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Layered Progressive Teaching Model: An Empirical Study on Engineering Fluid Mechanics Course

Juan Fu[1,a,*], Zhenhuan Ye[1,b], Ming Lv[2,c]

[1]School of Engineering, Zunyi Normal University, Zunyi, 563006, China
[2]School of Mechanical, Electronic and Control Engineering, Beijing Jiaotong University, Beijing, 100044, China
[a]fujuan@outlook.com, [b]yzh@zync.edu.cn, [c]minglv@bjtu.edu.cn
[*]Corresponding author

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Abstract: Engineering fluid mechanics is a challenging foundational course due to its high cognitive demands. This study introduces the "Layered Progressive Teaching Model" (LPTM), integrating Bloom's Taxonomy with Cognitive Load Theory. The model establishes a comprehensive framework through three key mechanisms: cognitive objective layering, progressive teaching activities, and collaborative feedback and evaluation. A quasi-experimental design at an undergraduate institution compared an experimental group (N=51) with a control group (N=69). Results showed that the experimental group significantly outperformed the control group in homework, final exam scores, and overall performance, with effect sizes of 1.64, 1.72, and 2.09, respectively. These findings demonstrate the model's effectiveness in improving student learning outcomes and provide insights for teaching reforms in complex engineering courses.

1. Introduction

Engineering education faces increasing challenges in fostering systems thinking and enhancing students' ability to solve complex problems. As engineering challenges become increasingly intricate, the demand for high-quality talent continues to rise. Engineering fluid mechanics, a foundational course in disciplines such as mechanical, chemical, and civil engineering, plays a crucial role in cultivating systems thinking and engineering problem-solving skills [1,2]. This course, characterized by theoretical abstraction, complex models, and multidimensional concepts, presents significant cognitive challenges while demanding advanced systems thinking and practical innovation capabilities [3].

Traditional lecture-based teaching methods have shown limitations in addressing these challenges. These approaches often lead to passive learning, hindering students' ability to systematically analyze and think critically about real-world engineering problems [4]. Current course designs frequently neglect students' cognitive development processes and fail to effectively balance knowledge transfer with skill cultivation [5]. Consequently, innovative teaching models grounded in cognitive development theory have become essential for engineering education reform, particularly in high-cognitive-load courses like fluid mechanics.

Bloom's Taxonomy and Cognitive Load Theory provide robust theoretical foundations for addressing these challenges. Bloom's Taxonomy outlines six cognitive levels—remembering, understanding, applying, analyzing, evaluating, and creating—offering a framework for progressive cognitive development [6, 7]. Studies have shown that active learning strategies based on this taxonomy significantly enhance critical thinking and problem-solving abilities in engineering education [8, 9]. Complementarily, Cognitive Load Theory focuses on optimizing learning resource allocation, providing crucial insights for task design in complex engineering courses [10]. Despite their widespread application, current research often focuses on single-theory approaches [11, 12].

To address these gaps, this study proposes a "Layered Progressive Teaching Model (LPTM)" for engineering fluid mechanics. This model organically integrates Bloom's Taxonomy and Cognitive Load Theory, establishing a comprehensive framework that encompasses cognitive objective layering, progressive teaching activities, and collaborative evaluation feedback. Through rigorous empirical methods [13], the study employs a quasi-experimental design to evaluate the model's effectiveness in enhancing students' learning outcomes and cognitive development. The results provide both theoretical guidance and practical paradigms for reforming high-cognitive-load engineering courses.

2. The Layered Progressive Teaching Model

Engineering Fluid Mechanics requires teaching reforms that effectively support students' cognitive development while optimizing learning resources. This study introduces the "Layered Progressive Teaching Model," which integrates Bloom's Taxonomy and Cognitive Load Theory to create a comprehensive instructional framework.

2.1. Theoretical Foundation and Model Construction

The model's theoretical foundation draws on established educational theories. Bloom's Taxonomy provides a framework for cognitive development, classifying cognitive processes into six levels: remembering, understanding, applying, analyzing, evaluating, and creating [6,7]. Cognitive Load Theory further enriches this foundation by providing principles for optimizing instructional design [10], particularly in complex learning environments like engineering education.

