thinking among college students, public service platforms are primarily utilized for learning assessment and community-based learning. The design strategy for learning assessment within public services centers on computational thinking, employing multi-dimensional evaluation metrics. These metric data are statistically analyzed based on different weightings to obtain a comprehensive evaluation of learners' computational thinking abilities. Community-based exchanges facilitated by public services primarily revolve around establishing open community platforms for computational thinking development. Learners and educators can form learning groups to exchange and share learning experiences and resources, as well as engage in discussions focused on specific computational thinking topics.

III. Results and discussion

III. A. Experimental Design

This section follows a computational thinking cultivation model based on a flipped classroom approach to moral education for instructional design. A teaching experiment was conducted at a certain university, with data collected and analyzed to validate the effectiveness of the cultivation model. Students from Class A (experimental class) and Class B (control class) of a housing policy ethics education course at a certain university were selected. The experimental class was taught using the method proposed in this paper, while the control class was taught using traditional teaching methods. The effectiveness of the method proposed in this paper on the development of computational thinking in university students' housing policy ethics education was explored from two perspectives: computational viewpoint and computational dimension.

III. B. Computational Perspective Test Analysis

III. B. 1) Reliability Analysis

Prior to conducting the teaching experiment, the author distributed a computational perspective questionnaire to two classes, collecting 220 valid questionnaires with a 100% response rate. Verifying the data quality of the measurement results is an important prerequisite for ensuring the validity of subsequent analyses. The study employed Cronbach's alpha reliability coefficient and split-half reliability to assess the reliability of the creativity dimension, critical thinking dimension, problem-solving dimension, algorithmic thinking dimension, and creativity dimension. The internal consistency of each dimension was analyzed using Cronbach's alpha reliability and split-half reliability tests. The Cronbach's alpha reliability coefficient and split-half reliability coefficient range from 0 to 1. The higher the coefficient value, the higher the reliability. Generally, a coefficient above 0.9 is considered to indicate excellent reliability, between 0.8 and 0.9 is considered good reliability, between 0.7 and 0.8 is considered adequate reliability, and below 0.7 indicates that the scale requires revision. SPSS Statistics was used to perform statistical analysis on the Computational Perspective Scale. The reliability test results for the Computational Perspective Scale are shown in Table 1. The overall reliability coefficient of the Computational Perspective Scale and the reliability coefficients of the five secondary dimensions—creativity, critical thinking, problem-solving, algorithmic thinking, and collaborative ability—are all between 0.7 and 1. Therefore, the scale demonstrates excellent internal consistency and high reliability.

Table 1: The calculation of the reliability test of the point of view

Dimension	Problem Number	Cronbach Α	Half Confidence	Case Number
Creative Dimension	6	0.865	0.887	N=220
Critical Thinking Dimension	3	0.82	0.812	
Problem Solving Dimension	4	0.823	0.812	
Algorithm Thinking Dimension	3	0.818	0.797	
Ability Dimension Of Cooperation	3	0.797	0.806	
Total	19	0.884	0.868	

III. B. 2) Validity Analysis

To ensure the rigor of the study, the author conducted confirmatory factor analysis on the revised scale to ensure that the modified scale still had high validity. The CFA model for the opinion scale is shown in Figure 2, and the fit of the model was tested.

