

Article

Improving Instruction in Groundwater Numerical Modeling Using Inquiry-Based Learning: Insights from a Grid Construction Case Study

Guanru Zhang ^{1,*}, Peng Lu ², Hao Tang ¹ and Yi Huang ^{1,*}¹ College of Ecology and Environment, Chengdu University of Technology, Chengdu 610059, China² Department of Earth and Atmospheric Sciences, Indiana University, Bloomington, IN 47405, USA

* Correspondence: zhangguanru18@cdut.edu.cn (G.Z.); huangyi@cdut.edu.cn (Y.H.)

Abstract

(1) Background: Groundwater numerical modeling education often suffers from passive student imitation, which limits the development of higher-order thinking and knowledge internalization. To address this challenge and promote a shift in instructional philosophy, inquiry-based learning (IBL) was implemented. However, the mechanisms underlying its effectiveness require further elucidation to guide this transformation. (2) Methods: This study was conducted with a cohort of 63 third-year environmental engineering students. It compares the outcomes of the IBL approach, focused on the geometric requirements of grid construction for the control-volume finite-difference (CVFD) method, against those of traditional instruction. (3) Results: The findings demonstrate that IBL's effectiveness is strongly moderated by students' prior knowledge. Learners with stronger prior knowledge exhibited a 330% increase in higher-order thinking ($p = 0.04$), reflected in a shift toward complex, terrain-adapted Voronoi grids. However, their understanding of core CVFD geometric concepts only improved moderately (34%), reflecting the nonlinear and by-product nature of knowledge acquisition in inquiry-based pathways. In contrast, students with weaker prior knowledge devoted most of their cognitive resources to basic concept understanding, and their limited cognitive schemas constrained their ability to process new information. Therefore, no measurable improvement was observed in either higher-order thinking or conceptual mastery in this group. (4) Conclusions: The key innovation of this study lies in revealing prior knowledge as a critical moderator, highlighting how the effectiveness of IBL depends on its interaction with the learner's individual characteristics. This mechanistic insight provides a cognitive framework for differentiated instructional design in engineering education, ensuring that pedagogical advancements translate into equitable learning gains.

Keywords: inquiry-based learning; higher-order thinking; knowledge internalization; prior knowledge



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1. Introduction

Numerical modeling of groundwater is a fundamental technology in both hydrogeological research and engineering practice. By solving complex governing equations of groundwater flow and solute transport through numerical methods [1–4], this technology enables the quantitative characterization and prediction of hydraulic head distribution, flow velocity variations, and contaminant migration and dispersion within aquifer systems.

It plays a critical role in various fields, including water resources development and management [5–8], groundwater pollution risk assessment and remediation [9–13], and the evaluation of hydrogeological impacts associated with major engineering projects such as mining, CO₂ storage, and geological disposal of nuclear waste [14–17].

For teaching numerical modeling and related software, instructors have explored various approaches focusing on tool innovation and the optimization of pedagogical methods. For tool innovation, efforts have focused on lowering entry barriers and enhancing interactivity, thereby facilitating the mastery of theoretical concepts and their initial integration with practical operations [18–23]. For example, Pérez-Sánchez et al. [18] had students build a Témez lumped hydrological model using Excel in hydrological modeling instruction, enabling them to assess the impact of climate on runoff while simultaneously mastering practical skills such as model calibration and parameter sensitivity analysis. This approach translates abstract hydrological cycle theories into computable spreadsheet logic. Delaigue et al. [21] created the airGRteaching R package (<https://hydrogr.github.io/airGRteaching/>, last access: 13 October 2025), which offers both a graphical user interface and simplified functions for a suite of hydrological models. The package includes comprehensive teaching vignettes for projects like streamflow reconstruction and climate change impact assessment, supporting a smooth learning curve from point-and-click exploration to script-based analysis. This structured approach demystifies the modeling workflow for students, allowing them to focus on core hydrological concepts and critical analysis of model performance without being overwhelmed by complex code initially. Gannon and Seibert [22] introduced an interactive, web-based version of a hydrological bucket-type model, providing access to 700 global catchments. This web app allows students to modify parameters, run automatic calibration via genetic algorithms, and analyze results directly in a browser, removing software installation barriers and maximizing accessibility. This “low-floor” access is particularly beneficial for students from diverse disciplinary backgrounds, as it enables immediate, active engagement with modeling concepts. The integration of physical models with software further enhances experiential learning. Li and Davis [24] designed a sandbox physical model to simulate real aquifer systems, enabling students to first observe flow paths using dye tracers for intuitive understanding, and then transition to numerical simulations using software such as GMS and Visual MODFLOW, thereby bridging the gap between physical phenomena and mathematical modeling.

From a pedagogical perspective, student-centered approaches are emphasized to shift from passive reception to active inquiry. For example, Huang et al. [25] incorporated cognitive apprenticeship instruction with 3D physical model in teaching 3D modeling, stimulating students’ metacognitive behaviors and ultimately leading to more effective problem-solving. Similarly, research by Georgakakos and Knighton [26] underscores the role of student-led learning in enhancing classroom engagement and stimulating student interest. They compared three teaching modalities—instructor-led lectures, student-led hydrological modeling, and student-led design evaluation—and found that the student-led modalities significantly increased the frequency of student-initiated interactions with the instructor and boosted student interest and career enthusiasm in hydrology, although written assessment scores showed no significant differences among the three modalities.

