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Knowledge Graph-Assisted Learning: Improving Academic Outcomes and Equity in Engineering Fluid Mechanics

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

[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, [d]25673555@qq.com
[*]Corresponding author

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Abstract: To address the challenges of abstract concepts, complex derivations, and polarized academic performance in Engineering Fluid Mechanics, this study introduces the Engineering Fluid Mechanics Knowledge Graph (EFM-KG), grounded in cognitive load and meaningful learning theories. A quasi-experimental design with non-equivalent control groups compared the final examination scores of an EFM-KG-assisted group (n=51) with a traditional instruction group (n=89). The experimental group's mean score increased by 15.0% (9.53 points), with a 28.1% reduction in standard deviation and a large effect size (Cohen's d=0.80). These findings confirm EFM-KG's effectiveness in enhancing academic performance and promoting educational equity by narrowing achievement gaps. This research provides robust evidence for knowledge graphs in engineering education and insights for optimizing instructional design.

1. Introduction

Engineering Fluid Mechanics (EFM), a core course for mechanical engineering majors, challenges students with abstract concepts and complex mathematical derivations [1, 2]. Students often struggle with misconceptions about abstract concepts that traditional lectures fail to correct [1], limited access to experimental teaching due to equipment and time constraints [2], and difficulties in online learning, such as technical issues and self-directed learning challenges [3]. These factors contribute to polarized academic performance, with some students falling behind due to weak foundations, leading to a "long-tail" score distribution [4]. Recent efforts in engineering education have introduced technologies like virtual simulation experiments [5] and intelligent tutoring systems [6] to improve learning outcomes and equity. However, these technologies often lack structured knowledge representation and personalized support tailored to fluid mechanics, underscoring the need for innovative teaching tools.

Knowledge Graphs (KGs) offer a structured approach to knowledge representation, showing promise in organizing and personalizing learning in science and engineering education [7, 8]. By using node-relationship networks, KGs visualize hierarchical knowledge structures, enabling students to build cognitive frameworks and optimize learning paths [7]. For instance, CourseKG employs deep learning for knowledge visualization and targeted teaching [7], while KG-PLPPM integrates cognitive diagnosis to create personalized learning paths, enhancing efficiency [8]. Yet, KG applications in engineering fluid mechanics remain underexplored, often limited by small sample sizes or weak experimental designs [7], and their potential to reduce cognitive load and promote educational equity is not fully validated.

Grounded in constructivist learning theory [9, 10] and cognitive load theory [11, 12], this study develops and implements the Engineering Fluid Mechanics Knowledge Graph (EFM-KG) to enhance academic performance, conceptual understanding, and cognitive load management. EFM-KG provides a visualized knowledge network as an “advance organizer” to support active exploration of concept relationships [9] and reduce extraneous cognitive load through structured presentation [11]. Using a quasi-experimental design with non-equivalent control groups, this study evaluates EFM-KG’s impact on students’ final grades and score distribution, offering empirical evidence for its application in engineering education and practical insights for optimizing instructional design and reducing achievement gaps.

2. Design and Implementation of EFM-KG

2.1. Theoretical Framework and Design Principles

The Engineering Fluid Mechanics Knowledge Graph (EFM-KG) is grounded in cognitive load theory [11] and meaningful learning theory [9]. Using a <entity-relation-entity> triplet structure, EFM-KG organizes knowledge to reduce extraneous cognitive load and support students in building cognitive structures by visualizing connections between Engineering Fluid Mechanics concepts. The design adheres to four principles: (1) Completeness: Covering core syllabus topics; (2) Hierarchy: Structuring knowledge logically across multiple levels; (3) Interconnectedness: Highlighting dependency and derivation relationships; (4) Operability: Enabling interactive learning and personalized navigation.

2.2. Construction Process

EFM-KG was developed in three stages.

