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Integrating Machine Learning and Morphogenetic Approach to Evaluate Constructivist Education Theory: A Sample of Chinese Teacher Education Trainees

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Abstract. *This study integrates a machine learning model (XGBoost) and the morphogenetic approach to evaluate the application of constructivist education theory in a compulsory pedagogy course for Chinese teacher education trainees. The study involved a control group (n = 769) and an experimental group (n = 1090) over the period 2012 to 2024 . The control group was taught using a traditional teacher-centered method, while the experimental group adopted a blended learning approach based on constructivist theory. In addition to traditional statistical analyzes, the XGBoost model was employed to predict student performance. The results indicate that although the average scores between the two groups were not significantly different, the experimental group showed a wider distribution of scores, with a higher proportion of excellent grades (19.72% vs. 13.78%) and a higher failure rate (2.66% vs. 1.69%). Furthermore, the prediction accuracy of the machine learning model exceeded 80%, with the prediction error typically within five percentage points. The integration of machine learning model (XGBoost) with the morphogenetic approach revealed that certain prediction errors could be linked to deeper socio-cultural challenges, particularly among students unfamiliar with autonomous learning. From a morphogenetic perspective, this study explores the applicability of constructivist education theory—developed from WEIRD samples—under different cultural and structural conditions. It suggests that balancing teacher-centered and constructivist teaching methods may better address the diverse needs of students from different backgrounds.*

Keywords: Constructivist education theory, Morphogenetic approach, Machine learning, Chinese teacher education trainees, Non-WEIRD samples, Critical thinking, Intrinsic motivation, Autonomy, Self-regulation, Social collaboration.

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1. **Introduction.** Glasersfeld [1] that constructivist education theory advocates for reducing external regulation to a more relaxed level, thereby providing learners with greater freedom to learn according to their own interests and pace. Horn et al. [2] argued that this theory has successfully cultivated many individuals with critical thinking skills in American society and is considered to have universal applicability. Bonk's research [3] further suggested that this theory might even replace teacher-centered teaching methods. However, Henrich et al. [4,5] found that much of Western scientific theory is based on WEIRD (Western, Educated, Industrialized, Rich, Democratic) samples, particularly American college students, which may not be sufficiently representative on a global scale. Zajda & Majhanovich [6] have raised concerns about whether Western educational theories are applicable to non-Western societies. For example, a study by Loyalka et al. [7] on the effectiveness of education revealed that after receiving university-level STEM education, Chinese students' critical thinking skills not only failed to improve but actually declined, in stark contrast to the gradual improvement observed in students from the United States, India, Russia, and other countries.

These research findings are particularly significant given the widespread adoption of constructivist education theory in China. Tan [8] showed that after the introduction of constructivist education theory in China, many education theorists regarded it as a key direction for educational reform. According to Chen's research [9], this theory gradually became an officially recognized mainstream teaching method, and this reform trend has clearly positioned universities as the primary experimental grounds for constructivist education theory. This study posits that the widespread adoption of constructivist education theory in Chinese universities over the past 20 years may be a contributing factor to the decline in critical thinking skills among some university students.

To better explore the potential effects of constructivist education theory in China, this study selected Chinese teacher education trainees as the sample. This group is unique, not only reflecting a deep Confucian cultural background but also having grown up in relatively authoritative family and school environments. Additionally, most of them come from rural areas with lower socio-economic status. By choosing to study in teacher education programmers at university, they ensure that they will become primary or secondary school teachers after graduation, thereby securing better social and economic status. Thus, they represent the educational experiences of the majority of Chinese students from primary to high school, forming a non-WEIRD (non-Western, non-Educated, non-Industrialized, non-Rich, non-Democratic) sample group. Figures 1 and 2 illustrate the environmental conditions of American university students and Chinese teacher education trainees, respectively. The learning motivation of Chinese teacher education trainees is more externally driven, being based on rewards, with less connection to intrinsic motivation. This study attempts to examine the effectiveness of constructivist education theory on this sample.

In recent years, machine learning has increasingly expanded its applications across various fields, including automation, pattern recognition, and educational predictions. Chiu et al. [10] demonstrated that machine learning models, particularly those integrated with machine vision, improve the accuracy and efficiency of automated systems. Sun et al. [11] validated the strength of machine learning in classification tasks, particularly in recognizing complex patterns, such as Nantong blue calico.

The growing integration of machine learning in education has the potential to revolutionize how we predict student performance and optimize teaching strategies. Recent studies emphasize the importance of advanced algorithms in addressing complex data challenges in education. For instance, Sun et al. [12] demonstrated how thin-plate spline interpolation (TPS) effectively handles missing data, a critical issue in building reliable educational datasets. Similarly, dynamic optimization techniques, as highlighted in the research on solar radiation algorithms by Chiu et al. [13], suggest that adaptive strategies can enhance system responsiveness, providing a blueprint for managing real-time variability in student engagement patterns.

Machine learning models such as XGBoost are particularly effective in analyzing complex datasets, allowing for more precise predictions. For example, Asselman, Khaldi & Aammou [14] showed how XGBoost accurately forecasts student outcomes by processing large-scale historical data. Gu et al. [15] further illustrated how attention mechanisms like CBAM can improve model accuracy, offering a means to refine personalized educational strategies by identifying subtle learning behaviors. Similarly, Nkomo & Nat [16] demonstrated the model's capacity to detect engagement patterns, enabling targeted interventions. These findings align with those of Hakkal & Lahcen [17], who explored how predictive algorithms can identify students needing additional support, thereby enhancing teaching strategies.

Given the complexity and diversity of this non-WEIRD sample, traditional educational theories may not fully capture the dynamics of learning motivation and performance. Thus, the integration of machine learning models such as XGBoost with constructivist teaching methods offers a valuable opportunity to explore the intersection of technology and pedagogy. By combining the predictive power of machine learning with constructivist education theory, this study aims to analyze the nuanced effects of both approaches on student outcomes.

Therefore, integrating the morphogenetic approach with machine learning models like XGBoost offers a more precise and comprehensive framework for evaluating constructivist education theory. This combination can enhance our understanding of how educational structures and cultural conditions impact the effectiveness of constructivist pedagogy, especially when analyzing large-scale educational data.

FIGURE 1. Environmental conditions for U.S. college students

FIGURE 2. Environmental conditions for Chinese teacher education trainees

2. **Literature Review.**

2.1. **Constructivist education theory.** Constructivist education theory [18, 19] emphasizes active student participation in the learning process, engaging intrinsic motivation through self-initiative to achieve learning goals. This theory explores the impact of intrinsic motivation, autonomy, self-regulation, and social collaboration on learners.

Intrinsic motivation refers to students' spontaneous participation in learning, driven by their interest and curiosity about the content. This motivation originates from internal needs rather than external rewards or punishments. Piaget [20] was the first to propose this concept, asserting that children learn spontaneously as they explore their environment. Later, Deci and Ryan [18], through Self-Determination Theory (SDT), further elaborated on the role of intrinsic motivation. They noted that when individuals voluntarily engage in activities they find interesting and fulfilling, they are more likely to experience intrinsic motivation. This not only leads to better performance and lasting behavioral changes but also improves psychological health and overall well-being. According to SDT [21, 22], the learning environment should support students' autonomy and meet their internal needs to promote machine learning experiences. Therefore, constructivist education theory [23] emphasizes providing students with an autonomous learning environment where they can freely explore and solve problems independently.

Autonomy refers to students' ability to freely choose their learning methods and paths, engaging in self-management, particularly in the absence of external control and pressure [24]. McCombs [24] also noted that students must possess certain cognitions about their own abilities and sense of control during the learning process, which helps enhance intrinsic motivation. Reeve [25] further highlighted that when students feel their autonomy is supported, their motivation to learn strengthens, they become more creative, and they are better able to face challenges. Overall, autonomy plays a crucial role in the learning process, as it can stimulate students' intrinsic motivation, thereby enhancing their learning experiences and outcomes [26].

Self-regulation refers to students' ability to monitor and adjust their learning strategies to effectively achieve their learning goals [27]. Zimmerman [28] particularly emphasized the importance of students possessing the ability to self-evaluate, set goals, and choose learning strategies. Further research [29] indicates that learners with strong self-regulation skills perform better academically and exhibit greater persistence in learning. A key aspect is for teachers to reduce their level of regulation to a more lenient degree [30] to better facilitate students' autonomous learning [31].

Constructivist education theory [32] also posits that learning is a social process, where students can foster self-motivation and solve problems through interaction and cooperation with others. Vygotsky's [33] sociocultural theory emphasized the importance of social collaboration in the learning process. He [33] introduced the concept of the Zone of Proximal Development (ZPD), suggesting that collaboration with peers or mentors during the educational process can help students develop their potential abilities, thereby enhancing self-motivation. Numerous studies [34, 35] support this perspective.

In conclusion, constructivist education theory [36] advocates that educators focus on four key areas to design more effective teaching methods and strategies to enhance learners' intrinsic motivation, thereby benefiting the development of their higher-order cognitive abilities. However, some studies [37, 38] have indicated that this theory may overly emphasize student initiative and autonomy, potentially neglecting the crucial role of teachers in the instructional process. For example, research [39] has shown that constructivist education theory may not be suitable for beginners, who require more direct guidance from teachers. Additionally, family background, socio-economic status, available educational resources, and cultural context significantly influence learners' motivation and abilities [40–42], and these factors are often insufficiently considered in discussions of constructivist education theory. Studies have noted that in non-Western cultural contexts, many students are accustomed to traditional methods of rote learning and repetition, or are unaccustomed to questioning teachers' authority. As a result, they [43] may find autonomous and cooperative learning challenging and may struggle with teacher-student interactions and the development of critical thinking skills.

Constructivist education theory assumes that all learners inherently possess intrinsic motivation towards various subjects or fields. However, this theory is primarily based on WEIRD samples, which may present limitations when explaining or assessing learners who lack intrinsic motivation and place greater emphasis on external demands and rewards.

Figure 3 illustrates the overall research route of this study, covering the research background, methods, data analysis, results, discussion, and conclusions. The research background section elucidates the necessity and theoretical foundation of the study. The research methods section outlines the experimental design, participants, and data collection methods. The data analysis section provides a detailed description of data processing and statistical methods. The research results section presents the main findings and outcomes of the data analysis. The discussion and conclusions section analyzes the significance of the research results, offers practical recommendations for application, and summarizes the implications for future research.