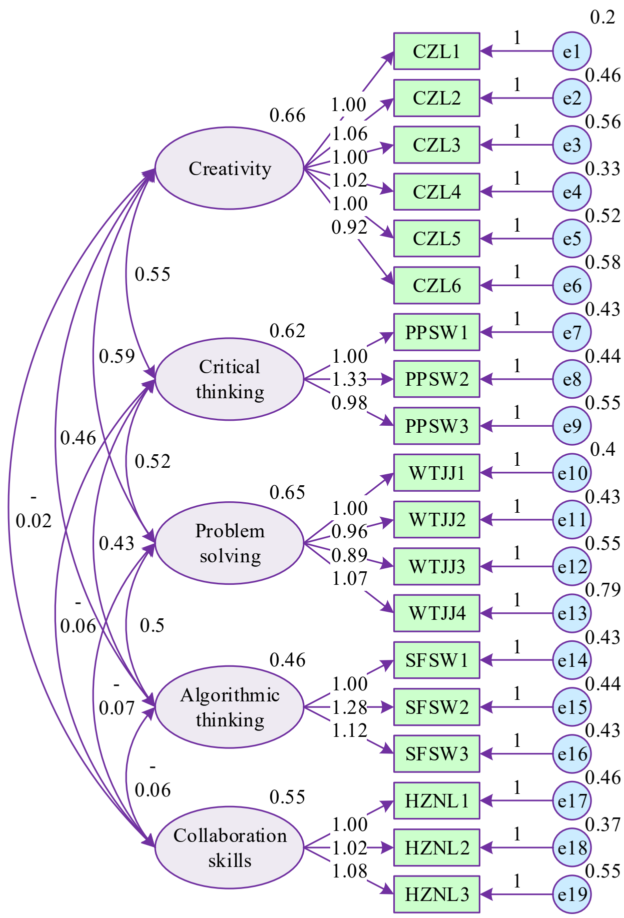

Figure 2: Calculate the CFA model of the Opinion Scale

Based on the results of the CFA model fit test for the Computational Perspective Scale, the CMIN/DF (chi-square to degrees of freedom ratio) is 2.711, within the range of 1–3, and the RMSEA (root mean square error of approximation) is 0.096, within the range of 0.08–0.1, indicating a moderate fit. Additionally, the IFI (Inflated Fit Index), TLI (Tucker-Lewis Index), and CFI (Comparative Fit Index) all exceed 0.8. Therefore, based on the analysis results, the CFA model of the Computational Perspective Scale demonstrates good fit. The CFA model fit test results are shown in Table 2.

Table 2: Calculate the CFA model fit test of the opinion scale

Indicator	Reference standard	Measured result
CMIN/DF	1 to 3 is excellent, and 3 to 5 is good	2.711
RMSEA	<0.05 is considered excellent, <0.08 is considered good, and <0.1 is considered average fit	0.096
IFI	A score greater than 0.09 is considered excellent, and a score greater than 0.08 is considered good	0.904
TLI	A score greater than 0.09 is considered excellent, and a score greater than 0.08 is considered good	0.88
CFI	A score greater than 0.09 is considered excellent, and a score greater than 0.08 is considered good	0.911

Under the premise that the CFA of the opinion scale has good fit, further examine the convergent validity (AVE) and composite reliability (CR) of each dimension of the scale. Calculate the standardized factor loadings of each measurement item on its corresponding dimension using the CFA model of the opinion scale, then calculate the convergent validity and composite reliability values of each dimension using the AVE and CR formulas. According to the standards, the minimum requirement for AVE is 0.5, and the minimum requirement for CR is 0.7, to indicate good convergent validity and composite reliability. The convergent validity and composite reliability of each dimension of the Computational Perspective Scale are shown in Table 3. The AVE values for all dimensions of the Computational Perspective Scale exceeded 0.5, and the CR values were all greater than 0.7. Overall, this indicates that all dimensions exhibit good convergent validity and composite reliability. Therefore, the Computational

Perspective Scale can be used to measure computational perspectives among experimental and control group students in educational experiments.

Table 3: Calculate the convergent validity and combined reliability

Path relationship	Estimate	AVE	CR
CZL1←Creativity dimension	0.786	0.543	0.885
CZL2←Creativity dimension	0.774		
CZL3←Creativity dimension	0.726		
CZL4←Creativity dimension	0.795		
CZL5←Creativity dimension	0.706		
CZL6←Creativity dimension	0.668		
PPSW1←Critical thinking dimension	0.761	0.596	0.814
PPSW2←Critical thinking dimension	0.836		
PPSW3←Critical thinking dimension	0.725		
WTJJ1←Problem-solving dimension	0.797	0.533	0.822
WTJJ2←Problem-solving dimension	0.76		
WTJJ3←Problem-solving dimension	0.657		
WTJJ4←Problem-solving dimension	0.714		
SFSW1←Algorithmic thinking dimension	0.699	0.541	0.772
SFSW2←Algorithmic thinking dimension	0.774		
SFSW3←Algorithmic thinking dimension	0.752		
HZNL1←Dimension of cooperation ability	0.734	0.588	0.797
HZNL2←Dimension of cooperation ability	0.823		
HZNL3←Dimension of cooperation ability	0.724		

III. B. 3) Independent sample data testing and analysis

To ensure that there were no differences in computational attitudes between the control class and the experimental class prior to the teaching experiment, the Computational Attitude Scale was administered to both classes. After the test, an exploratory analysis was conducted on the pre-test data of the Computational Perspective Scale. The results of the normality test for the pre-test data of the Computational Perspective Scale for the control class and experimental class are shown in Table 4. As shown in the table, the P-values for the total score, creativity, critical thinking, problem-solving, algorithmic thinking, and collaborative ability of the control class and experimental class were all less than 0.05, indicating that they did not follow a normal distribution.