(1) Knowledge Extraction: Core concepts (e.g., ideal fluid, incompressible fluid), equations (e.g., Euler’s, Bernoulli’s, continuity), and applications were identified from the Engineering Fluid Mechanics syllabus and textbook, spanning five modules: Introduction, Fluid Statics, Fluid Kinematics, Ideal Fluid Dynamics, and Dimensional Analysis and Similarity Theory.

(2) Relationship Modelling: Logical relationships, such as theoretical derivations (e.g., Euler’s to Bernoulli’s equation), applications (e.g., Bernoulli’s equation to Venturi tube), and conceptual affiliations, were mapped using solid and dashed lines.

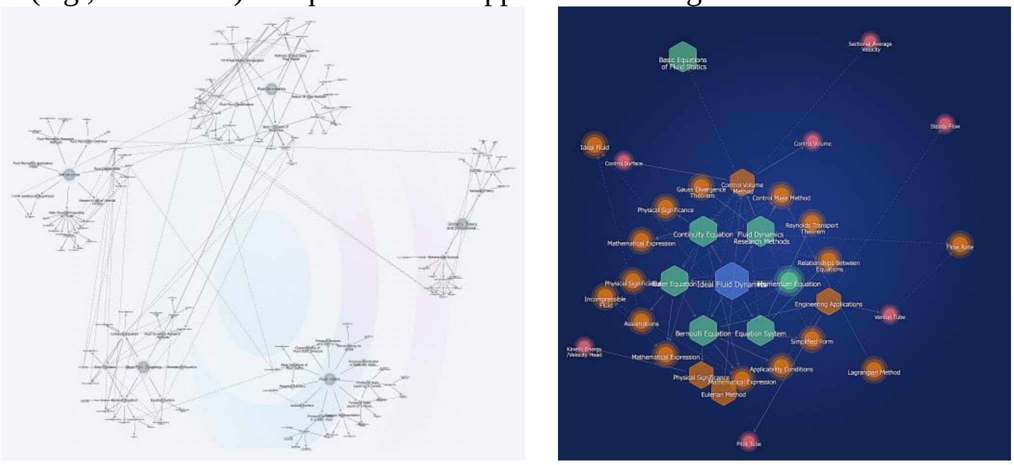
(3) Structure Validation: The prototype graph was deployed on the “Xuexitong” platform, where the teaching team verified node connections, logical accuracy, and knowledge coverage.

2.3. Platform Implementation and Features

Deployed on the “Xuexitong” platform, EFM-KG offers: (1) Visualized Browsing: A node-link network with color- and shape-coded nodes representing knowledge points and lines indicating relationships. Students can click nodes for detailed content. (2) Interactive Exploration: Supports zooming and dragging to navigate from the full course graph to module-specific sub-graphs (e.g., Ideal Fluid Dynamics). (3) Learning Paths: Guides students through logical knowledge progressions via connected paths.

2.4. Knowledge Graph Structure

Figure 1 displays the EFM-KG structure on the “Xuexitong” platform. The complete graph (Figure 1a) integrates five modules: Introduction, Fluid Statics, Fluid Kinematics, Ideal Fluid Dynamics, and Dimensional Analysis and Similarity Theory, linked by core concepts. The Ideal Fluid Dynamics sub-graph (Figure 1b) centres on key theories (e.g., Euler’s and Bernoulli’s equations) and applications (e.g., Venturi and Pitot tubes), illustrating progression from assumptions (e.g., ideal fluid) to equations and applications using solid and dashed lines.



a) Complete course knowledge graph b) Ideal Fluid Dynamics sub-graph

Figure 1: Knowledge graph constructed on the “Xuexitong” platform.