2.2. **Examining the effectiveness of implementing constructivist education theory in China through a morphogenetic approach.** When assessing the feasibility of an educational method, social and cultural factors cannot be ignored. Archer [44], through the morphogenetic approach, studied the interplay between structure, culture, and agency in depth. She [45] analyzed the expansion of educational systems in European countries, revealing how structural conditions such as resource allocation, educational policies, and administrative management influence the development of educational systems. From a morphogenetic perspective, constructivist education theory overlooks the impact of social and cultural factors on agency. Agents' behavior is driven not only by self-motivation but also constrained by social structures and cultural conditions. The same applies to learning motivation. Although constructivist education theory explores the relationship

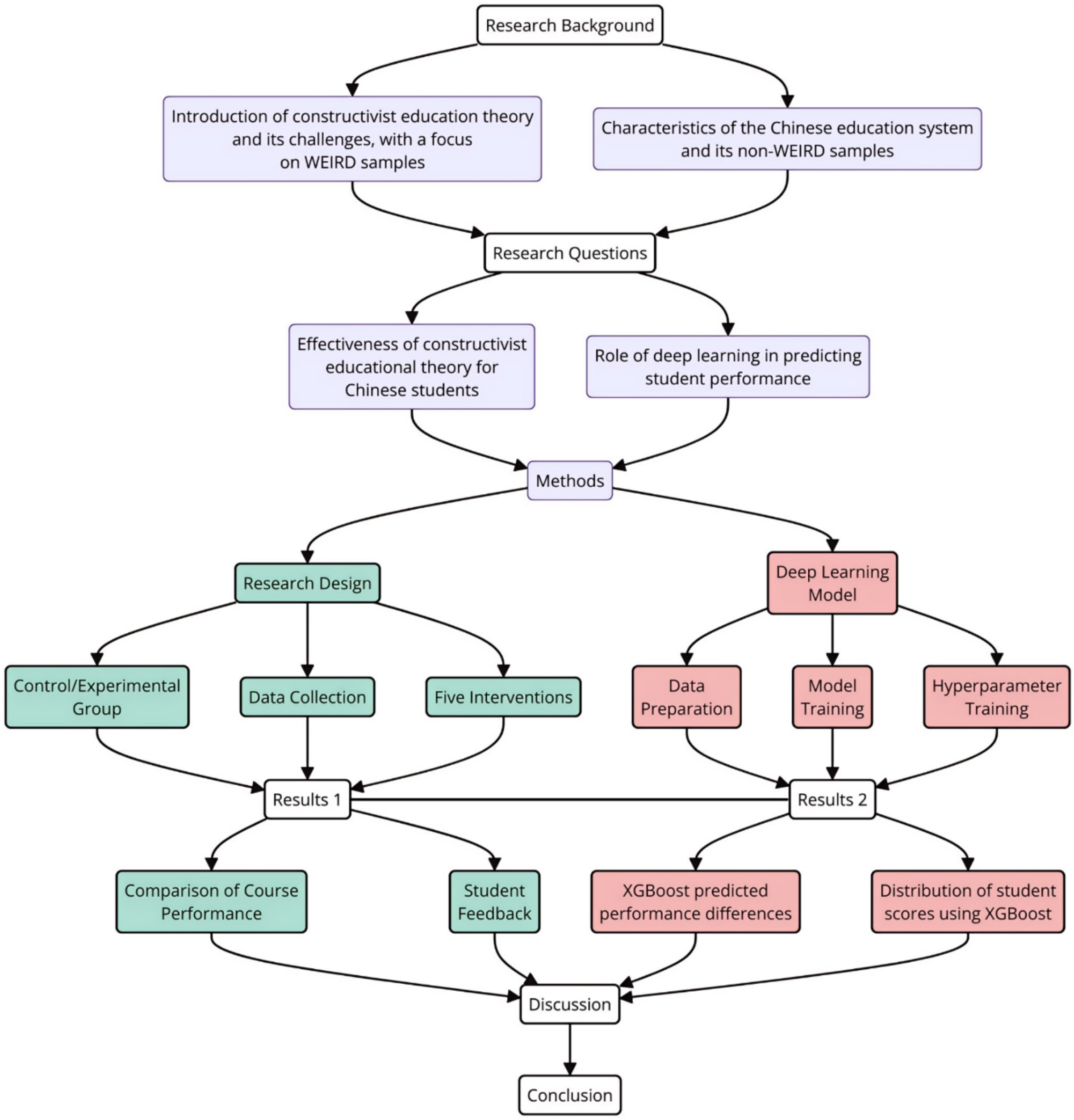

Figure 3. Research route

between intrinsic motivation and self-motivation, it pays less attention to the influence of social structures and culture on agency.

The civil service examination system in Confucian society, as a rigorous examination system, embodied the idea that 'those who excel in their studies should be appointed to official positions.' Over its existence of a thousand years, it shaped students' adaptation to learning methods and their learning motivations [46]. Huang [47], using achievement motivation theory, proposed the concept of vertical distinctiveness to explain the learning behavior and motivation of Chinese students, influenced by family prestige and parental expectations. Vertical distinctiveness differs from what Deci & Ryan [18] describe as external motivation; instead, it can be placed within the framework of the morphogenetic approach and viewed as socio-cultural interaction motivation.

The role of teachers in China's primary and secondary education system is fundamentally different from that in Western education systems. Chinese teachers enforce strict standards for students' learning and behavior, sometimes employing severe methods such as corporal punishment to compel students to overcome learning difficulties [48]. This approach aligns with the Confucian principle of strict disciplinary education, encapsulated in the saying 'spare the rod, spoil the child' [49, 50]. From a morphogenetic perspective, the emphasis on teacher authority and strict enforcement of teaching in China transcends strong teacher regulation and can be classified as socio-cultural interaction regulation.

Chinese universities, established in the late Qing Dynasty by emulating Western universities [51], are structurally closer to student-centered teaching models, such as the credit system and degree awarding [52], compared to primary and secondary schools. However, the strong teacher regulation present in the Qing Dynasty's civil service examination system, such as the routine assessments conducted by examiners on scholars [53], has been retained. This is evident in institutional design features such as teacher authority and the significant weight placed on final exam scores. In terms of teacher regulation, Chinese universities incorporate elements that both emulate Western practices and continue Confucian educational traditions.

Despite the gradual influence of constructivist education theory on the entire Chinese education system, some socio-cultural interaction regulation methods are no longer permitted by policy, yet certain strong teacher regulation methods still persist [40, 54]. From a morphogenetic perspective, significant differences in teacher regulation exist between the Chinese and Western education systems. By using teaching methods and the strength of teacher regulation as two main axes to analyze the structure and culture of Chinese primary, secondary, and tertiary education compared to Western education systems, these differences become clearer, as shown in Figure 4.

The position of each point in the diagrams reflects the degree of teacher regulation and the strength of teaching methods in both Chinese and Western education systems. It should be noted that the structural and cultural conditions of Western education are largely integrated, and therefore no distinction is made between them in the diagram. In contrast, the structural conditions of Chinese education have been rapidly influenced by the West, leading to swift changes—what Archer refers to as morphogenesis. However, the cultural conditions have been slower to change, resulting in relatively slower or even stagnant cultural transformation, a phenomenon referred to as cultural morphstasis [44].

Constructivist education theory often underestimates the importance of structure and culture and their impact on agency. These socio-cultural interaction factors in the non-WEIRD sample are essential considerations in this study. Understanding these factors is crucial for a comprehensive assessment of the potential effects of constructivist education theory in China.

2.3. **Research questions.** This study employs a *morphogenetic approach* to explore the effectiveness of constructivist education theory within the context of Chinese education. There are notable differences between the Chinese and American education systems. First, from a structural perspective, although Chinese university teachers have begun to adopt constructivist education theory, the Chinese education system remains teacher-centered from the primary school level, with teaching focused around a series of standardized exams. Secondly, from a cultural perspective, Confucian educational principles in China emphasize the close connection between academic achievement and social status, which profoundly impacts educational structures and learners. Thirdly, from an agency perspective, students exercise their own agency in education but are also influenced by structural and cultural conditions. This study examines the effectiveness of constructivist education theory under these conditions and addresses two key questions:

FIGURE 4. Morphogenetic analysis of teaching methods and teacher regulation in Chinese and Western education systems

(1) How effective is constructivist education theory for Chinese teacher education trainees?
(2) What is the specific application of constructivist education theory for Chinese teacher education trainees under the structural, cultural, and agency conditions outlined in the *morphogenetic approach*?

3. Methods.

3.1. Morphogenetic approach.

(1) Participants. The participants were students from a teacher education programmer at an ordinary university in a province in China, hailing from various regions within the province. Before the course began, the researchers informed the students about the study and obtained their consent. The study received approval from the university's ethics committee (Approval Number: 2023-10-01). The participants were divided into two groups. The control group consisted of 769 participants from 23 classes across 9 different majors, with enrolment years ranging from 2012 to 2017. The experimental group included 1,090 participants from 29 classes across 9 different majors, with enrolment years from 2017 to 2024. Table 1 provides the demographic information of the 1,859 participants.
(2) Research design.This study was conducted within the context of the 'Pedagogy' course, a compulsory subject for teacher education students, taught by the first author. The course was delivered by 10 different instructors following a predetermined curriculum, with teachers randomly assigned to classes each time. The students came from various majors, which posed some challenges for the author in maintaining consistent participant engagement throughout the twelve-year teaching period from 2012 to 2024.

Table 1. Demographic characteristics of control and experimental groups ($n = 1,859$)

Control Group ($n = 769$)				Experimental Group ($n = 1090$)			
		n	%			n	%
Gender	Male	322	41.8	Gender	Male	246	22.5
	Female	447	58.1		Female	844	77.4
Age	18	240	31.2	Age	18	0	0
	19	206	26.8		19	964	88.4
	20	323	42		20	126	11.5
Major	Arts	59	7.7	Major	Chemistry	100	9.1
	Mathematics	50	6.5		Science Education	26	2.4
	Music	95	12.5		Arts	236	21.7
	Physical Education	155	20.1		Mathematics	320	29.4
	Preschool Education	55	7.1		History	102	9.4
	Computer Science	139	18		Geography	51	4.7
	Education Technology	71	9.2		Music	100	9.1
	Ideological and Political Education	99	12.8		Physics	90	8.2
	Physics	46	5.9		Physical Education	65	5.9

A post-test design was employed in this study. The control group followed a teacher-centered instructional approach, where the teacher played a dominant role in determining course content and pacing, with little emphasis on stimulating students' intrinsic motivation. In contrast, the experimental group used an instructional approach based on constructivist education theory, aiming to reduce teacher regulation as much as possible. Each class employed its respective teaching method for an entire semester (16 weeks).

