2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #50397

Enhancing Spatial Visualization Skills: A Longitudinal Analysis of Iterative Practice and Assessment Data

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Enhancing Spatial Visualization Skills: A Longitudinal Analysis of Iterative Practice and Assessment Data

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Abstract

Spatial visualization skills are critical prerequisites for success in engineering, yet the wide variance in student baseline abilities poses a significant challenge to traditional instructional methods. This paper investigates the effectiveness of an iterative, online practice model designed to foster spatial proficiency through mastery learning. Conducted over a six-year period (2019–2025) with Georgia State University's engineering students, the study utilized a structured framework consisting of paired pre- and post-assessments and a series of three iterative online workbooks. Unlike time-limited assessments, the workbooks prioritized deliberate practice by allowing unlimited attempts. Statistical analysis using paired t-tests revealed a highly significant improvement in spatial proficiency ($p < 0.001$), with post-test scores increasing despite a 50% reduction in testing time, indicating enhanced cognitive fluency. Cluster analysis identified three distinct learning trajectories: High-Efficiency learners, Persistent Improvers, and a High-Effort/Low-Gain group. Notably, while the model proved resilient during the COVID-19 pandemic's shift to remote learning, the discovery of a "practice plateau" among high-effort learners suggests that quantitative repetition alone does not guarantee mastery for all students. The findings also emphasize that cumulative assessment performance is a stronger predictor of terminal success ($r = 0.82$) than total engagement time.

Key words: Spatial Visualization, Online Assessment, Student Learning Trajectories

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1. Introduction

Spatial visualization skills—the ability to mentally manipulate and rotate two- and three-dimensional objects—are recognized as critical prerequisites for success in engineering and related technical fields [1]. Proficiency in these skills is a strong predictor of academic performance in core engineering curricula, such as computer-aided design (CAD), mechanics, and structural analysis [2]. As engineering problems become increasingly complex, the capacity for robust mental modeling remains a cornerstone of professional competency [3].

Despite their importance, developing these skills presents a significant challenge in modern engineering education [4]. Students often exhibit a wide variance in baseline spatial abilities, and a "one-size-fits-all" instructional approach frequently leaves underprepared students behind [5].

There is a pressing need for intervention models that provide iterative, high-frequency practice while allowing for different learning paces [6].

This paper investigates an online practice model designed to address these challenges. Conducted over a six-year period (Fall 2019 to Summer 2025), the study utilizes a structured framework of paired pre- and post-assessments alongside iterative workbook sets. While the assessments function as time-limited measures of proficiency, the workbooks prioritize mastery through unlimited attempts. By analyzing this longitudinal data, this study seeks to evaluate overall trends in skill enhancement and identify the specific trajectories students follow as they move toward spatial proficiency.

2. Methodology

2.1. Participants and Settings: Multi-year Data Collection (2019–2025).

Data for this study were collected over a six-year period, spanning ten distinct academic sections from Fall 2019 to Summer 2025 (Table 1). The participant pool consisted of engineering students, with a total cumulative enrollment of 188 students. Section sizes remained relatively consistent, ranging from a minimum of 10 to a maximum of 24 students per term. To ensure the generalizability of the findings across various instructional environments, data collection encompassed the Fall, Spring, and Summer semesters.

Regarding assessment participation, 166 students (88% of total enrollment) completed the pre-test, while 138 students (73% of total enrollment) completed the post-test, providing a robust longitudinal dataset for tracking skill acquisition. The core intervention of this study—the structured online workbook series—was implemented starting in the Fall 2022 semester and continued through Summer 2025 across six sections. Participation rates for the iterative practice sets were high: 100 students engaged with Workbook 1, 86 with Workbook 2, and 88 with the final Workbook 3. This comprehensive, multi-year data collection framework provides a statistically sufficient sample size to analyze divergent student trajectories and the long-term effectiveness of the iterative practice model.