3. Methodology

3.1. Research Design

This study used a non-equivalent group historical control quasi-experimental design to evaluate the impact of EFM-KG on final examination scores of mechanical engineering undergraduates. The experimental group (n=51, 2022 cohort) used EFM-KG on the “Xuexitong” platform alongside traditional lectures, while the control group (n=89, 2021 cohort) received only traditional lectures. To ensure consistency, both groups were taught by the same instructor, used identical textbooks and syllabi, covered core knowledge points, and completed a 16-week course. Control measures included: (1) standardized teaching content and progression; (2) equivalent examination paper design; and (3) blind grading to reduce bias. Examination papers (100 points: 40 multiple-choice, 10 true/false, 10 fill-in-the-blank, 40 subjective) aligned with the syllabus and were validated for content and difficulty by fluid mechanics experts.

3.2. Participants

Participants were third-year mechanical engineering undergraduates enrolled in Engineering Fluid Mechanics. The experimental group (2024-2025 Fall, n=51, 42 males, 9 females, mean age=20.73, SD=1.02) and control group (2023-2024 Fall, n=89, 64 males, 25 females, mean age=20.96, SD=1.25) met selection criteria: (1) registered students; (2) completed the 16-week course; and (3) obtained valid final exam scores. Baseline comparisons showed no significant differences in age (Mann-Whitney U=2455, p=0.404) or gender (χ^2=1.40, p=0.237), ensuring group comparability. Prior academic performance was excluded from analysis, as the focus was on EFM-KG's direct effects, with future studies planned to explore prior abilities' impact.

3.3. Data Collection

Final examination scores (100 points, closed-book) were collected via the academic administration system, aligned with the syllabus. Quality control included: (1) standardized grading with detailed rubrics for objective and subjective questions; and (2) blind grading, with control group papers graded by the course instructor and experimental group papers by an uninvolved colleague. Papers were anonymized (showing only student IDs) to ensure objectivity. Data were stored and processed anonymously, adhering to research ethics and data protection guidelines.

3.4. Statistical Analysis Strategy

Descriptive statistics (mean, standard deviation, median, interquartile range, extreme values) assessed score distribution. Normality was tested using Shapiro-Wilk (supplemented by Kolmogorov-Smirnov), and variance homogeneity with Levene's test. Independent samples t-tests were used for group differences if assumptions were met; otherwise, Welch's t-test with Bootstrap confidence intervals (10,000 resamples) was applied. Effect sizes (Cohen's d, Hedges' g, Glass's Δ) evaluated educational significance, interpreted per Cohen's standards (0.5=medium, 0.8=large). Analyses were conducted in Python with α=0.05 (two-tailed).

4. Results

4.1. Descriptive Statistics

Final examination scores for the Engineering Fluid Mechanics course were collected from 140 students. The control group (2021 cohort, n=89) received traditional lectures, while the experimental group (2022 cohort, n=51) used EFM-KG on the "Xuexitong" platform alongside lectures. Table 1 summarizes descriptive statistics, and Figure 2 shows score distribution

Table 1: Descriptive Statistics of Final Scores

Group	N	Mean	95% CI	SD	Min	Q1	Median	Q3	Max
Ctrl. G	89	63.58	[60.82, 66.34]	13.10	31.00	56.00	62.50	72.00	98.00
Exp. G	51	73.11	[70.46, 75.76]	9.42	51.00	66.00	73.00	80.00	93.00

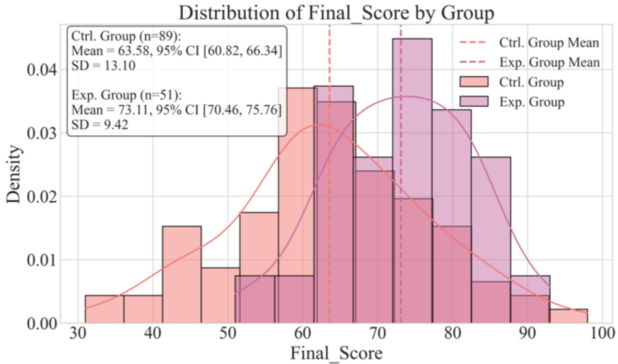


Figure 2: Score Distribution for Control and Experimental Group.