Although various modern technologies have been introduced into the teaching of groundwater numerical modeling, the problem of students engaging in passive imitation remains fundamentally unresolved. In terms of knowledge acquisition, student learning extends no further than memorizing concepts and replicating procedures, making it difficult for them to construct an interconnected knowledge framework. From the perspective of cognitive development, they lack deep engagement with numerical methods and modeling

logic, which limits the growth of higher-order thinking skills. Consequently, when faced with complex real-world engineering problems, they often exhibit insufficient capacity for independent analysis, systematic evaluation, and innovative problem-solving. Therefore, overcoming the limitations of passive imitation and superficial learning, thereby enhancing knowledge internalization and promoting the higher-order thinking development—has become one of the central challenges in the current reform of groundwater numerical modeling education.

In summary, despite the integration of various modern technologies, a fundamental challenge persists in groundwater numerical modeling education: the prevalence of passive imitation among students, which severely limits the development of higher-order thinking and knowledge internalization. To address this issue, this study introduces inquiry-based learning (IBL)—a student-centered instructional approach rooted in constructivist learning theory [27–31]—into course design and teaching practice. Beyond evaluating its overall efficacy, the research also investigates the underlying cognitive mechanisms through which IBL enhances higher-order thinking and facilitates knowledge internalization.

This study focuses on the geometric requirements of the control-volume finite-difference (CVFD) method in grid construction as an instructional entry point. A cohort of 63 third-year environmental engineering students was divided into traditional instruction groups and IBL groups for comparative analysis. In line with the theoretical tenets of inquiry-based learning, we hypothesize that its implementation will foster higher-order thinking skills and facilitate knowledge internalization more effectively than traditional teaching methods.

2. Materials and Methods

2.1. Participants and Instructional Design

The participants are 63 third-year undergraduate students majoring in Environmental Engineering at Chengdu University of Technology, China. This study is conducted within the course Pollution Hydrogeology, which includes a four-class hour laboratory component on groundwater numerical modeling designed to teach the finite-difference method, construction procedure of numerical modeling, an introduction to MODFLOW, and hands-on operation of the Groundwater Modeling System (GMS) software (v10.8). Grid construction instruction upon which this study focused is delivered during the MODFLOW introduction. This segment covers CVFD method employed in MODFLOW6, the geometric requirements that CVFD places on grid construction, and commonly used grid types.

The geometric requirements of CVFD in grid construction instruction serve as the entry point for this study. To investigate whether IBL can significantly promote students' basic knowledge digestion and higher-order thinking, this study utilizes four pre-existing instructional groups established by the university's academic administration. These groups are randomly allocated to two instructional conditions: two groups (Groups A1 and A2) are taught using a traditional lecture format for CVFD geometric requirements, while the other two groups (Groups B1 and B2) receive IBL. Teaching effectiveness is evaluated using an anonymous questionnaire administered after the class.

Traditional learning: Using PowerPoint slides and oral lecture, the instructor presents CVFD geometric requirements for grid construction.

Inquiry-based learning: The instruction concerning the CVFD geometric is delivered using IBL, which consists of four phases: orientation, conceptualization, investigation, and conclusion and discussion [28]:

- **Orientation phase:** Topic background is provided to motivate students. Students are asked to imagine a scenario, "After graduation, your employer assigns you to develop groundwater modeling software, and you plan to adopt the CVFD method. To write

efficient and correct code, you first need to identify any special geometric requirements that CVFD imposes on connectivity between grid cells, since improper grid handling can result in mass non-conservation and inaccurate results”.

- Conceptualization phase: The instructor provides targeted prompts and guides students to decompose the overarching problem into several specific, investigable sub-questions. The prompts are designed to scaffold the analytical process, including: “When water and solutes flow from one cell to another, which physical quantity is most closely related to the geometric relationship between cells?”; “Which models covered in this course can be used to quantitatively represent that quantity?”; and “How can those models be used to quantitatively examine geometric relationships between grid cells?”
- Investigation phase: Students work in groups of three to four and analyze the sub-questions using textbooks, online resources, group discussion, and model derivation. During this phase, the instructor actively monitors this process by visiting each group, listening to their discussions, and providing guidance to ensure students remain focused on the core objectives.
- Conclusion and discussion phase: Each group nominates a representative to present their derivation and conclusions. The instructor commends students’ exploratory efforts and collaboration, provides professional feedback on strengths and weaknesses of the derivations, and concludes with a rigorous model-based analysis and final remarks.

2.2. Questionnaire

An 11-item questionnaire (Supplementary Materials), scored using a defined rubric to facilitate statistical analysis (Table 1), is designed to evaluate the efficacy of IBL on learning outcomes. The items are grouped into four types as below. Type 1 question directly assesses the instructional effect on the CVFD geometric requirements. Types 2–4 questions serve as an expanded assessment, designed to determine whether the learning outcomes of IBL extend beyond the immediate instructional content to exert broader impacts on students’ cognitive and metacognitive domains, including fundamental knowledge, software operational skills, and confidence in groundwater simulation.

Table 1. Questionnaire design.

Question Types	Descriptions	Number of Sub-Questions	Score Setting	Comments
Type 1	Choice of grid and the reason	2	Answers A-E are scored 1–5, respectively	Scores only represent specific choices.
Type 2	Basic knowledge of groundwater flow and solute transport	4	Answers A-C are scored 1–3, respectively	The higher the score, the better the professional knowledge
Type 3	Operational skills in numerical simulation software of groundwater	3	Answers A-C are scored 1–3, respectively	The higher the score, the better the software operation skills
Type 4	Confidence in simulating actual groundwater contamination processes	2	Answers are scored 1–10, respectively	The higher the score, the greater the level of confidence

- (1) Grid Selection Rationale: Respondents are presented with a contamination scenario involving a point pollution source in an aquifer, simulated using a CVFD-based software. They are asked to select the most appropriate grid from several options and justify their choice.