Table 1: Student Participation and Assessment Completion (2019–2025)

Semesters	Class Sizes	Pre-test participants	Post-test participants	Workbook 1 participants	Workbook 2 participants	Workbook 3 participants
Fall 2019	24	22	17	-	-	-
Fall 2020	29	21	11	-	-	-
Summer 2020	20	18	16	-	-	-

Fall 2022	23	18	19	22	21	19
Spring 2023	21	19	18	19	10	14
Summer 2023	10	10	10	10	10	10
Fall 2023	22	22	16	15	16	18
Spring 2024	23	21	18	20	21	19
Summer 2025	16	15	13	14	8	8
Total	188	166	138	100	86	88

2.2. Intervention: Design and Structure of the Three-Set Online Workbook.

2.2.1 Proficiency Assessments: Quiz 1 and Quiz 2

The assessment instruments were designed to measure high-level spatial cognition by adapting established psychometric methodologies, specifically drawing from the Mental Rotation Test (MRT) for 3D mental manipulation [7] and the Purdue Spatial Visualization Test: Rotations (PSVT:R) for analogical rotation tasks [8], [9].

Quiz 1 (Pre-test) serves as a 15-item comprehensive diagnostic tool with a 30-minute time limit. To ensure construct validity, it incorporates diverse spatial tasks including 2D/3D mental rotations (Q1–Q6), pattern folding (Q7–Q11), and cross-section identification (Q13). Advanced spatial reasoning is further tested through surface and edge matching (Q14) and multiple-selection (MS) orthogonal projection views (Q15).

Quiz 2 (Post-test), while maintaining a 15-item structure, introduces a rigorous 15-minute time limit to evaluate the transition from accuracy to cognitive fluency. In addition to core rotation and folding tasks, Quiz 2 incorporates "Hole Punching" (Q12–Q13) to measure mental unfolding and spatial visualization in 3D-to-2D transitions. The use of multiple-choice (MC) and matching (MCH) formats across both quizzes ensures a standardized evaluation of spatial proficiency.

2.2.2. Iterative Intervention: Workbook Series (WB 1, 2, and 3)

The intervention model utilizes three sequential workbooks designed to facilitate mastery learning through high-frequency, iterative practice. Unlike the time-limited quizzes, these workbooks focus on deliberate practice, allowing unlimited attempts without time restrictions.

Workbook 1 & 2: These sets establish foundational proficiency in 2D/3D rotations and 2D piece assembly. A critical component is the integration of Surface and Edge Matching (Q16 in both

WBs), which requires students to mentally bridge the gap between isometric (pictorial) views and 2D orthogonal projections—a core competency in engineering graphics. Workbook 2 further challenges students with pictorial view identification and expanded cross-section identification.

Workbook 3: As the advanced mastery module, WB 3 shifts toward complex engineering-specific visualization. It emphasizes high-order synthesis, such as identifying auxiliary views (Q1–Q2), constructing missing orthogonal views (Q4), and synthesizing 3D isometric views from 2D orthogonal data (Q3, Q5).

By grounding the item design in MRT and PSVT:R frameworks, this structured intervention ensures that students progress from basic mental transformation to the sophisticated multi-view synthesis required for technical engineering fields.

2.3. Data Collection

Data collection for this study focused on two primary dimensions: learning outcomes and behavioral engagement metrics.

2.3.1. Quantitative Metrics (Learning Outcomes): The primary measure of spatial visualization skill enhancement was derived from the scores of the pre-test (Quiz 1) and post-test (Quiz 2). Each quiz score was recorded as a percentage of correct answers. These metrics provide a direct comparison of proficiency gains before and after the intervention.

2.3.2. Engagement Metrics (Mastery-oriented Behavior): To evaluate the depth of student interaction with the intervention, engagement was tracked through the online learning management system. The key metric was the Time Spent Attempting to Achieve Mastery, defined as the cumulative time a student invested in each workbook until a perfect score (100%) was attained. Unlike traditional one-time assessments, this metric captures the iterative nature of the student's effort to reach the predefined mastery threshold.

2.4. Data Analysis

Statistical analyses were performed to validate the effectiveness of the iterative model and to categorize divergent student learning patterns.

2.4.1. Comparative Analysis: Paired t-tests [10] were conducted to compare pre-test and post-test scores, determining whether the observed improvements in spatial visualization skills were statistically significant across the longitudinal period.