The teacher-centered teaching method involved weekly lectures based on predetermined textbook content, in-class question-and-answer sessions, and minimal pre-class preparation for students. The constructivist teaching approach encompassed three key aspects: stimulating intrinsic motivation (using process-oriented assessment methods), enhancing autonomy (assigning pre-class video tasks and reference readings), and strengthening self-regulation (through self-assessment) and social collaboration (via group cooperative learning). Table 2 outlines the specific content of these two teaching methods.

Given that the students in the experimental group had primarily experienced teacher-centered learning before university, this study utilized the *Super Star* online learning management platform to design five reinforcement measures (see Table 3) to better engage them in this new style of teaching.

(3) Data collection. Before the implementation of the two teaching methods, all participants were informed about the data collection process and consented to participate in the study. Quantitative data were primarily collected from the control group, including pre-class preparation levels and final exam scores. Data from the experimental group encompassed both quantitative and qualitative aspects. Quantitative data included final exam scores and records from the *Super Star* online learning platform, such as the frequency, completion rates, and scores of each student's learning activities. Qualitative data were obtained from student interviews.

Table 2. Contents of two teaching methods

Groups	Teaching methods
Control Group	Teacher-Centered Teaching Method (1) Learning stimulation: A small amount of pre-class preparations was assigned. (2) Knowledge transfer: Lectures by the teacher. (3) Learning interaction: Classroom discussions.
Experimental Group	Constructivist Teaching Method (1) Intrinsic motivation stimulation: Activities such as pre-class video assignments, class reports, simulated classroom, on-line quizzes and discussion forum. (2) Autonomy enhancement: Designed pre-class video assignments, recommended three reference books for students to independently choose learning contents. (3) Self-Regulation capability strengthening: Designed on-line quizzes and discussion forums to promote students' self-assessment and learning strategy adjustment. (4) Social collaboration: Designed group collaborate learning activities, such as class reports and simulated classrooms.

Table 3. Intervention measures to enhance student engagement

Intervention Measure	Purpose	Description
Learning Management and Reminders	Enhance student compliance with pre-class assignments	Send weekly reminders through the Super Star to students who haven't completed tasks
Reinforcement of Academic Integrity	Promote academic honesty	Emphasize academic integrity and apply penalties for violations like plagiarism or cheating
Clear Penalty Policies for Task Submission	Ensure timely task completion	Inform students that late submissions will result in grade deductions
Immediate Support and Assistance	Provide learning support	Offer support via messages or emails; use class time (ten minutes) to clarify pre-class video issues
Positive Encouragement and Feedback	Foster student engagement	Encourage participation through verbal feedback and engage passive students with cold-calling

To address Research Question 1, this study primarily measured intrinsic motivation, autonomy, self-regulation, and social collaboration through quantitative data. The methods for measuring intrinsic motivation included: firstly, examining the completion of pre-class video assignments and online quizzes; secondly, analyzing student participation in classroom presentations and simulated classes to assess their interest and engagement with the course content. Autonomy was measured by: firstly, recording students' independent selection of pre-class video assignments and reference materials to evaluate their ability to make autonomous choices in the learning process; secondly, analyzing students' initiative and creative thinking in forum discussions related to course topics. Self-regulation was measured by: firstly, evaluating students' self-assessment and strategy adjustment abilities through online quizzes and forum discussions; secondly, monitoring students' role-taking, task allocation, and goal-setting abilities in group collaborative learning activities to assess their self-management skills in a team environment. Social collaboration was measured by: firstly, observing students' cooperation in group tasks, including role-taking and task allocation; secondly, assessing the completion of group projects and the quality of interaction among group members to understand their collaborative abilities. Additionally, the final exam scores of both groups were compared to explore the ultimate learning outcomes under different teaching methods. The evaluation criteria for the two teaching methods are compared in Table 4.

To address Research Question 2, this study primarily used qualitative data, integrating the structural, cultural, and agency conditions of the *morphogenetic approach* to examine the impact of constructivist teaching on students' learning. The specific data included the first author's observations and records of students' preparation, participation, learning progress, and potential issues during offline teaching, as well as feedback from online discussions related to the course.

Table 4. Comparison of assessment criteria for the two teaching methods

teacher-centered assessment criteria	percentage	student-centered assessment criteria	percentage
		pre-class video assignments	8
		class report	8
pre-class preparations	40	simulated classroom	8
		on-line quizzes	8
		discussion forum	8
final exam	60	final exam	60

Additionally, during interviews with students in the experimental group, the following course feedback questions were used:

(a) Structural questions: How does the student-centered constructivist teaching differ from the teacher-centered teaching (mainly lecture-based) you have experienced before? Which of the two teaching methods do you prefer?

(b) Cultural questions: During the learning process, are there any family, cultural, or social factors that influence your learning behavior? If so, what are they?

(c) Agency questions: How would you evaluate your active participation in this course? For example, what specific factors prompted you to actively engage in pre-class videos or simulated classrooms?

(4) Data Analysis. The quantitative data analysis involved calculating the mean and standard deviation of course grades for participants in both groups and comparing the differences in the mean scores between the two groups. At the university where this study was conducted, course grades are divided into five levels: A = Excellent (90 and above), B = Good (80-89), C = Medium (70-79), D = Fair (60-69), and F = Fail (below 60). A Pearson chi-square test and a Grade Point Average (GPA) index test were conducted on the course grades of students in both groups. The GPA index was calculated using the following formula [55]:

$$GPA = \frac{0n_F + 1n_D + 2n_C + 3n_B + 4n_A}{n} \tag{1}$$

In this formula, n_A, n_B, n_C, n_D, and n_F represent the number of students achieving grades of Excellent, Good, Medium, Fair, and Fail, respectively, with n being the total number of students.

In addition, data on study time, duration, and the number of completed activities were collected from the experimental group to explore their performance in terms of intrinsic motivation, autonomy, self-regulation, and social collaboration.

The qualitative data analysis involved categorizing the course feedback and interview responses from the experimental group. During the categorization process, the authors discussed the similarities and differences in the classifications to ensure their validity and consistency. The classification codes are denoted as 'ep-number'; for example, ep3 refers to the third participant in the experimental group.

3.2. **Machine learning model.**

(1) Model selection. XGBoost is a gradient-boosted decision tree (GBDT) model and a widely used ensemble learning method in machine learning. By combining multiple weak learners (typically decision trees) into a powerful predictive model, XGBoost is widely applied in both classification and regression tasks. Compared to traditional gradient boosting algorithms, XGBoost offers higher speed and efficiency through features such as parallel computation, regularization, and automatic handling of missing values, making it highly effective in many competitions and real-world applications.
(2) Data preparation. Student historical performance data was extracted from a CSV file, containing final grades from multiple cohorts. The grades of earlier cohorts were used as training features (X), while the grades of subsequent cohorts were used as the target variable (y). This process enabled the model to learn patterns in past performance to predict future students' outcomes.
(3) Model training. XGB Regressor, a regression model provided by XGBoost, was employed for training. XGB Regressor iteratively minimizes the loss function (such as mean squared error), adjusting the weights of each tree to enhance the overall accuracy of the predictions.
(4) Hyper parameter tuning. The model's parameters, including the learning rate, tree depth, and subsample ratio, were adjusted to influence the model's learning speed and complexity. Hyper parameters were fine-tuned using cross-validation to find the optimal combination that maximized the model's accuracy.
(5) Visualization of results. The model's performance was visualized through the adjustment of hyper parameters, such as learning rate, tree depth, and subsample ratio. Cross-validation was used to identify the best combination of hyper parameters to improve model accuracy, and the results were displayed for analysis.

4. **Results.**

4.1. **The Effectiveness of Constructivist Education Theory.** The control group had an average score of 79.79 with a GPA of 2.62, while the experimental group had an average score of 79.60 with a GPA of 2.66. According to the results of an independent samples t-test, the p-value was 0.68, which is much higher than the significance level of 0.05. This indicates that there is no statistically significant difference in the average scores between the control and experimental groups. However, further examination of the standard deviations revealed that the control group had a standard deviation of 9.21, while the experimental group had a standard deviation of 10.20. This suggests that the experimental group had a wider score distribution, indicating greater individual variability in adaptability.

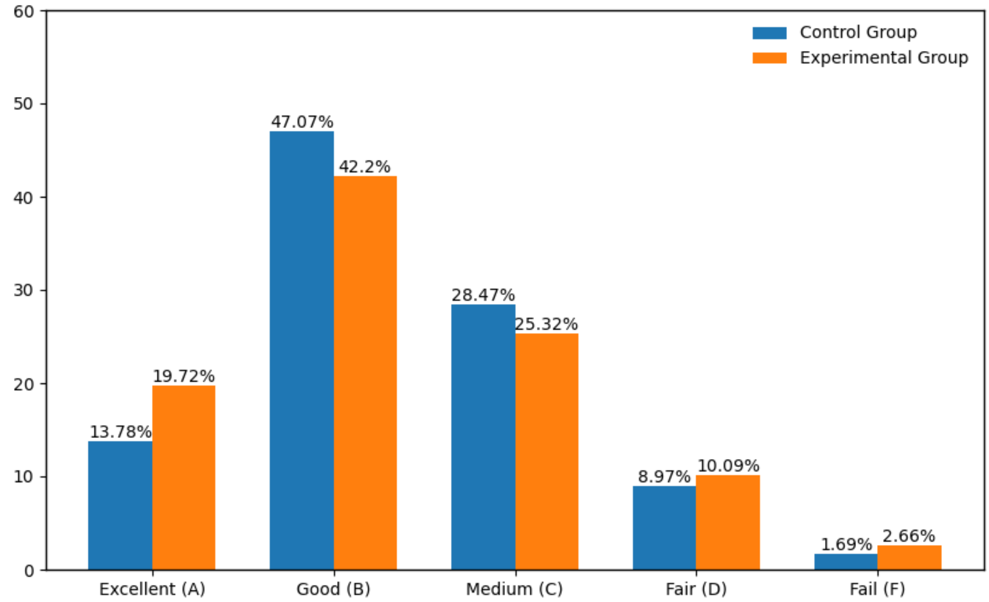

FIGURE 5. Comparison of the grade distribution on a five-point scale between the control group and the experimental group

To investigate this further, the distribution of grades across the five-level grading system was analyzed for both groups. The results showed that 19.72% of students in the experimental group achieved an excellent grade, notably higher than the 13.78% in the control group. However, the proportions of students in the experimental group achieving good, medium, and fair grades were all lower than those in the control group. Additionally, the proportion of students failing was higher in the experimental group at 2.66%, compared to 1.69% in the control group. This is illustrated in Figure 5, which shows the distribution of students across the five grade levels (excellent, good, medium, fair, and fail) under teacher-centered instruction (control group) and constructivist instruction (experimental group). These results suggest that the constructivist teaching method had varying impacts on students across different grade levels.