These theoretical perspectives have shown significant impact in engineering education. Research has demonstrated their effectiveness in improving students' conceptual understanding and problem-solving abilities [12, 14]. The multimedia learning principles derived from these theories [15] provide additional support for designing effective instructional strategies.

2.2. Integrated Framework Development

This study proposes a comprehensive framework, "Cognitive Objective Layering, Progressive Teaching Activities, Collaborative Evaluation Feedback," which deeply integrates Bloom's Taxonomy with Cognitive Load Theory.

(1) Cognitive Objective Layering: This mechanism establishes clear pathways for cognitive development, with objectives carefully structured to support progressive learning. Tasks are designed to balance cognitive demands at each stage, ensuring effective knowledge construction while avoiding cognitive overload.

(2) Progressive Teaching Activities: These activities translate theoretical objectives into practical learning experiences. Tasks are sequenced to support cognitive development while maintaining appropriate cognitive load levels, enabling students to build complex understanding through

structured progression.

(3) Collaborative Feedback and Evaluation: Continuous feedback mechanisms are integrated throughout the teaching process, enabling dynamic adjustments to both task design and implementation. This iterative process ensures that teaching strategies remain aligned with cognitive objectives while responding to students' learning needs.

2.3. Case Study: Implementation of LPTM in Teaching Bernoulli's Equation

The teaching of Bernoulli's equation provides an illustrative case study for implementing the LPTM framework. As a fundamental principle in fluid mechanics, Bernoulli's equation expresses the relationship between pressure, velocity, and elevation in fluid flow systems, making it both conceptually important and practically challenging for engineering students.

In implementing cognitive objective layering, the teaching process began with establishing a solid understanding of the equation's physical foundation. Students were first guided to comprehend how Bernoulli's equation represents energy conservation in fluid flow, expressing the relationship between pressure head, velocity head, and elevation head. Through visual simulations and demonstrations, students grasped the energy transformation process along streamlines. Critical assumptions, including steady flow, inviscid flow, and flow along a streamline, were emphasized to ensure proper application boundaries were understood.

The progressive teaching activities then advanced to practical applications through a carefully structured sequence. In pre-class preparation, students engaged with interactive modules demonstrating energy conservation principles and completed online assessments to ensure readiness for in-class activities. During class sessions, instruction progressed from analyzing simple pipe flow systems to more complex configurations. Students worked through industrial cases involving pipe networks, pump systems, and flow measurement devices, with difficulty levels increasing gradually to maintain optimal cognitive load.

As students developed proficiency, they advanced to higher-order applications through team-based projects. These projects required students to design and optimize fluid systems, such as pump networks or ventilation systems, using computational fluid dynamics (CFD) software for validation. This phase integrated multiple concepts beyond Bernoulli's equation, including considerations of head loss, pump selection, and system optimization, challenging students to develop comprehensive engineering solutions.

The feedback system operated continuously throughout this process. Digital response systems provided immediate feedback on concept understanding, allowing for rapid identification and correction of misconceptions. Weekly assignments progressively built from basic calculations to complex system analysis, while design projects evaluated both technical accuracy and innovative thinking. Student performance data and reflections guided ongoing adjustments to teaching strategies and task difficulty levels.

This implementation of LPTM in teaching Bernoulli's equation demonstrated how structured cognitive progression, coupled with appropriate feedback mechanisms, can enhance students' ability to move from basic comprehension to sophisticated engineering applications. The effectiveness of this approach is further supported by the experimental results presented in subsequent sections, particularly in students' improved performance on complex problem-solving tasks.

3. Research Methods

3.1. Experimental Design

The study was conducted at an applied undergraduate university, involving two Engineering

Fluid Mechanics classes: an experimental group (N = 51) and a control group (N = 69). To ensure internal validity, both groups were taught by the same instructor and followed identical course content and schedules over one semester (32 class hours). The experimental group implemented the LPTM framework, while the control group followed traditional lecture-based instruction. Students in both groups shared similar academic backgrounds, being from the same major and year of study.