Table 4: The results of the normal test were measured before the table

		Total score	Creativity	Critical thinking	Problem solving	Algorithmic thinking	Cooperative ability
Control class	Statistic	0.93	0.911	0.846	0.894	0.875	0.864
	P	0.005	0.010	0.000	0.001	0.001	0.000
Experimental Class	Statistic	0.885	0.859	0.814	0.843	0.853	0.893
	P	0.001	0.000	0.000	0.000	0.000	0.002

Therefore, an independent samples nonparametric test was conducted on the pre-test data of the two classes. The results of the independent samples nonparametric test for the pre-test of the experimental class and the control class are shown in Table 5. As shown in the table, prior to the implementation of the teaching experiment, the p-values for total scores, creativity, critical thinking, problem-solving, algorithmic thinking, and collaborative ability were all greater than 0.05 for both the control class and the experimental class. Therefore, there were no significant differences between the control class and the experimental class in terms of total scores and individual dimensions, meeting the requirements for the implementation of the teaching experiment.

Table 5: The non-parametric test results were calculated

Dimension	Control Class	Experimental Class	Z	P
Total Score	73(60.39~82.23)	78(67~85)	-1.608	0.101
Creativity	22(19.36~26.78)	29(20~29)	-1.629	0.09
Critical Thinking	11(10.39~13.94)	16(11~13)	-0.969	0.332
Problem Solving	19(12.51~19.61)	15(16~20)	-1.287	0.178
Algorithm Thinking	13(10.61~13.75)	10(11~14)	-0.854	0.375
Cooperative Ability	8(6~8)	8(10~9)	-1.639	0.104

After the teaching experiment concluded, the Computational Perspectives Scale was administered again to both the experimental and control groups, and relevant data were collected. An exploratory analysis was conducted on the post-test results of the Computational Perspectives Scale. The results of the normality test for the post-test results of the Computational Perspectives Scale in the control and experimental groups are shown in Table 6. As shown in the table, after the teaching experiment, the p-values for the total score, creativity, critical thinking, problem-solving, algorithmic thinking, and collaborative ability in both the experimental class and the control class were all less than 0.05, indicating that the data did not follow a normal distribution.

Table 6: The results after calculating the opinion scale

		Total score	Creativity	Critical thinking	Problem solving	Algorithmic thinking	Cooperative ability
Control class	Statistic	0.955	0.969	0.891	0.883	0.854	0.898
	P	0.203	0.336	0.001	0.001	0.000	0.001
Experimental Class	Statistic	0.913	0.788	0.753	0.869	0.761	0.923
	P	0.006	0.000	0.000	0.000	0.000	0.003

Therefore, a nonparametric test was conducted on the post-test data of the two classes. The results of the independent samples nonparametric test for the post-test of the attitude scale between the control class and the experimental class are shown in Table 7. As shown in the table, after the teaching experiment, the p-values for total scores, creativity, critical thinking, problem-solving, algorithmic thinking, and collaborative ability were all less than 0.05 for both the control group and the experimental group. Therefore, there were significant differences between the control group and the experimental group in terms of computational perspectives, both overall and across dimensions. This indicates that the method described in this paper effectively promoted positive changes in students' computational perspectives.