To assess the adaptability of students in both groups to different teaching methods, this study analyzed the distribution of course grades across three stages: before the pandemic (2012–2017), during the pandemic (2018–2022), and after the pandemic (2023–2024). The focus of this analysis was on the experimental group, as they underwent a teaching adjustment due to the COVID-19 pandemic in 2019. Although the experimental group consistently followed constructivist education theory, they switched to online teaching during the pandemic and only returned to blended learning after the pandemic ended. The sample sizes before and after the pandemic were 995 and 95, respectively.

The results show that under the teacher-centered teaching approach before the pandemic, student grades exhibited a higher median (81 points) and lower variability, indicating generally good performance under this model. During the pandemic, although some students were able to adapt to the online teaching method, the overall grade median increased, but variability also rose (with an average score of 80.97, a standard deviation of 10.30, and a median of 83 during this period). This reflects significant differences in students' self-learning abilities and adaptability in the online environment, leading to a more dispersed distribution of grades. After the pandemic, under the blended learning model, the median grade decreased, and variability reduced (with an average score of 73.22, a standard deviation of 6.67, and a median of 72 during this period). These analyzes provide a clearer understanding of the impact of different teaching methods on student performance and their adaptability to various teaching approaches. The student grades before, during, and after the pandemic are shown in Figure 6.

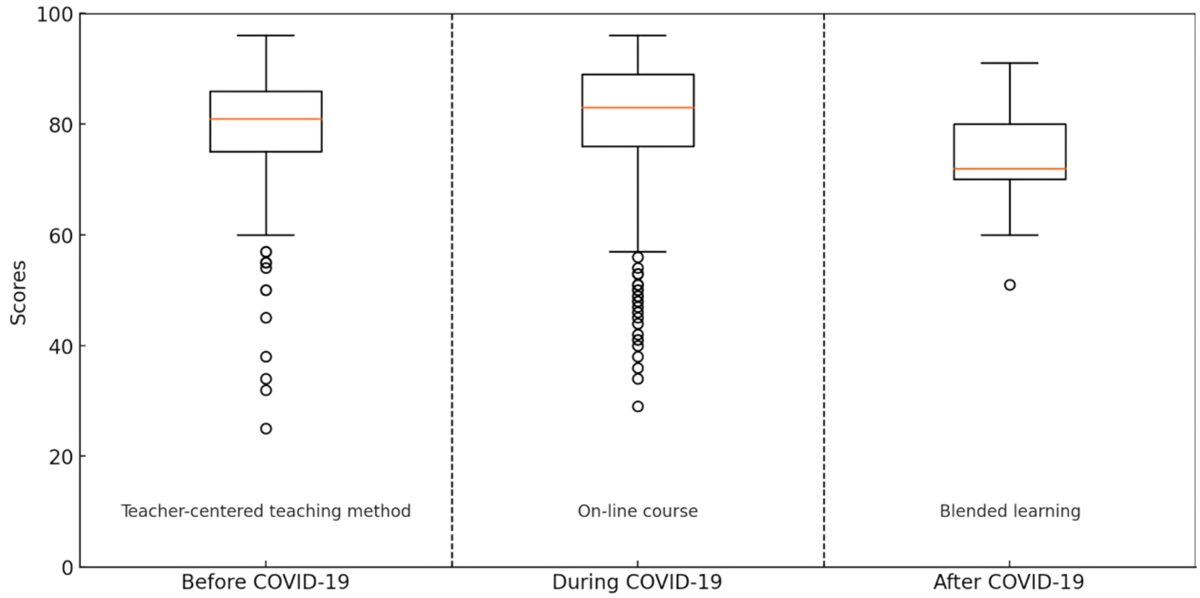

FIGURE 6. Comparison of student scores before, during, and after COVID-19 under different teaching methods

To investigate the relationship between pre-class preparation and course scores under the teacher-centered teaching method, this study selected nine classes with the smallest standard deviations from the control group for regression analysis.

For this analysis, the R-squared formula was used to perform a regression analysis, where the R-squared value measures how much of the variation in course scores can be explained by pre-class preparation. The formula is as follows:

$$R^2 = \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \tag{2}$$

where y_i represents the actual values, $\hat{y}_i$ the predicted values, and $\bar{y}$ the mean value. A higher R-squared value indicates that pre-class preparation has a stronger explanatory power for course scores.

Figure 7 illustrates the correlation between pre-class preparation scores and course scores. The analysis reveals significant differences in the R^2 values across different classes, with the highest R^2 being 0.81 and the lowest 0.49. A higher R^2 indicates that pre-class preparation has a stronger explanatory power for course scores in some classes, where students who performed well in preparation generally achieved higher course scores. Conversely, a lower R^2 suggests that pre-class preparation has less impact on course scores in certain classes, implying that other factors may be at play.

Furthermore, the regression lines (used to represent the relationship between pre-class preparation scores and course scores) are relatively short across all classes, particularly with eight classes showing regression lines spanning from 60 to 80 points, and one class with scores concentrated above 80 points. This indicates that under the teacher-centered teaching method, students' scores are relatively concentrated with smaller individual differences. To illustrate the relationship between pre-class video assignment scores and

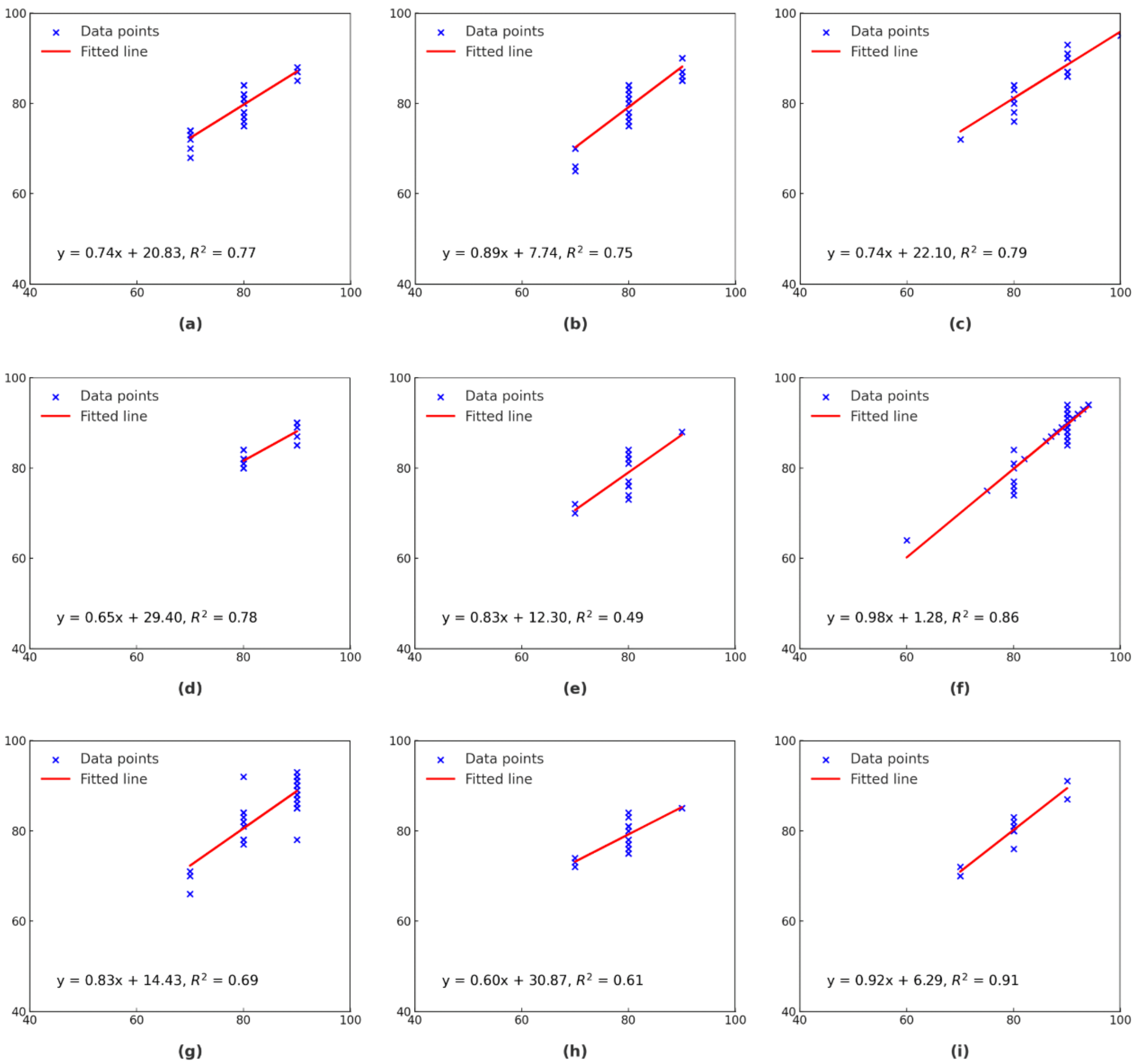

Figure 7. Correlation analysis of course scores and pre-class preparation scores in nine teacher-centered classes

course scores under the constructivist teaching method, this study selected nine classes with the largest standard deviations from the experimental group for regression analysis. Figure 8 presents the results for these classes. Compared to the control group, the experimental group shows a high degree of consistency in R^2 values, ranging from 0.91 to 0.98, indicating that the constructivist teaching method has a generally strong explanatory power across different classes.