2.4.2. Trajectory Identification: To explore divergent student behaviors, Cluster Analysis was utilized [11], [12], [13]. By grouping students based on their initial proficiency, total practice time, and final scores, this study identified distinct learning trajectories. This approach allows for a more nuanced understanding of how different student archetypes—such as those who achieve mastery quickly versus those who require high-frequency repetition—interact with the iterative practice model.

2.4.3. Relationship Analysis: Correlation analysis (Pearson's *r*) was employed [14] to examine the relationship between engagement metrics (time spent on workbooks) and performance gains (score change). This analysis aimed to identify if higher time investment in the mastery-oriented model directly translated to superior learning outcomes.

2.4.5. Learning Variable Correlation & Impact Analysis
The relationships among variables are summarized through the developmental flow of Learning Readiness (Pre-test), Engagement Process (Workbooks), Incremental Achievement (Test 1–3), and Terminal Proficiency (Final Exam).

3. Results and Discussion

3.1. Evaluation of Spatial Proficiency Improvement

The comparative analysis of pre-test (Quiz 1) and post-test (Quiz 2) scores, as illustrated in Figure 1, demonstrates a statistically significant enhancement in students' spatial visualization proficiency ($p = 4.72 \times 10^{-12}$).

- Gains in Performance and Efficiency: The analysis of pre- and post-test scores reveals a significant improvement in students' spatial proficiency following the intervention. The mean score increased from 7.93 (±2.59) in the pre-test to 9.93 (±3.06) in the post-test, representing an average performance gain of 2.00 points. A paired t-test confirmed that this improvement is statistically highly significant ($t = 7.6817$, $p < 0.001$). Beyond the raw score increase, a notable gain in efficiency was observed; while the pre-test was administered over 30 minutes, the post-test was completed in just 15 minutes. This 50% reduction in testing time, coupled with higher accuracy, demonstrates that students not only acquired deeper spatial knowledge but also developed greater fluency and cognitive efficiency in applying these skills. The convergence of increased scores and reduced task time highlights a substantial advancement in both the mastery and the processing speed of spatial tasks.

- Individual Progress Trajectories: The slope graph in Figure 1 (right) highlights that the majority of the 121 participants—those who completed both the pre- and post-tests and remained enrolled throughout the semester—exhibited a clear upward trend in their performance. Several students who initially scored below 5.0 on the pre-test showed remarkable progress, surpassing the class mean in the post-test. This suggests that the iterative practice model is particularly effective for students starting with lower initial spatial skills.

- Statistical Significance: The extremely low p-value obtained from the paired-samples t-test confirms that the observed improvements are highly robust and can be attributed to the structured intervention of the online mastery workbooks rather than random variance.

Table 2: Summary of Descriptive Statistics for Assessments and Intervention

Metric	Quiz 1 (30 min. Max 15 points)	Quiz 2 (15 min. Max 15 points)	Workbook 1 (Time: min)	Workbook 2 (Time: min)	Workbook 3 (Time: min)
Mean	7.93	9.93	2580	2189	2133
Std. Deviation (SD)	2.59	3.06	5802	6679	4593
Maximum	13	15	34826	44153	22043
Minimum	1.2	3	6	4	5