- (2) Fundamental Knowledge: Items evaluate the students' levels of fundamental knowledge in groundwater flow and solute transport, including basic hydrogeological principles, Darcy's law, advection, and hydrodynamic dispersion.
- (3) Software Operational Skills: Items evaluate students' ability to use numerical simulation software through questions on grid generation, exporting computational results, and understanding numerical simulation methods.
- (4) Groundwater Simulation Confidence: This category gauges students' confidence in applying numerical simulation software to real-world contaminant transport problems, as well as their level of caution when evaluating simulation results.

2.3. Key Criteria for Assessing Teaching Effectiveness

Question 1.1—"Using a groundwater numerical simulation software based on the control-volume finite-difference to simulate the transport of pollutants released by point pollution sources in the aquifer. What is the most appropriate grid?"—is the key for evaluating instructional effect on the CVFD geometric requirements. The answer design is based on the core CVFD geometric principle that the line connecting the centroids of two adjacent control volumes must be orthogonal to their shared interface and intersect it at an appropriately averaged position [3], and also reflects the difference in cognitive levels.

Answer A (rectangular grid) serves as one of the indicators for assessing students' understanding of the geometric requirements of CVFD. Its simple geometry and regular rectangular structure create an intuitive, one-to-one correspondence with the geometric requirements of CVFD, allowing students to confirm its compliance through basic recall and recognition. Answer C (Voronoi grid), which complies with the CVFD geometric requirements, serves not only as a criterion for assessing knowledge mastery but also as a key indicator for evaluating higher-order thinking development. To identify its correctness, students must first look beyond its complex visual appearance and engage in in-depth analysis to verify its geometric validity. Subsequently, they must weigh this compliance against its practical advantage in terrain conformity, making a multi-criteria decision. This complete process—from analysis and verification to multi-criteria decision-making—is a typical manifestation of higher-order thinking. Answer B (warped rectangular grid) functions as a distractor, with a cognitive demand level between the other two. Although it may fit the terrain more closely, it fails to meet the CVFD geometric requirements, requiring students to discern its subtle noncompliance despite its superficial plausibility.

Therefore, in terms of mastery of CVFD geometric principles, Answers A and C are used as assessment criteria. A stronger student preference for A and C indicates that the IBL is effective in facilitating the understanding of CVFD geometric requirements. To evaluate shifts in thinking patterns, Answer C is specifically employed as an indicator. A higher selection rate of C suggests that IBL effectively promotes the development of students' higher-order thinking skills.

2.4. Data Acquisition and Analysis

The questionnaire is distributed via an online survey platform (www.wjx.cn). At the end of the laboratory session, students access the survey via a QR code shared through the mobile Tencent QQ application. Participation is voluntary and anonymous. Responses are exported to Microsoft Excel for organization and subsequently analyzed in IBM SPSS Statistics (v30).

Score data are presented as means and standard deviations. The Shapiro–Wilk test is applied to assess normality. Between-group differences are evaluated using the Mann–Whitney U test, with statistical significance defined as $p \leq 0.05$. Score distributions

are visualized with box plots, and answer-selection patterns are further explored using frequency histograms.

Question 1.1 serves as the primary indicator for evaluating instructional effectiveness. For this item, we compare differences between Groups A1 and A2, and between Groups B1 and B2, using the Mann–Whitney U test. No statistically significant difference is observed between Groups A1 and A2 ($p = 0.61$), whereas a statistically significant difference is found between Groups B1 and B2 ($p = 0.05$). Consequently, Groups A1 and A2 are merged into a single larger group (Group A1 + A2) for subsequent analyses, while Groups B1 and B2 are retained as separate groups for more detailed examination. Table 2 presents the mean scores, standard deviations, and Shapiro–Wilk test results for all four question categories across groups.

Table 2. Statistics of Groups A and B scores.

Question Types	Group A1 + A2 ($n = 30$) ^a			Group B1 ($n = 14$)			Group B2 ($n = 19$)		
	Mean	Standard Deviation	Normality Test ^b	Mean	Standard Deviation	Normality Test	Mean	Standard Deviation	Normality Test
Type 1	4.2	1.1	0.02	4.1	1.1	0.01	3.7	0.9	0.03
Type 2	8.8	1.2	0.001	7.9	0.7	0.01	8.5	1.7	0.001
Type 3	6.2	0.8	0.001	4.8	1.4	0.001	6.1	1.2	0.003
Type 4	13.3	3.7	0.06	12.1	2.1	0.12	12.0	4.2	0.08

^a n represents sample number; ^b The Shapiro–Wilk test is used to check normality.