However, the regression lines in the experimental group are relatively long, reflecting a broad distribution of student scores. At least four classes have regression lines spanning from 40 to 80 points, suggesting a greater diversity in student performance within these classes. The longer regression lines indicate that under the constructivist teaching method,

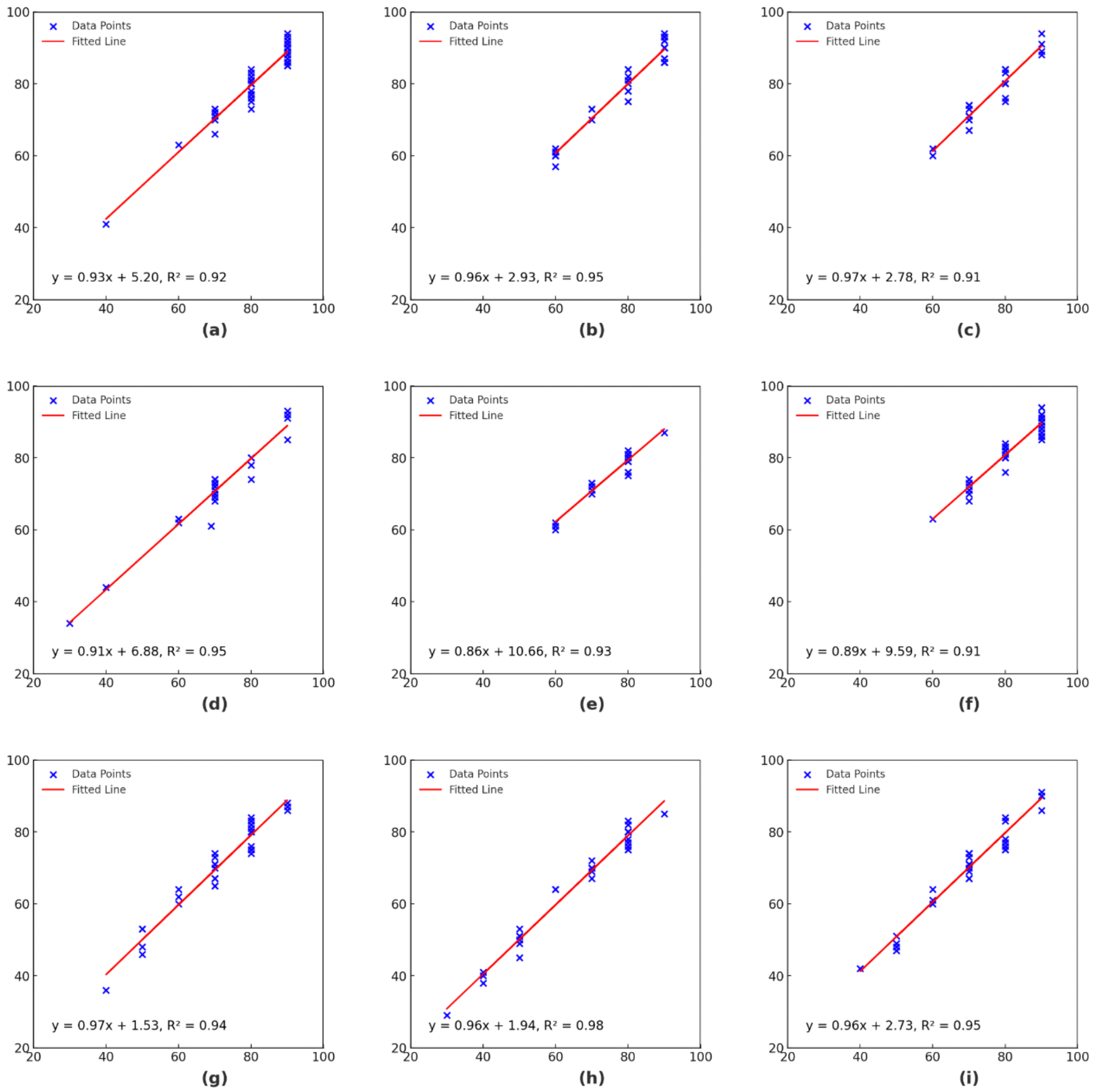

FIGURE 8. Correlation analysis of course scores and pre-class video assignments scores in nine constructivist classes

there is significant variation in student scores, likely related to differences in students' self-regulation abilities and levels of engagement.

Pre-class video assignments have a significant impact on overall course performance, some students scored relatively low on both the assignments and their course grades. This suggests that within the constructivist teaching method, students' self-regulation abilities and engagement levels play a crucial role in the diversity of final outcomes. For example, in some classes, while most students performed well, a minority failed to fully benefit from this teaching method, resulting in notably lower scores. The increased individual variation may indicate that the constructivist approach is highly effective for some students, yet poses challenges for others who may struggle to adapt to this method, requiring additional support and guidance.

The above analysis further indicates that the teacher-centered teaching model provides a relatively stable learning environment, resulting in more consistent student performance. In contrast, the constructivist teaching approach is more effective at stimulating individual student potential, although its outcomes can vary depending on the student's level of engagement.

Table 5. Performance of experimental group students

Dimension	Task Description	Percentage of Students	Observational Details
Intrinsic motivation	Completion of pre-class videos	5%	Watch course videos punctually and with autonomy each week
		30%	Completed watching the day before or on the day of class
		2%	Did not watch any course videos throughout the term
	Completion of online quizzes	5%	Completed quizzes on time
		80%	Cheated by looking up answers in books or online during the quiz
		2%	Did not complete any online quizzes
Autonomy	Watching pre-class videos and duration	5%	Watched videos on time and repeatedly, total duration exceeded video length
		50%	Watched videos on the day of the class, rushed to complete, viewing time less than total video length
		62%	Concentrated completion of pre-class video assignments in a short period before the course deadline (tasks were not completed on time)
	Reading reference books	2%	Actively read reference books
	Participation in discussion forums	55%	Visited discussion forums periodically and commented briefly on several course topics
		2%	Never replied to any discussion forum posts
Self-regulation	Participation in online quizzes and discussion forums	5%	Actively participated in discussion forums
		80%	Participated once a month, showing poor self-regulation
Social collaboration	Active participation in group collaborative learning activities	5%	Approximately 1-2 students in each group actively completed tasks
		95%	Waited for group leader to assign tasks, showing perfunctory behavior

Finally, an analysis of the experimental group's performance in terms of intrinsic motivation, autonomy, self-regulation, and social collaboration revealed that only a small proportion of students, approximately 5%, demonstrated high levels of intrinsic motivation, actively completing tasks on time and participating in activities. The majority of students, however, exhibited lower levels of intrinsic motivation and engagement, as shown in Table 5.

To better understand the impact of the two teaching methods on students' learning outcomes, an error analysis was conducted in this study. Specifically, 80 students were randomly selected from the control group, and their measuring scores and calculating scores were compared. The measuring scores were directly obtained from the final exam, while the calculating scores were predicted based on the pre-class preparation and class report scores under both teaching methods. The 'Error' column in the tables shows the difference between the calculating scores and the measuring scores. These data help assess the validity of the two teaching methods and their approximation to the actual results.

The error analysis of the calculating and measuring scores of the 80 students in Table 6 indicates that the prediction errors under the teacher-centered teaching method are

Table 6. Results of teacher-centered teaching method measurement

Student No.	Measuring Scores	Calculating Scores	Error	Student No.	Measuring Scores	Calculating Scores	Error
261	32	30	-2	713	83	80	-3
11	90	90	0	55	90	90	0
212	81	80	-1	175	89	90	1
282	75	70	-5	339	76	80	4
182	81	80	-1	77	91	90	-1
248	89	90	1	560	87	90	3
79	86	90	4	67	75	70	-5
618	82	80	-2	324	60	60	0
64	82	80	-2	640	80	80	0
98	79	80	1	482	83	80	-3
418	82	80	-2	397	65	60	-5
300	78	80	2	743	88	90	2
586	89	90	1	149	88	90	2
320	81	80	-1	240	80	80	0
609	87	90	3	368	87	90	3
396	76	80	4	235	75	70	-5
665	77	80	3	417	55	50	-5
502	96	100	4	224	77	80	3
451	81	80	-1	376	74	70	-4
352	88	90	2	725	73	70	-3
78	76	80	4	480	70	70	0
549	80	80	0	82	96	100	4
66	90	90	0	297	82	80	-2
400	81	80	-1	709	70	70	0
315	76	80	4	487	87	90	3
526	82	80	-2	542	64	60	-4
369	45	40	-5	617	71	70	-1
450	64	60	-4	337	71	70	-1
159	75	70	-5	260	92	90	-2
347	88	90	2	34	90	90	0
452	65	60	-5	426	92	90	-2
745	89	90	1	211	72	70	-2
73	80	80	0	40	87	90	3
421	81	80	-1	216	81	80	-1
427	82	80	-2	697	83	80	-3
193	77	80	3	209	67	70	3
571	80	80	0	491	90	90	0
232	80	80	0	620	67	70	3
389	84	80	-4	119	82	80	-2
102	84	80	-4	423	76	80	4

relatively small, suggesting that this method has a higher accuracy in predicting student performance. This could imply that the teacher-centred approach is more stable, effectively managing and guiding students' learning progress, resulting in students' actual performance being closer to the predicted outcomes.

Table 7 presents the error analysis of the calculating and measuring scores of 80 students under the constructivist teaching method. While there is some degree of discrepancy between the predicted and actual scores for some students, the overall error is relatively small. This suggests that the constructivist teaching method has a certain degree of effectiveness in predicting students' academic performance, reflecting their actual exam results to some extent. However, these errors also indicate that the application of the constructivist method may vary in its effectiveness across different students.

4.2. **Exploring the specific content of Constructivist education theory through a morphogenetic approach.** The analysis based on the morphogenetic approach revealed that most students in the experimental group were accustomed to teacher-centered teaching methods during their primary and secondary education and had little exposure to constructivist education in the past. These students tended to focus more on grades and exam results, with the goal of enhancing their family's social and economic status.

Table 7. Results of constructivist teaching method measurement

Student No.	Measuring Scores	Calculating Scores	Error	Student No.	Measuring Scores	Calculating Scores	Error
32	89	90	1	962	83	80	-3
414	77	80	3	804	86	90	4
536	71	70	-1	276	72	70	-2
744	84	80	-4	621	70	70	0
793	90	90	0	433	72	70	-2
569	73	70	-3	360	88	90	2
721	75	70	-5	894	94	90	-4
579	74	70	-4	947	83	80	-3
87	74	70	-4	454	50	50	0
645	87	90	-3	717	74	70	-4
114	70	70	0	89	86	90	4
1056	82	80	-2	883	92	90	-2
980	91	90	-1	293	89	90	1
784	81	80	-1	297	72	70	-2
307	82	80	-2	524	80	80	0
821	53	50	-3	964	94	90	-4
838	82	80	-2	71	74	70	-4
426	90	90	0	716	86	90	4
634	70	70	0	366	83	80	- 3
443	80	80	0	656	82	80	- 2
875	84	80	-4	175	81	80	- 1
324	87	90	3	322	90	90	0
948	88	90	2	757	71	70	-1
919	77	80	3	60	88	90	2
890	88	90	2	669	90	90	0
515	81	80	-1	774	72	70	-2
334	82	80	-2	351	96	100	4
261	71	70	-1	343	66	70	4
650	80	80	0	24	80	80	0
437	71	70	-1	850	83	80	- 3
1012	85	80	-5	637	88	90	2
179	60	60	0	685	70	70	0
845	73	70	-3	214	62	60	-2
328	80	80	0	287	81	80	- 1
787	84	80	-4	337	83	80	-3
248	89	90	1	794	83	80	-3
709	81	80	-1	482	80	80	0
459	64	60	-4	533	75	70	-5
929	61	60	-1	758	80	80	0
108	63	60	-3	320	82	80	-2

Upon entering university, they continued to favor teacher-led instructional methods and generally showed little interest in constructivist teaching elements.