Table 7: The non-parametric test results after calculating the opinion scale

Dimension	Control class	Experimental Class	Z	P
Total score	76.5(67.36~83.38)	89(84~96)	-5.364	0
creativity	28(23.44~24.97)	30(27~34)	-5.094	0
Critical thinking	12(11.26~15.27)	11(12~16)	-2.295	0.027
Problem solving	17(13.12~15.76)	18(19~22)	-5.616	0
Algorithm thinking	10(8.71~12.98)	19(13~15)	-6.01	0
Cooperative ability	13(10.29~13.54)	15(11~15)	-2.282	0.032

III. C. Computational Thinking Test Analysis

III. C. 1) Paired sample t-test analysis of pre- and post-test total scores

The data were analyzed using SPSS statistical software. Since the sample size exceeded 30, a paired-sample t-test could be conducted on the pre- and post-test data of the experimental class. The results of the paired-sample t-test for the pre- and post-test scores of computational thinking in the experimental class are shown in Table 8. The data indicate that the pre-intervention test scores ($M = 52.397$, $SD = 22.213$) were lower than the post-intervention test scores ($M = 82.686$, $SD = 21.372$), and this difference was statistically significant: $t(41) = (11.62)$, $p < 0.001$, CI = [22.652, 35.055]. Therefore, it can be concluded that the test scores of the experimental class after the teaching intervention showed a highly significant improvement compared to the test scores before the intervention.

Table 8: The t-test results of the matching samples

	Number of cases	Average value	Standard deviation ·	The difference is 95%	Confidence interval limit	t	df	Sig.
Post-test	40	82.686	21.372	22.652	35.055	11.62	43	0.000
Pre-test	40	52.397	22.213					

A paired-sample t-test was conducted on the pre- and post-test data of the control group. The results of the paired-sample t-test for the control group's computational thinking pre- and post-test scores are shown in Table 9. The pre-intervention test scores of the control group (M = 15.36, SD = 5.006) were lower than the post-intervention test scores (M = 21.65, SD = 4.392), and this difference was statistically significant: t(41) = (9.885), p < 0.001, CI = [4.892, 7.396]. Therefore, it can be concluded that the test scores of the control group after the teaching intervention showed a significant improvement compared to the test scores before the experimental intervention. Thus, the method described in this paper has a highly significant effect on cultivating students' computational thinking in the control group.

Table 9: The t-test results of the sample matching the pre - and post-test scores

	Number of cases	Average value	Standard deviation ·	The difference is 95%	Confidence interval limit	t	df	Sig.
Post-test	40	21.65	4.392	4.892	7.396	9.885	43	0.000
Pre-test	40	15.36	5.006					

After conducting a paired sample t-test analysis of the total scores of the computational thinking pre- and post-tests for the two classes, it can be concluded that the students in both the experimental class and the control class showed a significant improvement in computational thinking after using the method described in this paper. The analysis of computational thinking performance further supports the findings of this study, confirming that using the method described in this paper for teaching can enhance computational thinking among college students.

III. C. 2) Independent sample t-test analysis of the total post-test scores for computational thinking

The results of the post-test independent samples t-test for computational thinking are shown in Table 10. The α value of the two groups of post-test data is 0.352 (greater than 0.05), and the P value is 0.005 (less than 0.01). There is a significant difference in the post-test scores for computational thinking between the two classes. Therefore, the method used in this study to cultivate computational thinking in college students in the experimental class is significantly more effective than that in the control class.

Table 10: The situation of independent sample t-test in the post-test

Class	Number of cases	Average value	Standard deviation	α value	P value
Laboratory class	40	81.545	18.581	0.352	0.005
Cross-reference class	40	68.975	22.088		

III. C. 3) t-test analysis of paired samples of stratified scores before and after computational thinking assessment

The results of the paired-sample t-test for the pre- and post-test scores of the computational thinking questions in the experimental class are shown in Table 11. The data indicate that the pre-intervention test scores of students in the experimental class (M=67.21, SD=22.288) were lower than their post-intervention test scores (M=92.63, SD=21.167), and this difference was statistically significant, t(15) = (6.334), p < 0.001, CI = [22.046, 35.853]. The students in the experimental class showed a significant improvement in their computational thinking test scores after using the method described in this paper compared to their test scores before the intervention. The data indicate that the pre-intervention test scores of students in the experimental class's abstract dimension (M=55.15, SD=17.467) were lower than their post-intervention test scores (M=84.75, SD=14.811), and this difference was statistically significant, t(15) = (6.833), p<0.001, CI = [19.798, 37.426]. The improvement in test scores for students in the experimental class in the abstract dimension after using the method described in this paper compared to their test scores before the intervention was extremely significant. In summary, based on the analysis of the data, students in the experimental class showed significant improvement in computational thinking test scores after using the method described in this paper.