3.2. Data Collection and Analysis Framework

The study employed a comprehensive assessment framework that captured multiple dimensions of student performance. The performance indicators and their respective contributions to the composite score are as follows: (1) Classroom Performance: Based on student participation in discussions, asking questions, and providing answers, accounting for 10% of the composite score. (2) Homework Assignments: Evaluated for accuracy, depth, and timeliness of submissions, contributing 20% to the composite score. (3) Rain Classroom Quiz Results: Real-time quiz responses tracked on the platform to assess immediate learning outcomes, contributing 20% to the composite score. (4) Final Exam Scores: A closed-book exam that measures students' understanding and ability to apply knowledge in complex contexts, contributing 50% to the composite score.

Statistical analysis followed a systematic approach to ensure a robust evaluation of the teaching model's effectiveness. The analysis protocol included: (1) normality testing using the Shapiro-Wilk test to determine appropriate statistical methods; (2) Mann-Whitney U tests for non-normally distributed data and independent-samples t-tests for normally distributed data; (3) effect size calculations using Cohen's d to assess the practical significance of observed differences; and (4) descriptive statistical analysis to summarize performance patterns across all indicators.

4. Results

This study evaluated the effectiveness of the Layered Progressive Teaching Model (LPTM) by comparing experimental and control groups across multiple performance indicators. The analysis demonstrates the model's impact on students' academic outcomes in this high-cognitive-load course.

4.1. Descriptive Statistics

Table 1 shows that the experimental group outperformed the control group across all performance indicators. The experimental group achieved a higher mean composite score of 79.771 (±7.494), compared to the control group's 64.300 (±7.333). Notable improvements were observed in final exam scores (35.529 vs. 24.050) and homework assignments (18.819 vs. 16.409).

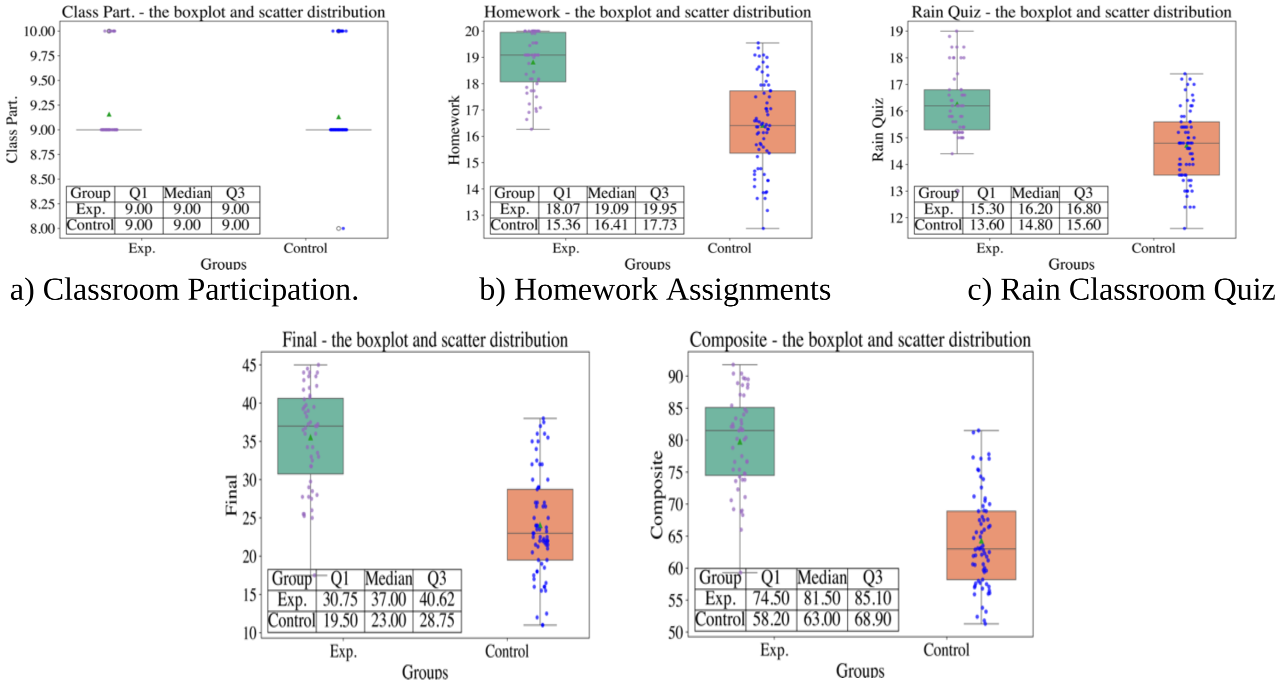
Figure 1 presents the boxplots and scatter distributions for the experimental and control groups across these performance indicators. These visualizations highlight the central tendencies and distribution patterns within the groups.