3. Results

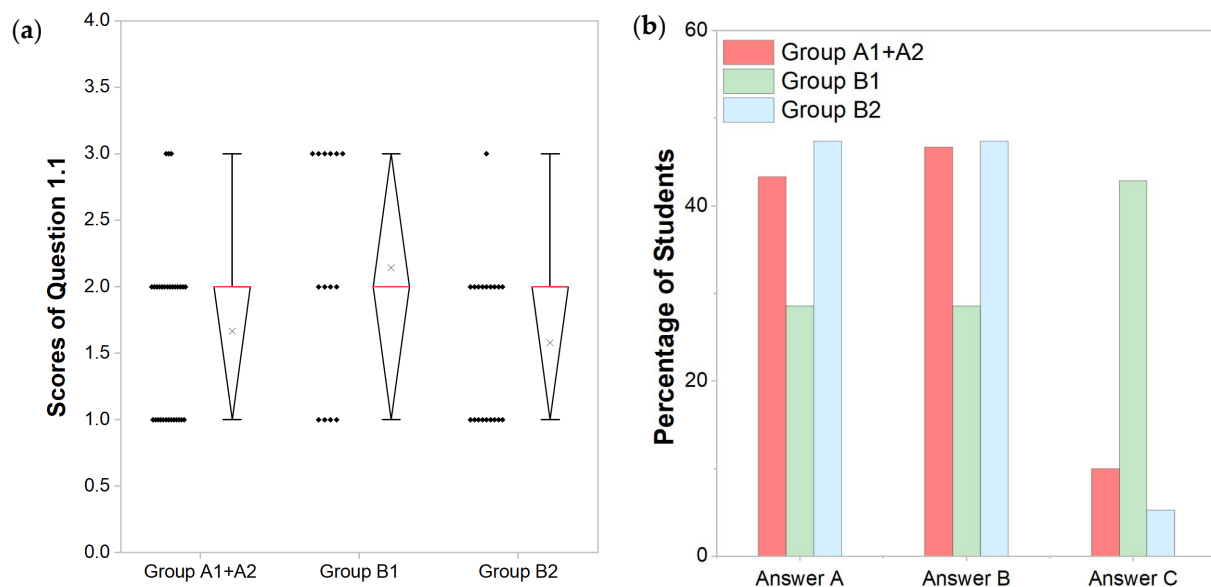
3.1. Divergence of IBL Outcomes in Knowledge and Cognitive Dimensions

To assess whether IBL leads to significant improvements in both higher-order thinking and understanding of CVFD geometric concepts, we conduct a one-tailed Mann–Whitney U test on the scores for Question 1.1. A comparison between Group B1 (inquiry-based learning) and Group A1 + A2 (traditional instruction) reveals a statistically significant trend-level difference with a medium effect size ($p = 0.04$; rank-biserial correlation $r = -0.27$; see Table 3). Both groups have a median score of 2.0, but the distribution patterns differ: in Group A1 + A2, the median exceeds the mean 1.7 ± 0.7 , while in Group B1, the median is slightly lower than the mean 2.1 ± 0.8 (Figure 1a). This reflects that students in Group A1 + A2 primarily select Answers A and B, whereas those in Group B1 tend to select Answers B and C. After excluding the incorrect Answer B, we observe a clear shift in answer preference from A to C among students receiving IBL. This shift suggests a notable enhancement in higher-order thinking. A further quantitative analysis using a frequency histogram (Figure 1b) shows that the proportion of students selecting Answer C increases from 10% in Group A1 + A2 to 43% in Group B1—a 330% increase, providing additional evidence for the significant effect of IBL on promoting higher-order thinking.

To evaluate whether students' understanding of the key geometric principles of the CVFD method improves, Answers A and C are combined into a single category. A one-tailed Mann–Whitney U test yields a non-significant result ($p = 0.21$) with a small effect size ($r = -0.17$), indicating that IBL does not lead to a statistically significant improvement in students' conceptual understanding of CVFD geometry. Despite the lack of a statistically significant effect on overall test scores, a frequency histogram analysis reveals a moderate improvement in understanding of the specific concept. The proportion of students correctly selecting the combination A + C increases substantially from 53% in Group A1 + A2 to 71% in Group B1, representing a moderate relative improvement of 34% on this particular item.

Table 3. Statistics of scores of type 1 questions.

Sub-Questions	Group A1 + A2 (<i>n</i> = 30)		Group B1 (<i>n</i> = 14)				Group B2 (<i>n</i> = 19)			
	Mean	Standard Deviation	Mean	Standard Deviation	U Test (A1 + A2 vs. B1) ^a		Mean	Standard Deviation	U Test (A1 + A2 vs. B2)	
					<i>p</i>	Rank-Biserial Correlation			<i>p</i>	Rank-Biserial Correlation
1.1 Choice of grid for a given scenario.	1.7	0.7	2.1	0.8	0.04 (one-tailed)	−0.27	1.6	0.6	0.39 (one-tailed)	−0.06
1.2 The reason for the grid selection.	2.5	0.9	2.0	0.8	0.11	−0.24	2.1	0.7	0.13	−0.22

^a Mann–Whitney U test.**Figure 1.** (a) Box plot and scatter diagram showing the distribution of numerical scores for Question 1.1 (black diamonds represent discrete point of scores and × represents mean). (b) Percentage of students selecting each answer option (A, B, C) for Question 1.1.

The mean score of Group B2 on Question 1.1 is 1.6 ± 0.6 , with a median of 2.0, which is closely comparable to that of Group A1 + A2. A one-tailed Mann–Whitney U test yields $p = 0.39$, indicating no statistically significant difference in scores between Group A1 + A2 and Group B2 on this question. Further quantitative analysis shows that only 5% of Group B2 select Answer C, and 53% select A + C, both proportions similar to those observed in Group A1 + A2. These findings suggest that for Group B2, IBL does not lead to a significant improvement in instructional outcomes.