The experimental group's mean score was 9.53 points higher (15.0% increase) than the control group's, with a 28.1% lower standard deviation (9.42 vs. 13.10) and a smaller interquartile range (14.0 vs. 16.0). Figure 2 illustrates the experimental group's scores (purple) concentrated around 70-80 points, approaching normality, while the control group's scores (red) were more dispersed, showing a long-tail in the 40-50 range. Non-overlapping 95% confidence intervals and distinct mean lines confirm the difference.

4.2. Normality and Variance Tests

Table 2 presents the results of normality and variance tests, which guided the selection of the appropriate statistical analysis.

Table 2: Normality, Variance Tests, and Test Selection.

Group	S-W p	K-S p	Normality	Levene's (F, p)	Homogeneity of Variance	Subsequent Test
Ctrl.	0.923	0.922	Met	(3.714, 0.056)	Met	Independent samples t-test / Welch's t-test
Exp.	0.899	0.998	Met			

Normality was confirmed using Shapiro-Wilk (control: p=0.923; experimental: p=0.899) and Kolmogorov-Smirnov tests (control: p=0.922; experimental: p=0.998), as shown in Table 2. Figure 3 (Q-Q plot) shows data points closely aligned with the normal distribution line, with minor deviations at extremes. Levene's test (F=3.714, p=0.056) indicated no significant variance difference, meeting homogeneity assumptions. Figure 4 (residual plot) shows random residual distribution around zero, supporting Levene's results.

Due to the marginal Levene's p-value (0.056) and unequal sample sizes, both independent samples t-test and Welch's t-test were used for robustness.

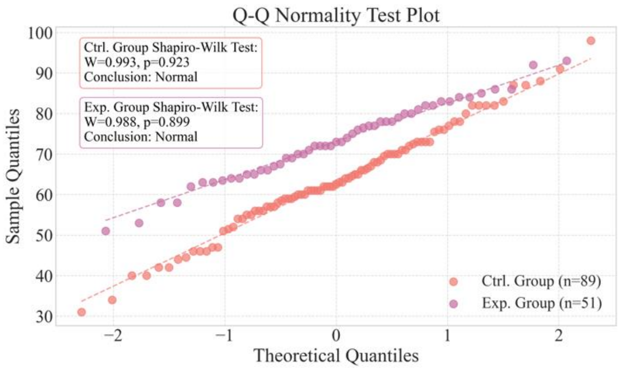


Figure 3: Q-Q Plot of Final Scores.

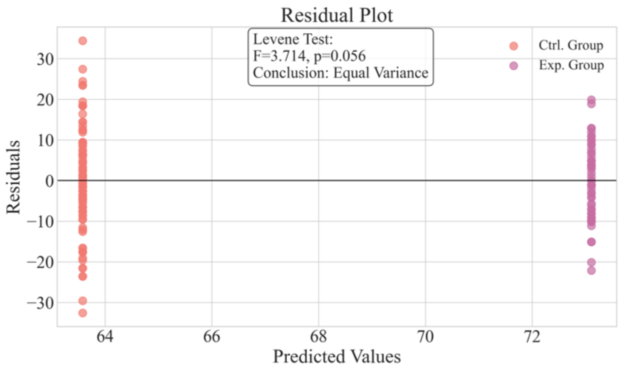


Figure 4: Residual Plot.

4.3. Statistical Tests

Table 3 presents inter-group comparison results.

Table 3: Statistical Test Results.

Test Method	t-value	df	p-value	Mean Difference	95% CI	Conclusion
Independent samples t-test	4.56	138	<0.001	9.529	[5.738, 13.165]*	Significant
Welch's t-test	4.98	130.88	<0.001	9.529	-	Significant

*Based on Bootstrap analysis (10,000 resamples) 95% confidence interval

Both tests confirmed a significant difference ($p<0.001$), with the experimental group's mean score 9.53 points higher. Bootstrap resampling (10,000 resamples) yielded a 95% CI of [5.74, 13.17], excluding zero, reinforcing the result.