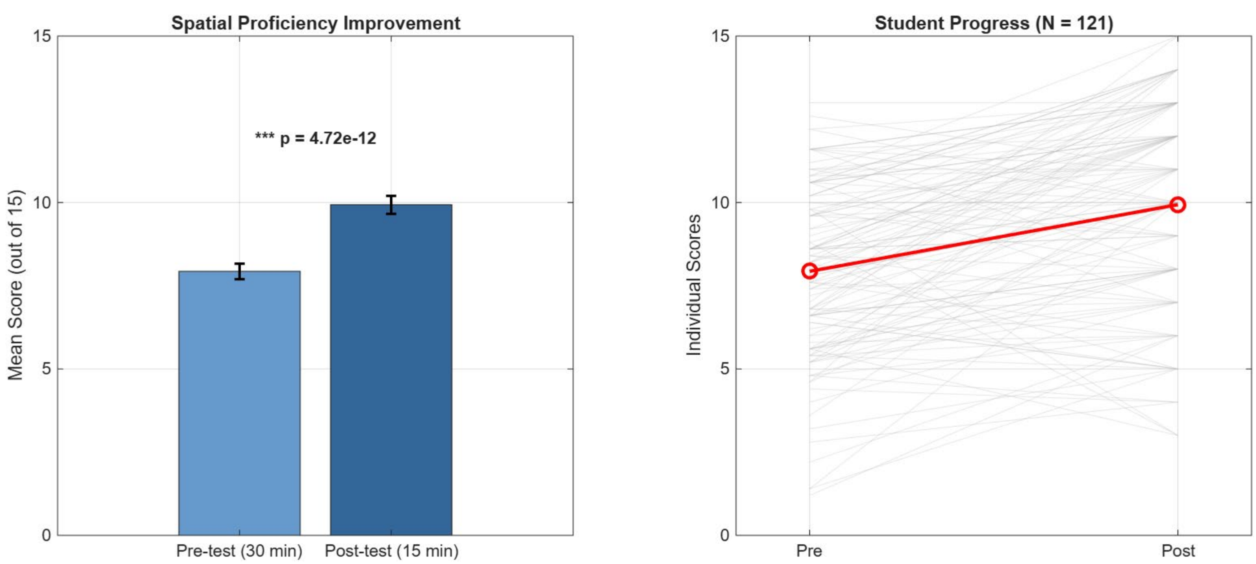

Figure 1. Spatial Proficiency Improvement and Individual student progress

3.2. Comparative Analysis of Student Trajectories and Learning Efficacy

The categorical disaggregation of student data reveals a profound non-linear relationship between instructional engagement and mastery achievement. As illustrated in the Comparative Analysis of Student Trajectories (Figure 2), three distinct learning patterns emerge, suggesting that quantitative effort does not universally translate into qualitative proficiency gains:

- Group 1: High-Efficiency (n = 37): This cohort represents the most optimal learning trajectory, achieving the highest average improvement (Avg Imp: 4.54). Notably, most participants in this group are positioned well above the zero-baseline, even with moderate total engagement. This suggests that these learners possess either a high baseline aptitude or an optimized cognitive strategy that allows for rapid mastery with minimal repetition.

- Group 2: Persistent Improvers (n = 36): Characterized as a stable and moderately growing group, these students achieved an average improvement of 1.26 points. Their distribution is primarily concentrated in the lower engagement range (10^1 to 10^2), demonstrating that fundamental practice within a limited timeframe can effectively facilitate steady developmental progress for a significant portion of the student body.

- Group 3: High-Effort/Low-Gain (n = 48): This group, which constitutes the largest segment of the study, presents a critical pedagogical challenge. Despite demonstrating the highest levels of engagement—spanning from 10^2 to 10^5 units—the average improvement was the lowest among all groups at 0.60. The broad distribution across the high-engagement spectrum coupled with marginal or even negative gains indicates a "practice plateau," where repetitive quantitative input fails to overcome cognitive bottlenecks.

- These findings underscore that "more practice" does not inherently guarantee higher achievement. The divergence between the High-Efficiency and High-Effort groups highlights a paradox of effort, emphasizing that educational interventions must shift from purely quantitative workbook requirements toward qualitative, trajectory-specific instructional support to maximize learning outcomes for all student archetypes.