Overall, the implementation of IBL leads to a significant enhancement of higher-order thinking skills in Group B1, while students' understanding of CVFD geometric concepts shows only moderate improvement. In contrast, Group B2 exhibits no significant gains in either higher-order thinking or conceptual understanding of CVFD geometry.

3.2. Divergence of IBL Outcomes in Reasoning for Grid Selection

Question 1.2 asks students to explain the reason behind their choice of grid type. The mean score for Group A1 + A2 is 2.5 ± 0.9 (Table 3), which is higher than Group B1's score of 2.0 ± 0.8 ; both groups share the same median score, which equals to their respective means. Although the Mann–Whitney U test indicates no statistically significant difference between the two groups ($p = 0.11$), a notable divergence in response patterns is

observed (Figure 2a): Group A1 + A2 primarily select Answers B and C, whereas Group B1 favors Answers A and C. Further quantitative analysis (Figure 2b) shows that in Group A1 + A2, 40% select Answer B and 43% select Answer C; in contrast, in Group B1, 36% choose Answer A and 36% choose Answer C. These results suggest that although statistical significance is not achieved (likely due to sample size limitations) the frequency analysis reveals a practically meaningful difference between the two groups in their reasoning for grid selection.

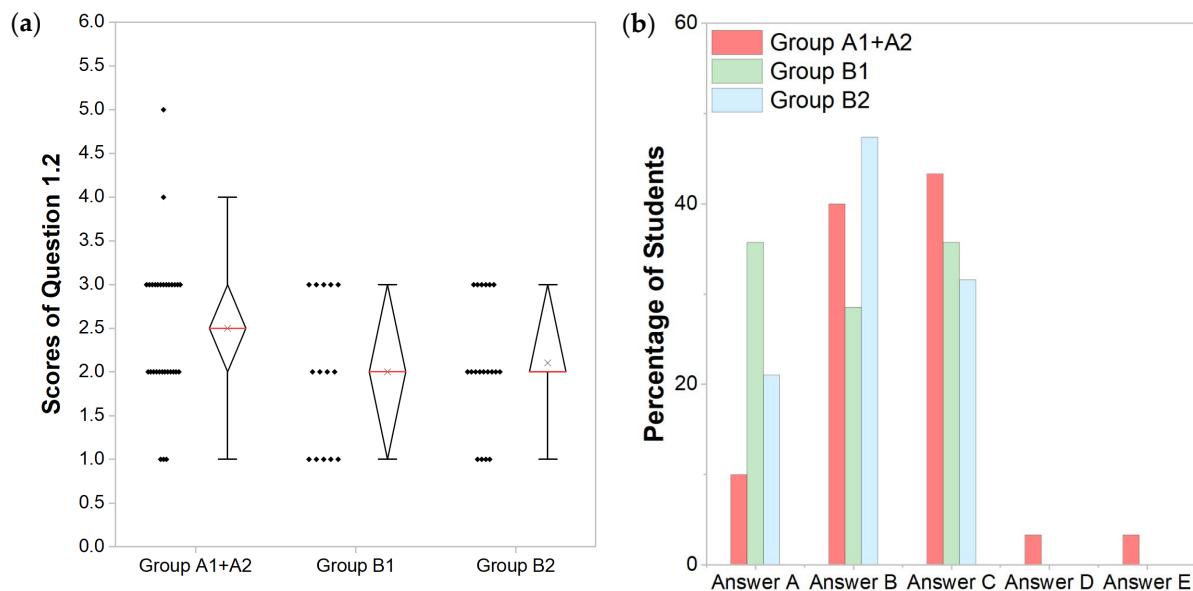


Figure 2. (a) Box plot and scatter diagram showing the distribution of numerical scores for Question 1.2 (black diamonds represent discrete point of scores and × represents mean). (b) Percentage of students selecting each answer option (A, B, C, D, E) for Question 1.2.

The mean score of Group B2 on Question 1.2 is 2.1 ± 0.7 , lower than that of Group A1 + A2, while both groups share the same median score (2.0). The Mann–Whitney U test yields $p = 0.13$, indicating no statistically significant difference between Group A1 + A2 and Group B2 in responses to Question 1.2. Further quantitative analysis reveals that for Group B2, the two most frequently selected answers are Answer B (47%) and Answer C (32%), closely comparable to the distribution observed in Group A1 + A2. These results suggest that for Group B2, IBL does not significantly alter students' reasoning for grid selection.

Following the implementation of IBL, students in Group B1 demonstrate enhanced higher-order thinking skills. As a result, their responses to Question 1.1 ("the choice of grid for a given scenario") shift from Answer A (rectangular grid), as commonly selected by Group A1 + A2, to Answer C (Voronoi grid). Since both grid types satisfy the geometric requirements of the CVFD method, this shift in grid selection prompts Group B1 students to differentiate between them by emphasizing other selection criteria. Consequently, in Question 1.2 ("the reason for the grid selection") the proportion of Group B1 students choosing Answer A ("Matches the terrain") increases markedly from 10% to 36%, a 260% increase, leading to a practically significant difference in answer patterns compared to Group A1 + A2. In contrast, for Group B2, IBL does not lead to significant improvements in either higher-order thinking or understanding of geometric concepts, and their responses to Question 1.2 show no substantial difference from those of Group A1 + A2.