As a result, despite being exposed to constructivist teaching, most students in the experimental group continued to assess and determine their level of participation based on the grades they received. During this process, as teacher regulation decreased, many students exhibited a more passive attitude, with some even struggling to engage in self-regulation. The detailed interview findings for students in the experimental group are presented in Table 8.

4.3. **Predicting student performance using Machine learning models.** To enhance accuracy, a more complex machine learning model, XGBoost, was used to analyze the performance of students from the past five cohorts and to predict the performance of students in the next five cohorts. The results were presented using an overlaid frequency histogram to illustrate the distribution of student scores for each cohort. On the X-axis, the final predicted scores are represented, ranging from 20 to 100, covering all possible scores that students might achieve. The Y-axis shows the number of students within each score range. Each colour corresponds to a specific cohort, and the dashed lines in different colours represent the predicted scores of students from the sixth to the tenth

TABLE 8. Interview responses on students' adaptation to constructivist teaching in the experimental group

Condition	Explanation	Participant	Comment
Structural	Learning style and habit	ep3	'I'm still accustomed to the teacher lecturing and students listening; I don't have the habit of studying before class so it's hard for me to motivate myself.'
		ep10	'The original teaching method was better than blended learning because the teacher lectures more.'
		ep5	'I felt that the pre-class videos and subsequent teacher explanations were repetitive teaching, wasting time, which made me less inclined to watch the pre-class videos in advance since the teacher would cover it.'
		ep4	'Teachers should lecture more; asking us to do group classroom reports is trying to evade their responsibilities, so I just went through the motions.'
Cultural	Culture background and learning motivation	ep2	'Reading reference materials seems unhelpful for improving grades as the final exam was primarily determined by textbook content.'
		ep10	'Online discussions didn't help with learning or future careers, so I was not keen on actively participating, just doing it to increase my course participation count.'
Agential	Learning behavior and self-regulation	ep6	'I wasn't very active in the discussion forum, but I believed I could get the basic score since the final exam accounted for 60%.'
		ep11	'I treated the regular reminders for learning tasks as just another notification, not as an actual penalty. '
		ep6	'I waited for the other members of the group to contact me for discussion, but they discussed without me, resulting in my missing out on participating in activities.'
		ep7	'I was quite proactive in learning and I had notified all group members to participate, but some did not respond or participate. However, since the teacher required each member to participate, I ended up taking on all the tasks myself.'

cohorts. The overlapping areas indicate that students from these cohorts are distributed within the same score ranges.

The majority of student scores are concentrated between 60 and 90, forming the central region of the predicted distribution, indicating that overall student performance tends to be above average. The solid blue line, also within this range, shows that most students' actual scores are similarly located in this band, demonstrating that the model provides a good prediction of student performance. There are fewer extreme scores below 30 and above 90.

Furthermore, the high overlap of score distributions across different cohorts suggests that the regression model predicts little significant difference in performance between these cohorts. Although the overall shape of the distributions is very similar, there are slight differences in the number of students within specific score ranges across cohorts. However, the central tendency remains around 75, which aligns with the typical performance of most students. Based on these predictions, the model provides an important basis for decision-making regarding students' final grades, facilitating an understanding of overall academic performance and the differences between cohorts, as shown in Figure 9 below.

The comparison between actual student scores and predicted scores, as shown in Figure 10, demonstrates that the model's prediction accuracy exceeds 80%. In most cases, the difference between the predicted and actual scores is less than five points. The horizontal axis (X-axis) of the figure represents the Student Index, a discrete variable used to differentiate between individuals, with a range from 0 to 800, indicating that the predictions and actual scores of 800 students were compared. The vertical axis (Y-axis) represents the students' final scores, with values ranging from approximately 30 to 100, which is a continuous variable. The variation on the vertical axis reflects the difference between each student's predicted and actual scores.

The blue dots represent the actual scores (Actual Future Scores), which are the observed true labels (actual values y). The yellow crosses represent the model's predicted scores (Predicted Future Scores), which are the predicted values output by the model (predicted values $\hat{y}$). From the figure, it can be seen that the vertical distance between the yellow crosses and the blue dots represents the residuals, that is, the error between the predicted and actual values. Formally, this can be expressed as:

$$Residual = y - \hat{y} \tag{3}$$

When the yellow crosses completely overlap with the blue dots, the model's prediction is accurate. The larger the vertical deviation, the greater the prediction error for that point.

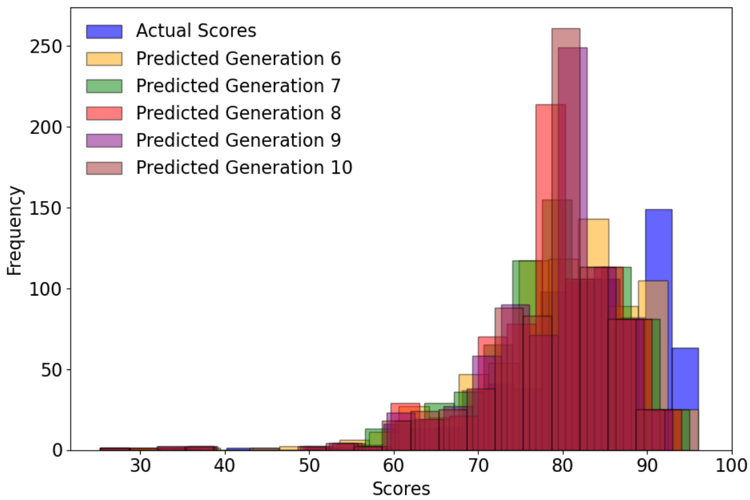

FIGURE 9. Distribution of predicted and actual student scores across cohorts using the XGBoost model

4.4. **Model performance.** In most cases, the positions of the yellow crosses and blue dots are very close, indicating that the model's predictions for these samples are fairly accurate, with small errors. At certain Student Indexes (e.g., in some low-score and high-score regions), the distance between the yellow crosses and the blue dots is noticeably larger, indicating significant errors in the model's predictions for these samples. These errors may reflect systematic bias or may be due to high variance, leading to over fitting or under fitting.

Most of the scores are concentrated between 70 and 90 (where the blue dots and yellow crosses are densely distributed), suggesting that the data distribution is relatively concentrated. In this range, the model's predictions are more accurate, with smaller residuals.

There are relatively few samples with lower scores (<50) and higher scores (>90), which may suggest that the model has weaker generalization ability for these extreme cases, resulting in larger prediction errors.

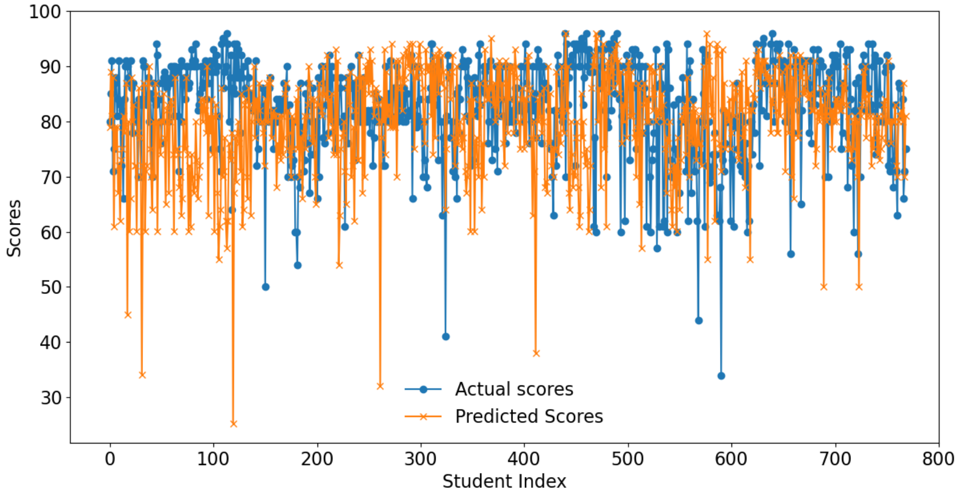

FIGURE 10. Comparison of actual and predicted student scores with residuals

5. Discussion.

5.1. Discussing the differences in the effectiveness of teaching methods.

In this study, despite implementing various approaches to reduce external regulation in teaching, it was found that only a few students were able to adapt to the constructivist education method. This is primarily because most learners lack the intrinsic motivation commonly observed in WEIRD samples. Chinese teacher education trainees often come from disadvantaged families, and their motivation to study is driven by the desire to change their family's social status, forming a socio-cultural interaction motivation. This type of motivation is only weakly linked to intrinsic motivation.

By incorporating the machine learning model XGBoost into the analysis of student performance, this study further revealed the differences in how students adapted to the constructivist education approach. The XGBoost model accurately predicted student outcomes, highlighting their performance in autonomous learning and engagement with constructivist tasks. Although most students displayed average performance, the model's predictions showed significant variation in task scores and final grades for some individuals, indicating that differences in autonomous learning abilities and motivation had a notable effect on the distribution of scores. The machine learning model not only forecasted overall trends but also helped uncover the varying impacts of different teaching methods under diverse cultural and structural conditions.

5.2. Cultural and structural factors in educational theory application.

Within the educational context of this study, particularly in China's primary and secondary school system, the cultivation of intrinsic motivation has not received sufficient attention. Intrinsic motivation is a gradually developing process that requires the support and promotion of the entire educational system, including family, school education, and the overall assessment system [56, 57]. The sudden shift in teaching methods and reduction in external regulation at the university level in China may lead to certain issues. For example, normal students who lack intrinsic motivation may struggle to adapt to the increased demands of autonomous learning, and as a result, may be unable to effectively utilize self-regulation to enhance learning outcomes. They might even resist participating in cooperative learning and social interactions. This situation was clearly reflected in the findings of this study.

Despite the Chinese government's promotion of student-centered constructivist education theory and the 'partial' reforms made to the structural conditions of higher education, the overall educational structure remains constrained by traditional structures and cultural influences.