From Figure 1, the following observations can be made.

(1) Classroom Participation: Similar distributions between groups, with overlapping interquartile ranges. (2) Homework Assignments: Experimental group showed higher scores with tighter distribution. (3) Rain Classroom Quiz: Experimental group demonstrated higher median scores with less variability. (4) Final Exam: Clear advantage for experimental group in both median and upper quartile scores. (5) Composite Scores: Notably higher scores for experimental group with narrower distribution.

Table 1: Means and Variances of Indicators for the Experimental and Control Groups.

	Experimental Group		Control Group	
	Mean	STD	Mean	STD
Classroom Participation	9.157	0.367	9.130	0.380
Homework Assignments	18.819	1.091	16.409	1.697
Rain Classroom Quiz	16.270	1.262	14.710	1.324
Final Exam	35.529	6.550	24.050	6.771
Composite Scores	79.771	7.494	64.300	7.333



a) Classroom Participation. b) Homework Assignments c) Rain Classroom Quiz

d) Final Exam e) Composite Scores

Figure 1: The boxplots and scatter distributions of five performance indicators.

4.2. Statistical Inference

A Shapiro-Wilk normality test was conducted to determine the appropriate statistical methods for further analysis. Table 2 summarizes the normality results for both the experimental and control groups.

Table 2: Shapiro-Wilk Normality Test Results.

	Experimental Group		Control Group	
	p-value	Normality Conclusion	p-value	Normality Conclusion
Classroom Participation	0.0000	Non-normal	0.0000	Non-normal
Homework Assignments	0.0002	Non-normal	0.2979	Normal
Rain Classroom Quiz	0.0193	Non-normal	0.6724	Normal
Final Exam	0.0246	Non-normal	0.0572	Normal
Composite Scores	0.1540	Normal	0.1094	Normal

Based on the Shapiro-Wilk normality test results (as shown in Table 2), appropriate statistical methods were selected for analysis. Significance tests revealed the following results, as summarized in Table 3.

Table 3: Significance test results.

	Statistical Test	p-value	Significance Conclusion
Classroom Participation	Mann-Whitney U test	0.7246	Not significant
Homework Assignments	Mann-Whitney U test	0.0000	Significant
Rain Classroom Quiz	Mann-Whitney U test	0.0000	Significant
Final Exam	Mann-Whitney U test	0.0000	Significant
Composite Scores	Independent-samples t-test	0.0000	Significant

4.3. Effect Size Analysis

Cohen's d effect sizes were calculated to assess practical significance. As shown in Figure 2, all indicators except classroom participation showed large effect sizes (>0.8), with composite scores demonstrating the highest effect (2.0901).

Effect sizes were interpreted as follows: small (d = 0.2), medium (d = 0.5), and large (d ≥ 0.8).

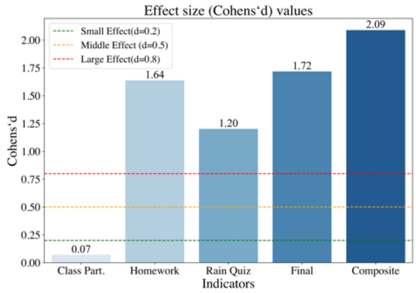


Figure 2: Cohen's d Effect Sizes for Each Indicator.