4. Discussion

4.1. Mechanisms of IBL in Enhancing Higher-Order Thinking and Knowledge Mastery

The implementation of IBL leads to a significant improvement in the development of higher-order thinking skills in Group B1. This effect stems from the fundamental restructuring of the learning paradigm, aligning with the core principle of constructivist learning theory that knowledge is actively built by the learner rather than passively received [32]. Students are transformed from passive recipients of information into active constructors and explorers of knowledge. This shift directly activates and strengthens higher-order thinking processes, such as analysis, evaluation, and creation [33–36].

The essence of IBL lies in its process-oriented nature, rather than content delivery, which directly fosters the development of higher-order thinking. For the geometric requirements of the CVFD method, IBL situates students within real-world problem contexts, creating an authentic situation for knowledge construction. The instructor then provides targeted prompts, acting as scaffolding to support students within their zone of proximal development [37], prompting them to independently explore questions such as: Which physical quantity is most closely related to the geometric relationship between cells? Which models introduced in the course can quantitatively represent this quantity? How can these models be applied to quantitatively assess the geometric relationships between grid cells? This process compels students to continually engage in the key cognitive activities of analysis (identifying and distinguishing the relevant physical quantities), evaluation (assessing the capacity of different models to quantify these quantities), and creation (developing a quantitative strategy to evaluate geometry)—all of which are classified as higher-order thinking skills in Bloom’s taxonomy of educational objectives [38,39]. Through this approach, students are no longer passive recipients of geometric rules, but rather active inquirers into the underlying geometric principles, thereby experiencing substantial gains in critical thinking, creativity, and problem-solving capabilities.

However, IBL process is inherently nonlinear, with students pursuing open-ended and sometimes unpredictable directions in their exploration [40,41]. This structural characteristic of IBL means that knowledge acquisition is a byproduct of solving specific problems encountered during inquiry, rather than following a comprehensive, pre-defined path. As a result, Group B1’s understanding of CVFD geometric concepts shows only moderate improvement, an outcome that can be attributed to the nature of the inquiry process itself.

4.2. The Role of Prior Knowledge in Diverging IBL Outcomes

The average final exam score for Group B1 is 74, higher than 61 for Group B2 (Figure 3). A one-tailed Mann–Whitney U test shows that this prior knowledge difference is statistically significant ($p = 0.001$), implying a fundamental disparity between the two groups in terms of their available cognitive resources and schema development [42–45]. The lower final exam scores of Group B2 suggest weaker mathematical and disciplinary foundations. As a result, when encountering new material, these students must allocate part of their attention to compensate for gaps in prerequisite knowledge, leaving fewer cognitive resources available for higher-order thinking. Moreover, their weak foundation implies a lack of efficient, automated schemas for integrating new information, thereby increasing extraneous cognitive load during learning. In contrast, Group B1’s superior performance indicates that they possess both greater cognitive resources available for higher-order thinking and more robust, well-developed schemas, providing a solid foundation for engaging with new material effectively.

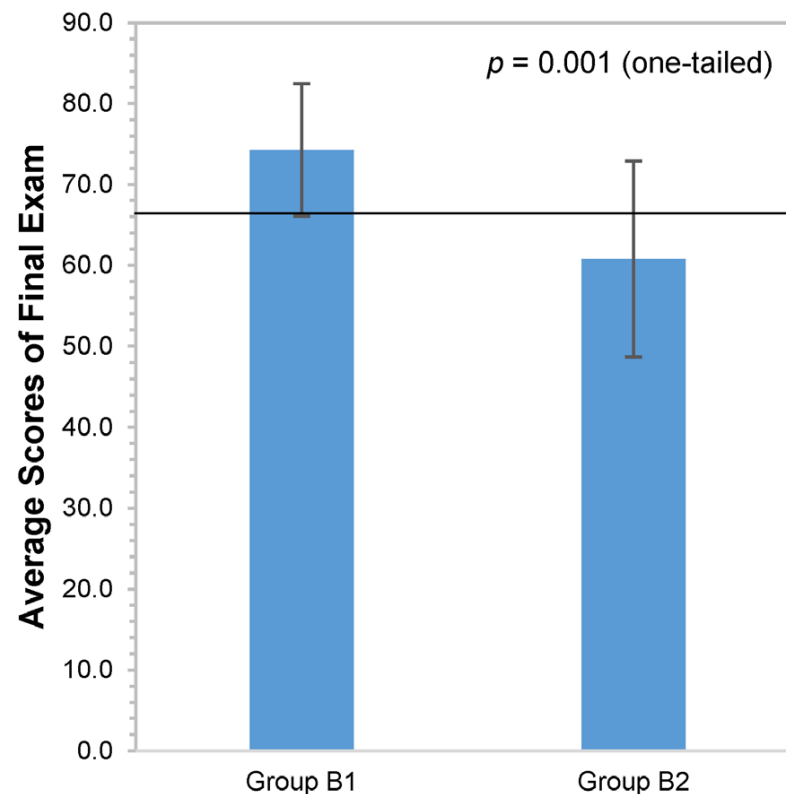


Figure 3. Average final exam scores of Group B1 and Group B2 (error bars represent ± 1 standard deviation). The one-tailed Mann–Whitney U test comparing final scores between the two groups yields $p = 0.001$. The black horizontal line indicates the overall average final exam score across all students in Groups A1, A2, B1, and B2.