Firstly, a characteristic of the Chinese university system is the relatively high threshold for admission but a comparatively lenient elimination mechanism; once admitted, students can usually graduate with relative ease. This phenomenon partly stems from the Confucian educational culture, which involved rigorous assessments of scholars but lenient elimination policies [54]. However, this 'difficult to enter, easy to graduate' system design may lead students to become highly dependent on external regulation.

Secondly, the Chinese education authorities increasingly use postgraduate admission rates as a key indicator of university teaching quality. This practice is related to the Confucian educational system, where government departments evaluated academies based on their success rates in the imperial examinations [58]. Some studies [59] have pointed out that these structural conditions force many Chinese universities to focus more on exam preparation, prioritizing students' employability over the development of critical thinking skills. Therefore, as an external regulating force, universities tend to emphasize employability rather than the cultivation of critical thinking.

These structural and cultural conditions are significantly different from those in Western universities and may have a negative impact on the self-regulation abilities of normal students. This impact is evident in the Chinese higher education context, where students sometimes express reservations about reforms in teaching methods. For example, studies [60] have shown that some students show little interest in Vygotsky's advocated social collaborative learning methods, particularly group work. This finding is supported by Cohen and Lotan's [61] research on heterogeneous classrooms in primary and secondary schools. This study also found that classroom presentation activities in constructivist teaching were not particularly popular among Chinese teacher education trainees, who displayed limited participation in these social collaborative activities, primarily to complete basic tasks.

From the perspective of the morphogenetic cycle, Chinese teacher education trainees make choices and adjustments based on their desires, needs, and abilities when faced with changes in structural and cultural factors. This helps to explain the findings by Loyalka et al. [7], which indicated a decline in critical thinking abilities among Chinese university students. Critical thinking requires the ability to question and challenge existing knowledge and viewpoints by identifying biases, assumptions, and weaknesses in the evidence [62]. Individuals growing up in WEIRD environments typically engage in autonomous learning within a relatively relaxed external regulatory environment and are familiar with social collaborative learning methods. In contrast, non-WEIRD samples, such as Chinese teacher education trainees, remain influenced by socio-cultural interaction regulation and socio-cultural interaction motivation when confronted with changes in teaching methods.

The machine learning model also highlighted the impact of different cultural and structural conditions on teaching effectiveness. In the Chinese education system, cultural and structural factors deeply influence student behavior and learning motivation. By analysing the differences between model predictions and actual outcomes, this study found that, under strong teacher regulation, student performance variability was minimal. In contrast, under the constructivist teaching model, individual differences in performance significantly increased. This reflects the moderating role of cultural and structural conditions on the effectiveness of different teaching methods.

Constructivist education theory [63] posits that if external motivation can provide support, feedback, and autonomy while aligning with an individual's intrinsic motivation, these measures can effectively promote self-motivation, thereby enhancing learning and work achievements. However, socio-cultural interaction motivation also impacts learners. Human agency is achieved through reflection and internal dialogue [64]. This study reveals how learners reflect on their learning process and develop action strategies under changing conditions of agency. Even if they are not beginners, as Kirschner et al. [39] suggested, they still adopt the learning patterns mentioned above, which affects the development of their critical thinking skills. If constructivist education theory incorporates a socio-cultural interaction perspective, it should enable a more comprehensive understanding of learner behavior from different cultural backgrounds, thereby broadening its applicability.

Although Lord [36]found in his experiment within an environmental science course that students in constructivist classrooms performed significantly better in exams and rated higher in terms of course engagement and satisfaction, the results of this study also support this conclusion. However, the proportion of students failing in the experimental group was relatively higher. This suggests that, within the sample of Chinese teacher education trainees, while the constructivist approach benefits some students, it may pose challenges for those unaccustomed to this style of learning. Comparing this with Lord's findings indicates that the effectiveness of the constructivist approach needs further consideration of the cultural and educational conditions in different societies.

Furthermore, while Lord's [36]study emphasized the effectiveness of student-centered activities, this study found that Chinese teacher education trainees, who are accustomed to strong teacher regulation, may require additional support to adapt to the constructivist learning method. In the experimental group, despite interventions to increase engagement, no significant effects were observed.

Finally, this study, based on a larger sample size than Lord's, also provided a detailed analysis of the distribution of grades on a five-level scale in the experimental group and conducted interviews with some students using a *morphogenetic approach*. This analysis highlighted the specific impact of the constructivist teaching method on students across different performance levels. Such detailed analysis offers richer data support and interpretation of the results. Additionally, from a morphogenetic perspective, this study suggests that the implementation of constructivist education theory must take into account the influence of China's educational structure and culture on individuals, providing more practical recommendations for future educational practice.

5.3. **Integrating insights from machine learning and the morphogenetic approach.** The integration of the *morphogenetic approach* and machine learning predictions in this study provides complementary insights into the effectiveness of constructivist education theory. While the *morphogenetic approach* reveals the underlying socio-cultural factors influencing student learning behavior, the XGBoost model offers a precise prediction of individual performance, highlighting patterns of engagement, autonomy, and intrinsic motivation.

The machine learning model, particularly through the residual analysis (as seen in Figure 10), shows that students with higher residuals—those whose predicted performance deviates significantly from their actual scores—are often those who struggle the most under constructivist teaching methods. These prediction errors may not simply be computational anomalies, but instead reflect deeper socio-cultural challenges that align with findings from the morphogenetic analysis. For instance, the model's higher residuals among students from rural backgrounds or those less familiar with autonomous learning may indicate that these students are constrained by structural conditions, such as traditional rote-learning methods prevalent in their early education.

This alignment between the morphogenetic insights and the machine learning results suggests that the variability in student performance under constructivist teaching can be partially explained by their socio-cultural backgrounds. The students' reliance on external motivation, as identified by the *morphogenetic approach*, was captured by the XGBoost model's prediction of lower performance in autonomous learning tasks. This reflects the difficulty some students face when transitioning from teacher-centered to student-centered pedagogies, especially when these students are culturally conditioned to seek external validation rather than self-regulation.

The combination of these approaches not only strengthens the validity of the findings but also highlights the limitations of applying constructivist education theory in a non-WEIRD context. The machine learning model identifies specific groups of students (e.g., those from lower socio-economic backgrounds) who may require additional support and differentiated strategies, aligning with the morphogenetic view that structural and cultural factors shape student agency and learning outcomes. This suggests that while constructivist methods have potential, they may need to be adapted to better align with the cultural and structural realities of non-WEIRD contexts, ensuring that students are not left behind due to a mismatch between pedagogical expectations and their socio-cultural experiences.

Ultimately, the predictive insights from machine learning reveal important trends that, when interpreted through the lens of the *morphogenetic approach*, deepen our understanding of the interplay between cultural, structural, and individual factors in shaping educational outcomes. This combined framework provides a more comprehensive approach for evaluating and refining educational methods, particularly for diverse student populations with varying degrees of familiarity with constructivist principles.

6. **Conclusion.** This study compared the application of teacher-centered and constructivist teaching methods among Chinese teacher education trainees and found significant differences in student performance between the two groups. While the experimental group using constructivist methods had a higher proportion of students achieving excellent grades, it also showed a higher failure rate compared to the control group. These results indicate that although constructivist education theory shows potential in Chinese universities, its implementation may be challenging on a wider scale. The variation in performance suggests that constructivist methods may not fully cater to all students, especially those lacking intrinsic motivation and autonomous learning skills, which are crucial for success in such an approach.

The introduction of the XGBoost machine learning model provided further insights into the diversity of student performance. By analyzing historical data, the model successfully predicted future student outcomes with a high degree of accuracy, particularly in managing complex datasets. The findings showed that while most students' scores were concentrated in the middle to high range, individual differences, especially under the constructivist teaching model, became more pronounced. These variations in performance highlight the significance of autonomous learning abilities and intrinsic motivation, reinforcing the need to consider these factors when implementing constructivist methods. The application of machine learning in educational prediction thus presents new avenues for improving teaching strategies by identifying student needs and optimizing educational interventions.

Moreover, the integration of machine learning insights with the morphogenetic approach provided a richer understanding of how cultural and structural factors influence learning outcomes. The residuals identified by the XGBoost model pointed to groups of students who struggled more with constructivist teaching, reflecting deeper socio-cultural challenges that hindered their adaptation to autonomous learning. These findings suggest that future educational reforms in China must consider not only the pedagogical approach but also the cultural and structural context in which students learn.

Therefore, future educational practice should explore a balanced application of teacher-centered and constructivist teaching methods to better meet the diverse needs of students. At the same time, the application of machine learning technology in education, particularly in predicting student performance and optimizing teaching strategies, offers new perspectives and tools. Further research should expand the sample size and introduce more variables to explore the broader application and effectiveness of machine learning in different educational contexts.

This study, employing a morphogenetic approach, emphasizes that the structural and cultural conditions of the Chinese education system profoundly influence student learning behaviors. The constructivist approach, while promising, encounters challenges when applied in a context where students' learning motivation is more externally driven. The Confucian cultural emphasis on academic success as a means of social mobility, combined with authoritative teaching environments, suggests that many students may struggle to fully engage with methods that rely heavily on intrinsic motivation. Therefore, the widespread adoption of constructivist education theory must carefully account for these cultural and structural factors to be effective.

It is important to acknowledge that this study's sample was limited to Chinese teacher education trainees, which may not fully represent the broader student population across Chinese universities. Consequently, the findings may not be general sable to all educational contexts in China. Future research should aim to include a wider range of student groups and settings to validate the applicability and effectiveness of constructivist education theory, especially in combination with machine learning models, across various cultural and structural conditions. Expanding the scope of the study could offer deeper insights into how these educational strategies can be optimized to support diverse student needs in different environments.

REFERENCES

[1] E. von Glasersfeld, *Radical constructivism: A way of knowing and learning*, The Falmer Press, London, 1995.

[2] M. B. Horn and H. Staker, *Blended: Using disruptive innovation to improve schools*, Jossey-Bass, San Francisco, 2015.

[3] C. J. Bonk, *The world is open: How web technology is revolutionizing education*, Jossey-Bass, San Francisco, 2009.

[4] J. Henrich, S. J. Heine, and A. Norenzayan, & Norenzayan, A. "The weirdest people in the world?" *Behavioral and Brain Sciences*, vol. 33, no. 2-3, pp. 61-83, 2010.

[5] J. Henrich, *The Weirdest people in the world: How the West became psychologically peculiar and particularly prosperous*, Farrar, Straus and Giroux, New York, 2020.

[6] J. Zajda, & Majhanovich (Eds.), *Globalization, cultural identity and nation-building: The changing paradigms*, Springer, Cham, 2021.