4.4. Effect Size Analysis

Effect sizes (Figure 5) showed Cohen's d=0.80 (95% CI: [0.44, 1.16]), Hedges' g=0.80 (95% CI: [0.44, 1.15]), and Glass's Δ=0.73 (95% CI: [0.53, 0.93]), indicating a large effect. Non-zero confidence intervals confirm robustness.

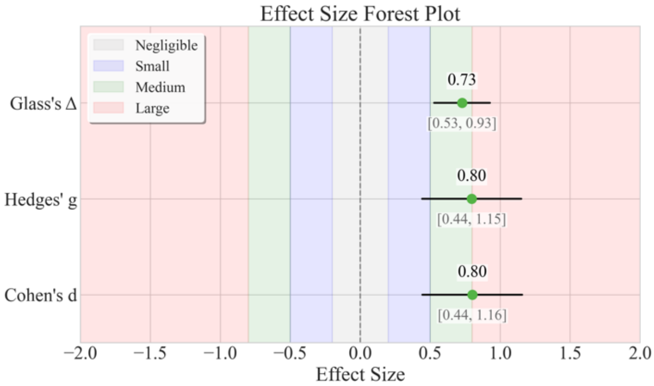


Figure 5: Effect Sizes for Group Differences.

In summary, the experimental group significantly outperformed the control group ($p<0.001$), with a large effect size (Cohen's d=0.80), demonstrating EFM-KG's effectiveness in improving scores and reducing score variability.

5. Discussion

5.1. Main Findings and Literature Comparison

This study used a quasi-experimental design to assess EFM-KG's effectiveness in an Engineering Fluid Mechanics course. The experimental group (n=51) showed a 15.0% (9.53-point) score increase, a 28.1% reduction in standard deviation, and a large effect size (Cohen's d=0.80) compared to the control group (n=89). These results provide strong evidence for knowledge graphs' value in engineering education.

EFM-KG extends prior work. Unlike Li et al. [7], who focused on computer science, EFM-KG succeeds in fluid mechanics, showing broader applicability. Sun et al. [8] improved efficiency via personalized paths but lacked rigorous controls; this study's design strengthens causal inference. While Solmaz et al. [5] used simulations for conceptual understanding, EFM-KG's node-relationship network better organizes knowledge, aligning with Kaye et al. [1] on correcting misconceptions.

5.2. Theoretical Mechanisms

Grounded in constructivist learning theory [9] and cognitive load theory [11, 12], EFM-KG's effectiveness likely stems from: (1) clarifying concept relationships to build cognitive structures; (2) reducing cognitive load via visualized networks; and (3) supporting varied learning styles with text, symbols, and graphics. The 15.0% score increase and 28.1% reduced standard deviation support these mechanisms.

However, cognitive load was not directly measured (e.g., via NASA-TLX), and knowledge structuring lacks quantitative validation. Future studies could use learning analytics, as in Papamitsiou et al. [13], to confirm these pathways. Still, EFM-KG's results align with Ausubel's meaningful learning framework [9]

5.3. Educational Equity and Practical Implications

EFM-KG reduced the score standard deviation by 28.1%, narrowing the achievement gap, especially for struggling students, supporting Theobald et al. [10] on equity in STEM. Its implementation on the "Xuexitong" platform was practical, with low burden on instructors and manageable costs, suggesting scalability.

However, the single-institution sample limits analysis of diverse backgrounds. Future work should test EFM-KG's equity effects across institutions, accounting for varied student foundations and resources.

5.4. Limitations and Future Research Directions

This study has limitations. First, the quasi-experimental design cannot fully rule out time-related or cohort differences (e.g., baseline abilities). Randomized controlled trials and covariance analysis could improve validity. Second, the single-institution sample limits generalizability; multi-institutional studies are needed to test EFM-KG across contexts. Third, relying on exam scores misses deeper impacts; future work should assess conceptual understanding, problem-solving, and motivation, possibly via qualitative methods. Finally, short-term focus warrants longitudinal studies on retention and transfer, alongside integration with AI or virtual reality.