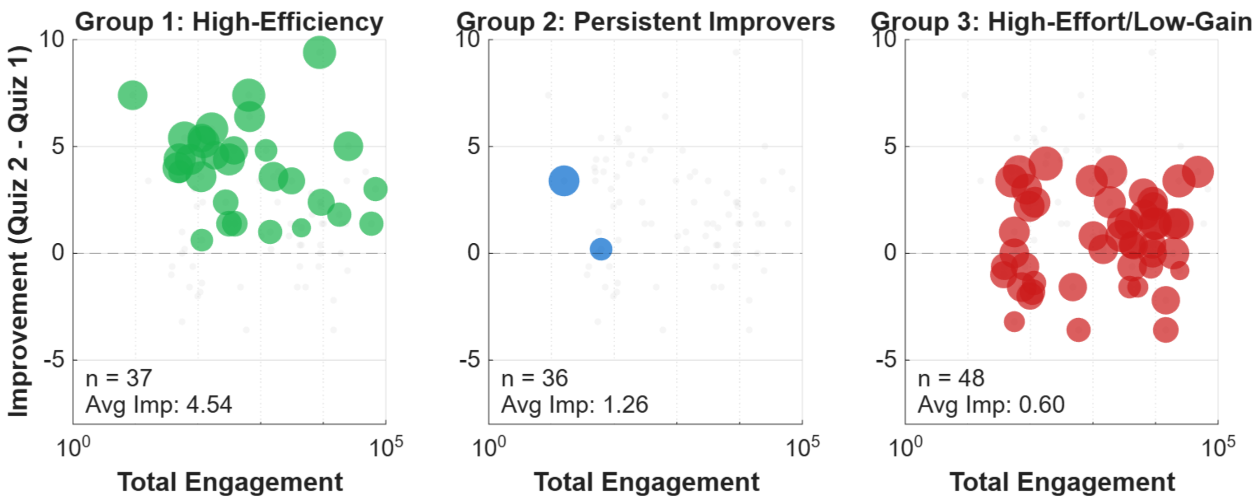

Figure 2. Comparative Analysis of Student Trajectories

3.3 Relationship Analysis: Correlation analysis (Pearson's *r*)

A Pearson correlation analysis was conducted to examine the relationships between Pre-Test scores,

- Post-Test scores, the Difference (gain score), and Total Engagement.Relationship Between Test Scores: A strong positive correlation ($r = 0.61$) was observed between Pre-Test and Post-Test scores, indicating that students with higher initial knowledge tended to perform better in the final assessment.

- Engagement and Academic Improvement: While the correlation between Post-Test scores and Total Engagement was weak ($r = 0.08$), a more notable positive correlation ($r = 0.22$) was found between the score Difference (improvement) and Total Engagement. This suggests that active participation in the learning process is more closely associated with the magnitude of knowledge gain rather than just the final attainment level.

- Negative Correlation with Initial Levels: Interestingly, a negative correlation ($r = -0.38$) was identified between Pre-Test scores and the Difference. This indicates a "ceiling effect" or that learners who started with lower baseline scores achieved more significant relative improvements through the intervention.