Table 11: The t-test results of the matching samples of the pre - and post-test scores

		Case number	Average value	Standard deviation	The difference is 95%	Confidence interval limit	t	df	Sig.
Total score	Post-test	40	92.63	21.167	22.046	35.853	6.334	15	0.000
	Pre-test	40	67.21	22.288					
Abstract	Post-test	40	84.75	14.811	19.798	37.426	6.833	15	0.000
	Pre-test	40	55.15	17.467					
Decomposition	Post-test	40	69.07	11.973	17.243	38.002	2.916	15	0.000
	Pre-test	40	40.66	21.107					
Algorithm	Post-test	40	93.7	21.391	30.768	30.363	5.324	15	0.000
	Pre-test	40	72.66	21.222					
Evaluation	Post-test	40	90.94	19.09	28.617	35.604	8.489	15	0.000
	Pre-test	40	55.85	25.174					
Summary	Post-test	40	49.2	15.487	13.468	25.991	5.814	15	0.000
	Pre-test	40	40.03	25.148					

The results of the paired-sample t-test for the pre- and post-test scores of the computational thinking questions in the control group are shown in Table 12. The data indicate that the pre-intervention test scores of students in the control group on the total score dimension (M=54.485, SD=25.151) were lower than their post-intervention test scores (M=81.01, SD=23.915), and this difference was statistically significant, $t(15) = (6.962)$, $p<0.001$, CI = [17.058, 32.469]. The test scores of students in the control group on the total score dimension after using the method described in this paper showed significant improvement compared to their test scores before the experimental intervention. The data indicate that the pre-intervention test scores of students in the control group in the abstract dimension (M=54.806, SD=17.233) were lower than their post-intervention test scores (M=72.015, SD=17.033), and this difference was statistically significant, $t(15)=4.528$, $p<0.01$, CI = [6.98, 31.285]. The improvement in test scores for students in the control group's abstract dimension after using the method described in this paper compared to their test scores before the experimental intervention was extremely significant. In summary, based on the analysis of computational thinking test data, students in the control group all showed significant improvement after using the method described in this paper.

Table 12: Test results of the matching sample of the test results

		Case number	Average value	Standard deviation	The difference is 95%	Confidence interval limit	t	df	Sig.
Total score	Post-test	40	81.01	23.915	17.058	32.469	6.962	15	0.000
	Pre-test	40	54.485	25.151					
Abstract	Post-test	40	72.015	17.033	6.98	31.285	4.528	15	0.000
	Pre-test	40	54.806	17.233					

Decomposition	Post-test	40	58.503	18.098	11.254	31.494	4.738	15	0.000
	Pre-test	40	36.119	21.563					
Algorithm	Post-test	40	76.136	27.815	18.729	26.332	1.529	15	0.003
	Pre-test	40	54.198	27.814					
Evaluation	Post-test	40	74.833	10.914	16.453	37.995	13.337	15	0.000
	Pre-test	40	58.878	15.748					
Summary	Post-test	40	61.381	18.829	19.391	37.207	5.974	15	0.000
	Pre-test	40	36.09	15.901					

IV. Conclusion

The cultivation of computational thinking is not only crucial for college students' future competitiveness in the field of science and technology, but also an important means to enhance their overall quality and innovative capabilities. This article explores the design of a new teaching model oriented toward computational thinking and investigates the feasibility and pathways for enhancing college students' computational thinking abilities under this new teaching model. The conclusions drawn from the article are as follows:

Based on the results of an independent samples nonparametric t-test conducted on the post-test scores of the control group and experimental group using the Computational Thinking Scale, it was found that the p-values for total scores, creativity, critical thinking, problem-solving, algorithmic thinking, and collaborative ability were all less than 0.05 after the teaching experiment. This indicates that the method described in this article effectively promoted positive changes in students' computational thinking.

The results of the paired-sample t-test for the pre- and post-test scores of the computational thinking questions in the control group showed that the pre-intervention scores (M=54.485, SD=25.151) were lower than the post-intervention scores (M=81.01, SD=23.915) in the total score dimension. This indicates that students in the control group demonstrated significant improvement after using the method proposed in this paper.