It is the differences in the available cognitive resources and schema level that leads to the divergent outcomes of IBL between the two groups. For Group B1, their well-developed schemas effectively reduce the extraneous and intrinsic cognitive load associated with learning the CVFD geometric requirements. With sufficient cognitive resources, they are able to allocate more mental capacity to higher-order thinking processes such as analysis, evaluation, and creation, leading to substantial gains in higher-order thinking ability. In contrast, Group B2's underdeveloped schemas result in low processing efficiency when handling new information, thereby substantially increasing their extraneous cognitive load. Moreover, their cognitive resources are heavily consumed by the effort to understand basic concepts, leaving little capacity for deeper cognitive engagement. As a result, improvements in both higher-order thinking and conceptual understanding of geometric principles remain minimal.

In summary, our findings establish prior knowledge as a pivotal moderator in IBL effectiveness. It functions as a cognitive gatekeeper, governing the availability of cognitive resources and the efficiency of schema development. For students with robust prior knowledge, IBL liberates cognitive capacity, channeling it toward higher-order thinking. Conversely, for students with weaker prior knowledge, the identical inquiry process induces cognitive overload, thereby stifling knowledge integration and critical engagement. Consequently, an individual's level of prior knowledge decisively determines their capacity to manage the cognitive demands of inquiry.

4.3. Broader Impacts of IBL Outcomes: From Cognitive Understanding to Metacognitive Calibration

To evaluate the broader impacts of IBL outcomes, we analyze student self-assessments across three domains: fundamental knowledge (Question 2), software operational skills

(Question 3), and simulation confidence (Question 4). Two sets of comparisons are conducted: Group A1 + A2 vs. Group B1 + B2 to examine the impact of the teaching approach, and Group B1 vs. Group B2 to assess the influence of prior knowledge level. Our analysis reveals that the significant effects are primarily driven by the learning outcomes of IBL, while prior knowledge dictates the pattern in self-assessment of operational skills.

First, the cognitive outcome of IBL—a deepened conceptual understanding—directly impacts students’ self-assessment of their fundamental knowledge (Question 2). The comparison between Group A1 + A2 and Group B1 + B2 shows that the teaching approach has a significant impact on these scores, as evidenced by the smallest and statistically significant p -values (Table 4). Figure 4a indicates that after IBL, students give lower self-ratings. This shift is not a sign of poorer knowledge but a broader impact of the cognitive outcome: the rigorous inquiry process furnishes students with a more sophisticated framework, leading them to more critically evaluate the state of their own conceptual understanding.

Table 4. One-tailed Mann–Whitney U test for scores on type 2–4 questions.

Question Types	Group B1 vs. Group B2		Group A1 + A2 vs. Group B1 + B2	
	p	Rank-Biserial Correlation	p	Rank-Biserial Correlation
Type 2	0.07	−0.25	0.01	−0.89
Type 3	0.01	−0.41	0.03	−0.23
Type 4	0.45	−0.03	0.04	−0.22

Second, the outcomes of IBL also have a clear metacognitive impact on students’ simulation confidence (Question 4). The comparison between Group A1 + A2 and Group B1 + B2 again shows a significant impact of the teaching approach (Table 4), with IBL students reporting lower confidence (Figure 4c). This decline signifies a broader impact on metacognitive calibration. The profound appreciation for model complexity gained during IBL equips students with the insight to form more realistic and calibrated professional judgments, thereby honing their ability to align self-efficacy beliefs with the actual demands of a complex task.

Finally, in contrast to the clear impact of IBL outcomes, the pattern for software operational skills (Question 3) is primarily determined by students’ prior knowledge. The Mann–Whitney U test confirms a statistically significant difference between Group B1 and Group B2 ($p = 0.01$, $r = -0.41$, Table 4), supporting this conclusion. Students with stronger prior knowledge (Group B1) report lower mean self-scores 4.8 (Table 2), demonstrating accurate metacognitive calibration of their practical skills. Conversely, students with weaker prior knowledge (Group B2) report significantly higher mean scores 6.1, which quantifies their optimistic bias and aligns with the metacognitive miscalibration characteristic of the Dunning–Kruger effect [46–48].

4.4. Limitations

The total sample size in this study is relatively small (30 students in Group A and 33 in Group B) and drawn from a single instructional context and student population. While this design facilitates controlled variable conditions and allows for in-depth analysis of underlying mechanisms, it also limits the generalizability of the findings to broader educational settings. Future research should aim to validate the robustness of these results through replication studies with larger and more diverse samples.