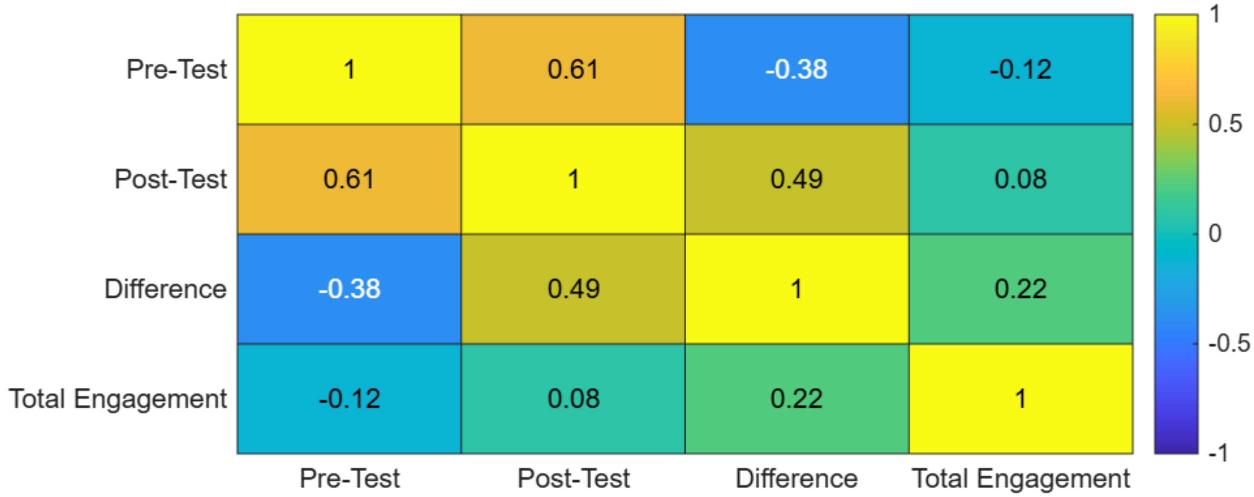

Figure 3: Correlation Matrix of Student Performance and Engagement

3.4 Resilience of the Online Mastery Model during the Pandemic (Fall 2022)

Despite the transition to fully remote instruction during the 2022 pandemic period, student performance gains in spatial visualization did not show a significant decline compared to in-person semesters. Analysis of the Fall 2022 data reveals that the improvement trajectory remained consistent with the overall longitudinal average. Several factors contribute to this observed resilience:

- Platform-Agnostic Nature of the Intervention: Since the assessments and workbooks were natively designed as online-based modules, the learning environment remained consistent regardless of the physical classroom's availability.

- Self-Paced Mastery as a Compensatory Mechanism: In the absence of face-to-face instructor feedback, the "unlimited attempts" feature of the workbooks empowered students to engage in self-directed remediation. Students were able to practice until reaching the mastery threshold (100%), effectively mitigating potential learning gaps caused by remote instruction.

- Maintained Cognitive Fluency: The fact that students achieved significant gains even under the rigorous 15-minute constraint of Quiz 2 during the pandemic suggests that the iterative practice model is robust enough to enhance cognitive processing speed independent of the instructional delivery mode (online vs. offline).

3.5 Learning Variable Correlation & Impact Analysis

The interrelationships between initial proficiency, engagement metrics, and cumulative academic achievement were evaluated through a Pearson correlation analysis, as summarized in the provided correlation matrix (Figure 4) [15]. The findings underscore the critical role of sustained performance and baseline competency in determining terminal academic success.

- Primary Predictors of Final Achievement: A robust positive correlation was observed between the Test Average and the Final Exam score (r = 0.82), identifying cumulative mastery of intermediate assessments as the most significant predictor of overall performance. Additionally, Quiz 1 (Pre-test) and Quiz 2 (Post-test) scores demonstrated moderate-to-strong positive correlations with the Final Exam (r = 0.58 and r = 0.52, respectively), suggesting that both initial aptitude and immediate post-intervention proficiency are reliable indicators of long-term retention.

- Initial vs. Post-Intervention Proficiency: A strong correlation exists between Quiz 1 and Quiz 2 (r = 0.61), indicating that students with higher baseline knowledge tended to maintain their performance advantage following initial instructional interventions.

- The Role of Workbook Engagement: Total workbook engagement (WB Total) exhibited a positive but relatively weak correlation with terminal success (Final: r = 0.28) and a moderate correlation with intermediate success (Test Avg: r = 0.35). Interestingly, engagement showed a negligible negative correlation with baseline scores (Quiz 1: r = -0.12), suggesting that quantitative effort in workbooks was distributed independently of a student's starting proficiency level.

- Consistency Across Assessments: The moderate positive relationship between Quiz 1 and Test Average (r = 0.55) further validates the influence of early-stage mastery on the progression of learning throughout the course.

While quantitative engagement in workbooks contributes to learning, the data suggests that cumulative assessment performance and initial proficiency are more decisive factors in achieving high terminal outcomes. This indicates that instructional focus should prioritize the conversion of engagement into measurable mastery during intermediate testing phases.