Despite these, rigorous controls and analysis affirm EFM-KG's instructional value.

6. Conclusion

This study confirms EFM-KG's effectiveness in an Engineering Fluid Mechanics course through a quasi-experimental design. The experimental group (n=51) achieved a 15.0% (9.53-point) score increase, a large effect size (Cohen's d=0.80), and a 28.1% reduction in score standard deviation compared to the control group (n=89). These results highlight EFM-KG's ability to enhance academic performance and promote educational equity by reducing achievement gaps, particularly for struggling students.

EFM-KG's visualized, structured knowledge representation offers an intuitive learning path, likely fostering deeper understanding and problem-solving skills. Its hierarchical design supports progression from basic concepts to applications, providing a model for teaching abstract engineering topics.

Educators are encouraged to pilot EFM-KG on platforms like "Xuexitong" to enhance teaching and learning outcomes. Future studies should investigate its mechanisms through interviews, behavioral analysis, or multi-dimensional assessments and confirm its applicability across institutions and diverse student populations. Despite limitations (e.g., historical control design, single-institution sample), EFM-KG provides a promising approach for engineering education reform, fostering student competitiveness and innovation.

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References

[1] Kaye, N.B., Ogle, J. and Benson, C.H. (2022) Overcoming Misconceptions and Enhancing Student's Physical Understanding of Civil and Environmental Engineering Fluid Mechanics. Physics of Fluids, 34, 041801.

[2] Shi, P., Fu, X. and Yang, J. (2024) Development and Evaluation of a Virtual Simulation Experiment System for the Course of Fluid Mechanics. The International Journal of Lifelong Education, 43, 123-135.

[3] Díaz, M.J., Caro, I. and Martín, R. (2023) Transforming Experimental Teaching of Fluid Mechanics and Heat Transfer Courses Due to the COVID-19 Pandemic. Education Sciences, 13, 650-662.

[4] Garrard, A., Bangert, K. and Beck, S. (2020) Large-Scale, Multidisciplinary Laboratory Teaching of Fluid Mechanics. Fluids, 5, 206-218.

[5] Solmaz, S., Kester, L. and Van Gerven, T. (2023) Virtual Reality-Based CFD Learning Environment for Fluid Mechanics Education. Education Sciences, 13, 764-776.

[6] Abedi, M., Bartolomeo, L.A. and Kumar, S. (2023) Exploring the Feasibility of a Large Language Model for Adaptive Learning in Fluid Mechanics Education. arXiv, 2305.15954. http://arxiv.org/abs/2305.15954

[7] Li, Y., Liang, Y. and Yang, R. (2024) CourseKG: An Educational Knowledge Graph Based on Course Information for Precision Teaching. Applied Sciences, 14, 2710-2724.

[8] Sun, L., Li, Y. and Zhang, C. (2023) KG-PLPPM: A Knowledge Graph-Based Personalized Learning Path Planning Method. Electronics, 14, 255-268. http://www.mdpi.com/2079-9292/14/2/255

[9] Ausubel, D.P. (1968) Educational Psychology: A Cognitive View. Holt, Rinehart and Winston, New York.

[10] Theobald, E.J., Hill, M.J. and Tran, E. (2020) Active Learning Narrows Achievement Gaps for Underrepresented Students in Undergraduate Science, Technology, Engineering, and Math. Proceedings of the National Academy of Sciences, 117, 6476-6483.

[11] Sweller, J. (1988) Cognitive Load during Problem Solving: Effects on Learning. Cognitive Science, 12, 257-285.

[12] Chandler, P. and Sweller, J. (1991) Cognitive Load Theory and the Format of Instruction. Cognition and Instruction, 8, 293-332.

[13] Papamitsiou, Z. and Economides, A.A. (2014) Learning Analytics and Educational Data Mining in Practice: A Systematic Literature Review of Empirical Evidence. Educational Technology & Society, 17, 49-64.