[7] P. Loyalka, O.-L. Liu, G. Li, E. Kardanova, I. Chirikov, S. Hu, N. Yu, L. Ma, F. Guo, T. Beteille, N. Tognatta, L. Gu, G. Ling, D. Federiakin, H. Wang, S. Khanna, A. Bhuradia, Z. Shi, and Y. Li, "Skill levels and gains in university STEM education in China, India, Russia and the United States," *Nature Human Behaviour*, vol. 5, no. 8, pp. 892-904, 2021.

[8] C. Tan, "Confucianism and education." In Noblit, G. (Ed.), *Oxford Research Encyclopedia of Education*, pp. 1-18, 2017.

[9] B.-S. Chen, "Speech at the national conference on undergraduate education in higher education in the new era (in Chinese)," *Higher Education in China*, no. Z3, pp. 4-10, 2018.

[10] Y.-J. Chiu, Y. Yuan, and S.-R. Jian, "Design and research of robotic arm recovery and grasping system based on machine vision." *Journal of King Saud University-Computer and Information Sciences*, vol. 36, article 102014, pp. 1-21, 2024.

[11] K.-K. Sun, J.-W. Huang, Y.-Y. Yuan, and M.-Y. Chen, "Classification and Recognition of the Nantong Blue Calico Pattern Based on Deep Learning," *Journal of Engineered Fibers and Fabrics*, vol. 19, pp. 1–17, 2024.

[12] K.-K. Sun, M. Gao, and B. Li, "Research on two interpolation algorithms for anthropometric data completion — a case study on the data of elderly males in Fujian, China," *Journal of Network Intelligence*, vol. 7, No. 4, pp. 1083-1101, 2022.

[13] Y.-J. Chiu, W.-Z.-Y. Wang, C. Hu, S.-Y. Lien, and B.-R. Zhang, "Maximum power development under varying solar radiation based on hysteresis-loop comparison of selected duty-cycle perturbation algorithms on a mobility scooter," *Journal of Network Intelligence*, vol. 8, No. 4, pp. 1540-1556, 2023.

[14] A. Asselman, M. Khaldi, and S. Aammou, "Enhancing the prediction of student performance based on the machine learning XGBoost algorithm," *Interactive Learning Environments*, vol. 31, no. 6, pp. 3360–3379, 2021.

[15] Y.-X. Gu, Y.-J. Chiu, and Y.-J. Shih, "Application of convolutional block attention module in marine biodiversity research using convolutional blocks: A deep learning method for pike genus recognition," *Journal of Network Intelligence*, vol. 9, No. 4, pp. 2438-2458, 2024.

[16] L. M. Nkomo and M. Nat, "Student engagement patterns in a blended learning environment: An educational data mining approach," *TechTrends*, vol. 65, pp. 808–817, 2021.

[17] S. Hakkal and A. A. Lahcen, "XGBoost to enhance learner performance prediction," *Computers and Education: Artificial Intelligence*, vol. 7, Article 100254, 2024.

[18] E. L. Deci and R. M. Ryan, *Intrinsic motivation and self-determination in human behavior*, Springer, New York, 1985.

[19] C. T. Fosnot, (Ed.). *Constructivism: Theory, perspectives, and practice* (2nd ed.), Teachers College Press, New York, 2005.

[20] J. Piaget, *The psychology of intelligence*, Routledge & Kegan Paul, London, 1950.

[21] E. L. Deci and R. M. Ryan, "The 'what' and 'why' of goal pursuits: Human needs and the self-determination of behavior," *Psychological Inquiry*, vol. 11, no. 4, pp. 227-268, 2000.

[22] J. Reeve, "Self-determination theory applied to educational settings." In E. L. Deci & R. M. Ryan (Eds.), *Handbook of self-determination research*, pp. 183-203, University of Rochester Press, Rochester, New York, pp. 183–203, 2002.

[23] D. H. Schunk, *Learning theories: An educational perspective* (6th ed.), Pearson, Boston, 2012.

[24] B. L. McCombs, "The role of the self-system in self-regulated learning," *Contemporary Educational Psychology*, vol. 11, no. 4, pp. 314-332, 1986.

[25] J. Reeve, "Teachers as facilitators: What autonomy-supportive teachers do and why their students benefit," *The Elementary School Journal*, vol. 106, no. 3, pp. 225-236, 2006.

[26] J. Zajda, *Globalization and education reforms: Creating effective learning environments*, Springer, Cham, 2021.

[27] P. R. Pintrich, "Continuities and discontinuities: Future directions for research in educational psychology," *Educational Psychologist*, vol. 29, no. 3, pp. 137–148, 1994.

[28] B. J. Zimmerman, "Models of self-regulated learning and academic achievement." In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theory, research, and practice*, pp. 1-25, Springer, New York, 1989.

[29] B. J. Zimmerman, "Becoming a self-regulated learner: An overview," *Theory into Practice*, vol. 41, no. 2, pp. 64-70, 2002.

[30] J. D. Vermunt and N. Verloop, "Congruence and friction between learning and teaching," *Learning and Instruction*, vol. 9, no. 3, pp. 257-280, 1999.

[31] J. D. Vermunt and V. Donche, "A learning patterns perspective on student learning in higher education: State of the art and moving forward," *Educational Psychology Review*, vol. 29, no. 2, pp. 269–299, 2017.

[32] R. E. Slavin, "Cooperative learning and academic achievement: Why does groupwork work?" *Anales de Psicología*, vol. 30, no. 3, pp. 785-791, 2014.

[33] L. S. Vygotsky, *Mind in society: The development of higher psychological processes*, M. Cole, V. John-Steiner, S. Scribner, & E. Souberman (Eds.), Harvard University Press, Cambridge, 1978.

[34] D. W. Johnson and R. T. Johnson, "An educational psychology success story: Social interdependence theory and cooperative learning," *Educational Researcher*, vol. 38, no. 5, pp. 365-379, 2009.
[35] R. K. Shah "Effective constructivist teaching learning in the classroom," *International Journal of Education*, vol. 7, no. 4, pp. 1-13, 2019.
[36] T. R. Lord, "101 reasons for using cooperative learning in biology teaching," *The American Biology Teacher*, vol. 63, no. 1, pp. 30-38, 2001.
[37] J. Brophy and T. Good, "Teacher behavior and student achievement." In M. C. Wittrock (Ed.), *Handbook of research on teaching* (3rd ed.), pp. 328-375, McMillan, New York, 1986.
[38] J. Hattie, *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*, Routledge, London, 2009.
[39] P. Kirschner, J. Sweller and R. E. Clark, "Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching," *Educational Psychologist*, vol. 41, no. 2, pp. 75-86, 2006.
[40] D. Y.-F. Ho, "Chinese patterns of socialization: A critical review." In M. H. Bond (Ed.), *The psychology of the Chinese people*, pp. 1–37, Oxford University Press, Oxford, 1986.
[41] F. Salili and K.-T. Hau, "The effect of teachers' evaluative feedback on Chinese students' perception of ability: A cultural and situational analysis," *Educational Studies*, vol. 20, no. 2, pp. 223-236, 1994.
[42] S. R. Sirin, "Socioeconomic status and academic achievement: A meta-analytic review of research," *Review of Educational Research*, vol. 75, no. 3, pp. 417-453, 2005.
[43] M. Dahl, *Failure to thrive in constructivism: A cross-cultural malady*, Sense Publishers, Rotterdam, 2010.
[44] M. S. Archer, *Realist social theory: The morphogenetic approach*, Cambridge University Press, Cambridge, 1995.
[45] M. S. Archer, *Culture and agency: The place of culture in social theory* (Revised ed.), Cambridge University Press, Cambridge, 1996.
[46] I. Miyazaki, *China's examination hell: The civil service examinations of Imperial China*, Weatherhill, New York, 1976.
[47] K.-K. Hwang, *Foundations of Chinese psychology: Confucian social relations*, Springer, New York, 2012.
[48] X. Zeng, *Educational assessment in China: Lessons and prospects*, Hong Kong University Press, Hong Kong, 1999.
[49] S. Hu, "Hu Shih." In *Living philosophies* (2nd ed.), pp. 235-263, Simon & Schuster, New York, 1931.
[50] M.-L. Chiang, *Tides from the West: A Chinese autobiography*, Yale University Press, New Haven, 1947.
[51] D. Reynolds, *China, 1898-1912: The Xinzheng revolution and Japan*, Harvard University Press, Cambridge, 2001.
[52] T. B. Weston, *The power of position: Beijing University, intellectuals, and Chinese political culture, 1898-1929* (1st ed.), University of California Press, Berkeley, 2004.
[53] R.-S. Qi, *Chinese scholarly honor* (in Chinese), Liaoning Education Press, Shenyang, 2006.
[54] B. A. Elman, *A cultural history of civil examinations in late Imperial China*, University of California Press, Berkeley, 2000.
[55] M. G. R. Voskoglou, *Finite Markov Chain and fuzzy logic assessment models: Emerging research and opportunities*, CreateSpace Independent Publishing Platform, Columbia, 2017.
[56] R. M. Milgram, *Counseling gifted and talented children: A guide for teachers, counselors, and parents*, Ablex Publishing Corporation, Norwood, 1991.
[57] J. Dewey, *Democracy and education: An introduction to the philosophy of education*, Macmillan, New York, 1916.
[58] B.-Z. Wang, *Ancient Chinese Academies* (in Chinese), The Commercial Press, Beijing, 1998.
[59] Y.-S. Liu, "Free choice and institutional selection: elite cultivation in the era of mass higher education–a case study based on Peking University" (in Chinese), *Peking University Educational Review*, vol. 15, no. 4, pp. 38-74+186, 2017.
[60] Y.-G. Wang, "An analysis of the pros and cons of the group discussion model of case teaching" (in Chinese), *Journal of Chongqing Institute of Science and Technology (Social Science Edition)*, no. 5, pp. 180-183, 2011.
[61] E. G. Cohen and R. A. Lotan, *Designing group work: Strategies for the heterogeneous classroom* (3rd ed.), Teachers College Press, New York, 2014.
[62] R. J. Sternberg and D. F. Halpern, *Critical thinking in psychology* (2nd ed.), Cambridge University Press, Cambridge, 2020.

[63] E. L. Deci, R. Koestner and R. M. Ryan, "A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation," *Psychological Bulletin*, vol. 125, no. 6, pp. 627-668, 1999.

[64] M. S. Archer, *Being human: The problem of agency*, Cambridge University Press, Cambridge, 2000.