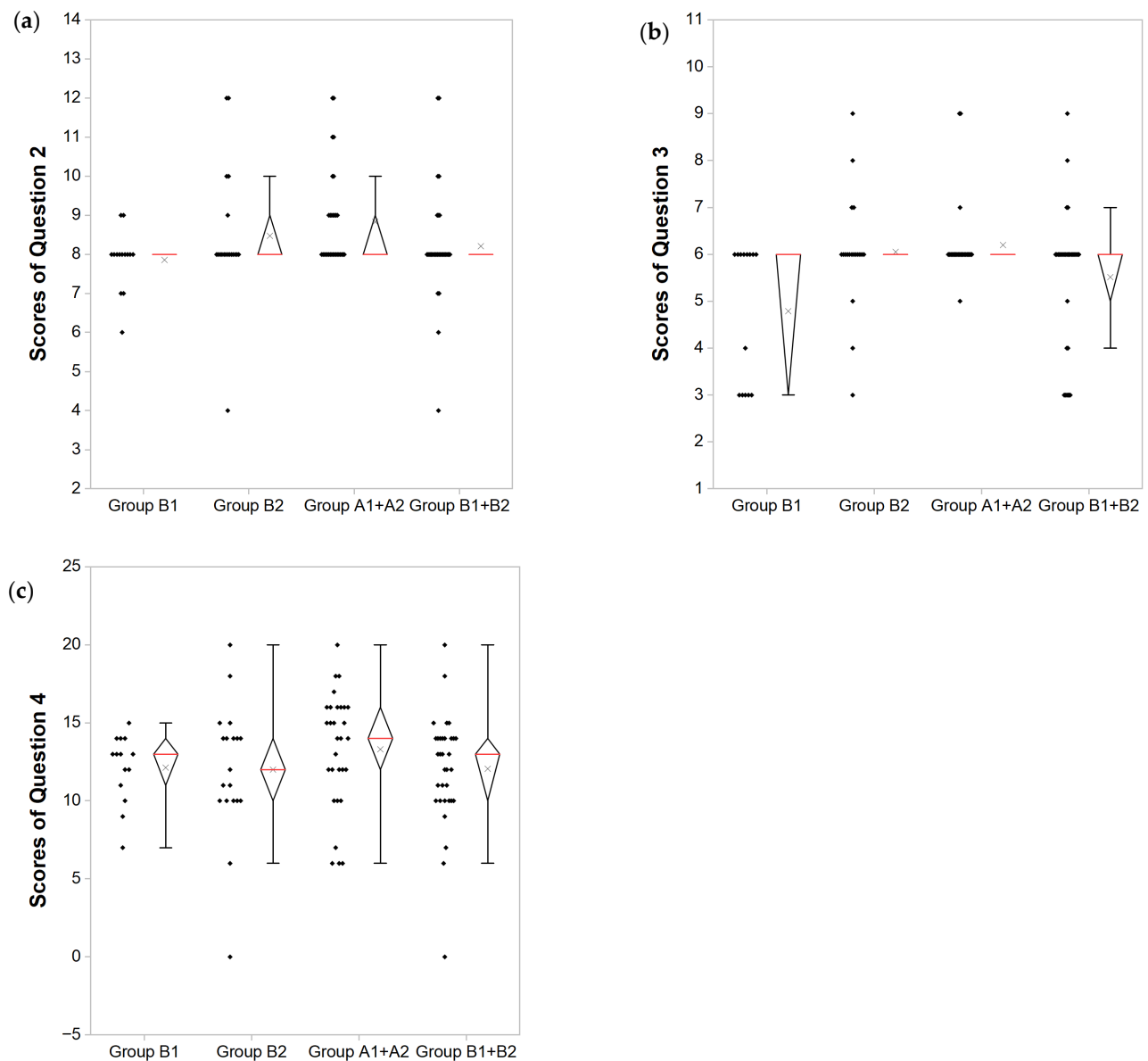


Figure 4. Box plot and scatter diagram for Questions 2 (a), 3 (b), and 4 (c) (black diamonds represent discrete point of scores and × represents mean).

5. Conclusions

This study reveals that IBL is effective in fostering both higher-order thinking and knowledge internalization, but its efficacy is fundamentally regulated by students' prior knowledge. The core innovation of this work lies in elucidating the differential cognitive response among learners and identifying prior knowledge as a pivotal mediating factor. This mechanistic insight represents an important contribution to the literature on engineering pedagogy.

Our findings affirm that IBL is a powerful tool for developing higher-order thinking skills, and a moderately effective one for reinforcing foundational knowledge internalization. Specifically, IBL leads to a 330% increase in the selection of complex, terrain-adapted Voronoi grids ($p = 0.04$), providing direct evidence of a significant enhancement in higher-order thinking skills, which is concretely manifested in the students' advanced analytical and evaluative decision-making. Its impact on the mastery of core CVFD geometric concepts is positive but limited, yielding a 34% improvement. This can be attributed to the

nonlinear, problem-oriented nature of IBL, wherein knowledge is acquired as a byproduct of solving specific problems.

Critically, the effectiveness of IBL is not universal but is strongly mediated by students' prior knowledge. Students with stronger prior knowledge (Group B1) are able to allocate cognitive resources efficiently in the inquiry process, achieving a substantial leap in higher-order thinking. By contrast, students with weaker prior knowledge (Group B2) expend most of their cognitive resources on grasping basic concepts. Coupled with underdeveloped schemas, which constrain the efficiency of processing new information, they consequently show no improvement in both knowledge acquisition and cognitive development. This key finding carries a critical practical implication for engineering education: the successful implementation of IBL requires differentiated instruction. Educators must tailor inquiry tasks and provide aligned instructional scaffolds based on students' prior cognitive readiness to achieve a synergistic enhancement of knowledge and skills.

It is important to acknowledge the limitations of this work. This study's findings are based on a relatively small sample size from a single institutional context, which necessarily limits the generalizability of the results. The exploratory nature of this research calls for further validation.

Therefore, future research should focus on several promising directions: (1) conducting larger-scale, cross-institutional validation to confirm the broader applicability of these findings; (2) integrating IBL with industry-standard digital modeling environments (e.g., MODFLOW 6, GMS) to enhance practical relevance and student engagement; and (3) conducting systematic psychometric testing of the evaluation tool to establish its reliability and validity across diverse student populations.

From a sustainability perspective, this study contributes to building critical capacity. By enhancing the higher-order thinking skills of future environmental engineers, our instructional approach helps cultivate the expertise necessary to address pressing groundwater sustainability challenges, from contamination remediation to sustainable resource management.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su172310659/s1>, Text S1: Questionnaire.

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