The statistical analysis confirms LPTM's substantial positive impact on student performance, particularly in areas requiring deeper cognitive processing. However, the minimal effect on classroom participation (d=0.07) suggests the need for additional strategies to enhance in-class engagement.

5. Discussion

The application and effectiveness of the Layered Progressive Teaching Model in engineering fluid mechanics demonstrates significant improvements in student performance through the integration of Bloom's Taxonomy and Cognitive Load Theory. This discussion focuses on the key findings and their implications.

5.1. Key Findings and Theoretical Implications

The experimental results revealed several significant patterns in the implementation of the teaching model. First, the substantial effect sizes observed in homework (d=1.6383), final exams (d=1.7188), and composite scores (d=2.0901) demonstrate comprehensive performance enhancement across multiple assessment dimensions. These improvements strongly suggest that the layered cognitive objectives successfully facilitated progressive skill development across different learning levels, aligning with Bloom's Taxonomy principles of cognitive development progression.

The optimization of task design emerged as another crucial finding, evidenced by strong performance in Rain Classroom quizzes (d=1.2019) indicating effective cognitive load management. The higher quality of homework completion further suggests successful balance between task complexity and student capability, supporting Cognitive Load Theory's emphasis on optimizing instructional design through appropriate task sequencing. This pattern of improvement across different assessment types validates the model's approach to managing cognitive load while maintaining academic rigor.

However, the limited impact on classroom engagement, as shown by the minimal effect on classroom participation (d=0.07), indicates potential areas for improvement in the model. This finding suggests the need for enhanced student-centered strategies within the current framework and highlights the importance of balancing structured progression with active engagement. The contrast between strong academic performance and limited classroom participation provides valuable insights for future model refinement.

5.2. Practical Value of the Theoretical Framework

The "Cognitive Objective Layering — Progressive Teaching Activities — Collaborative Evaluation Feedback" framework demonstrated significant practical value in several aspects. The clear learning pathways established by the model were evidenced by improved performance across various assessment types, suggesting successful implementation of the cognitive development framework. The effectiveness of task progression was shown by consistent performance improvements throughout the semester, particularly in assignments requiring higher-order thinking skills. The dynamic feedback mechanisms incorporated into the model proved particularly successful, as supported by enhanced homework and quiz performance, indicating effective knowledge consolidation and application.

5.3. Limitations and Future Directions

Despite the model's significant effectiveness, several important limitations warrant careful consideration. The implementation scope was limited to a single course at one institution, raising questions about broader generalizability across different engineering disciplines and educational contexts. The limited improvement in classroom participation suggests a need for more effective strategies to enhance student engagement during face-to-face interactions. Additionally, the current assessment framework primarily focused on cognitive outcomes, potentially overlooking important affective and social dimensions of learning.

Looking forward, future research should address these limitations through several key approaches. Implementation should be expanded across multiple institutions and disciplines to validate the model's effectiveness in diverse educational contexts. Enhanced strategies for classroom engagement need to be developed and integrated into the existing framework to promote more active student participation. Longitudinal studies should be conducted to assess the long-term impact of the model on students' professional development and academic achievement. Finally, assessment metrics should be broadened to include affective and social dimensions of learning, providing a more comprehensive understanding of the model's impact on student development.

6. Conclusion

The "Layered Progressive Teaching Model" demonstrates significant effectiveness in improving student performance in engineering fluid mechanics. The experimental results show substantial improvements in academic outcomes, with significant effect sizes in homework assignments, final examinations, and overall performance. The model's success validates the value of integrating

Bloom's Taxonomy with Cognitive Load Theory in designing complex course instruction.

The study provides both theoretical guidance and practical paradigms for engineering education reform. The "Cognitive Objective Layering — Progressive Teaching Activities — Collaborative Evaluation Feedback" framework offers a structured approach for implementing progressive teaching strategies in high-cognitive-load courses. Future research should focus on expanding the model's application across different institutions and disciplines while enhancing classroom engagement strategies.

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