References

[1] Wang, Y. (2022, December). A comparative study on the effectiveness of traditional and modern teaching methods. In Proceedings of the 2022 5th International Conference on Humanities Education and Social Sciences (ICHESS 2022) (Vol. 720, pp. 270-7).
[2] Jarilkapovich, M. A. (2025). The Role of Modern Education and The Teacher's Pedagogical Skills in The Application of Pedagogical Teaching Methods. International Journal of Pedagogics, 5(04), 266-268.
[3] Akçayır, G., & Akçayır, M. (2018). The flipped classroom: A review of its advantages and challenges. Computers & Education, 126, 334-345.
[4] Kara, C. O. (2016). Flipped classroom. Tıp Eğitimi Dünyası, 15(45).
[5] Hawks, S. J. (2014). The flipped classroom: now or never?. AANA journal, 82(4).
[6] Galindo-Dominguez, H. (2021). Flipped classroom in the educational system. Educational Technology & Society, 24(3), 44-60.
[7] Awidi, I. T., & Paynter, M. (2019). The impact of a flipped classroom approach on student learning experience. Computers & education, 128, 269-283.
[8] Kurniawan, A. (2021). Flipped Classroom. Model Pembelajaran Era Society 5.0, 1, 37.
[9] Hand, M. (2014). Towards a theory of moral education. Journal of Philosophy of Education, 48(4), 519-532.
[10] García-Moriyón, F., González-Lamas, J., Botella, J., González Vela, J., Miranda-Alonso, T., Palacios, A., & Robles-Loro, R. (2020). Research in moral education: The contribution of P4C to the moral growth of students. Education Sciences, 10(4), 119.
[11] Frisancho, S., & Delgado, G. E. (2018). Moral education as intercultural moral education. Intercultural Education, 29(1), 18-39.
[12] Harefa, D., Hulu, F., & Siswanti, W. (2024). Mathematics learning strategies that support Pancasila moral education: Practical approaches for teachers. Afore: Jurnal Pendidikan Matematika, 3(2), 51-60.
[13] Meivawati, E., Kartowagiran, B., & Rustini, T. (2018). Evaluation of character and moral education in elementary school. The Online Journal of New Horizons in Education, 8(4), 63-72.
[14] Dahlbeck, J. (2017). A Spinozistic model of moral education. Studies in Philosophy and Education, 36(5), 533-550.
[15] Kristjánsson, K. (2017). Moral education today: Ascendancy and fragmentation. Journal of Moral Education, 46(4), 339-346.
[16] Jdaitawi, M. (2019). The effect of flipped classroom strategy on students learning outcomes. International Journal of Instruction, 12(3), 665-680.
[17] Rahimjanovna, S. M. (2020). Teaching ethics to students in technology education. Asian Journal of Multidimensional Research (AJMR), 9(3), 119-122.
[18] Parsons, T. D. (2021). Ethics and educational technologies. Educational Technology Research and Development, 69(1), 335-338.

[19] Goldberg, S. L., & Levy, D. E. (2023). Not just public housing: an ethical analysis of expanding smoke-free housing policies in the United States. Public Health Reports, 138(3), 401-405

[20] Ellis, S., & Moss, G. (2014). Ethics, education policy and research: the phonics question reconsidered. British Educational Research Journal, 40(2), 241-260.

[21] Pillay, P., & Sayeed, C. M. (2017, December). Ethical Values and Corruption in Housing Service Delivery: Comparative Reflections from South Africa and India. In Proceedings of the 13Th European Conference on Management, Leadership and Governance (Ecmlg 2017) (pp. 374-381).

[22] Beard, K. S. (2019). Getting on track: Aligning the achievement gap conversation with ethical educational practice. International Journal of Leadership in Education, 22(1), 30-54.

[23] Jesús Moreno León,Marcos Román González,Estefanía Martín Barroso,María Zapata Cáceres,Marcos Jiménez & Gregorio Robles. (2025). Enhancing computational thinking skills in early education: exploring the efficacy and feasibility of unplugged methodologies. Thinking Skills and Creativity,58,101879-101879.

[24] Gemma Sala Sebastià,Adriana Breda & Vicenç Font. (2025). Characterising computational and geometric thinking in pre-service Early Childhood Education teachers by playing with MatataLab. Education and Information Technologies,(prepublish),1-25.