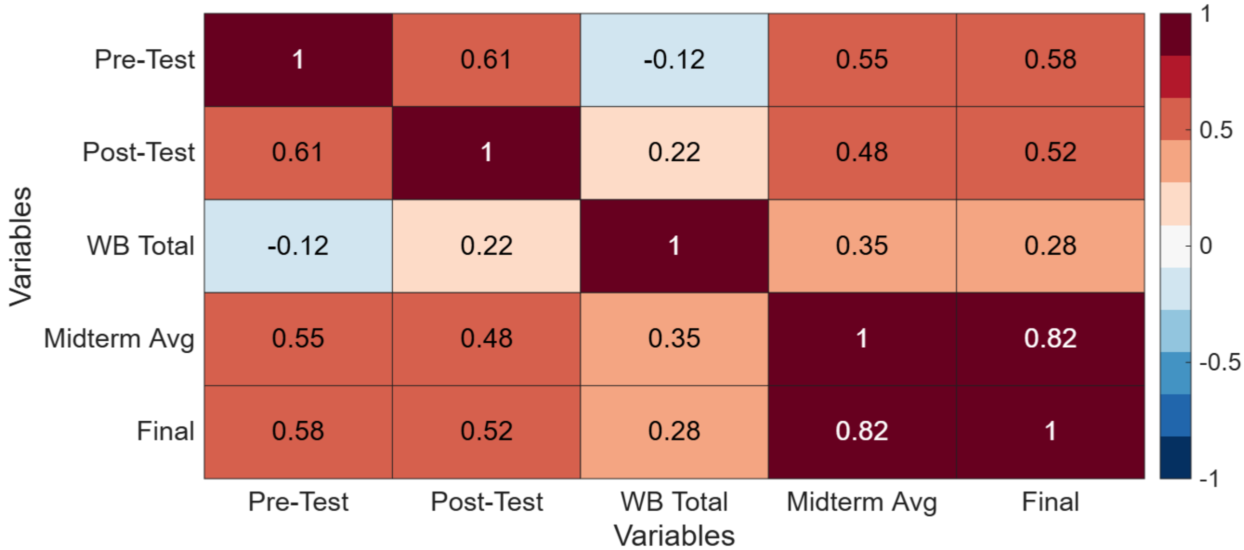

Figure 4: Learning Variable Correlation Heat Map

4. Conclusion

The results of this study confirm that the iterative, mastery-oriented online workbook model is a highly effective intervention for enhancing spatial visualization skills. First, the comparison between pre- and post-tests revealed that despite a 50% reduction in testing time for the post-test, scores significantly improved. This suggests that the initial assessment and subsequent intervention not only bridge knowledge gaps but also foster greater fluency and cognitive efficiency in spatial reasoning.

Second, the study identified distinct growth patterns based on initial proficiency. Students who scored above average on the pre-test exhibited a steady, incremental improvement as they progressed through the three workbook sets. Conversely, many students who initially scored below average achieved radical performance gains through consistent workbook engagement, often surpassing the class mean.

However, the analysis also revealed a "practice paradox": a significant number of students who scored poorly on the pre-test remained at a "practice plateau" or showed declining scores despite spending an extensive amount of time on the workbooks. This confirms that repetitive, self-directed workbook learning alone does not guarantee improvement for all learners, particularly those facing specific cognitive bottlenecks. Finally, the model's effectiveness was validated by the fact that students achieved consistent score improvements even during the pandemic's fully remote instruction period, proving the robustness and resilience of the online-based intervention.

5. Limitations and Future Work

While the mastery-oriented model proved effective, this study identifies opportunities for future research to deepen the understanding of spatial visualization development:

- Qualitative and Behavioral Investigation: Future studies should incorporate student interviews or eye-tracking to understand why "High-Effort/Low-Gain" learners fail to translate time into mastery. Additionally, investigating student-initiated engagement—such as whether students seek help or initiate peer discussions beyond the digital platform—could provide deeper insights into the social-cognitive aspects of learning.

- Adaptive and Instructor-Guided Pedagogy: To address the limits of simple repetition, future iterations should integrate AI-driven adaptive feedback that provides trajectory-specific guidance. Furthermore, exploring non-self-paced or instructor-guided variations of the intervention would help determine the optimal balance between autonomous mastery and instructional scaffolding.

- Longitudinal Impact and Academic Correlation: Tracking these students in subsequent advanced engineering courses, particularly CAD-focused curricula, would determine the multi-year impact of this intervention. Further research will also examine how workbook engagement and score improvements correlate with broader academic performance data, such as cumulative GPA, to validate the intervention's role in overall student success.

6. Acknowledgement

This work was supported by the Center for Excellence in Teaching & Learning's Quality Enhancement Plan Grant at Georgia State University Perimeter College.

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