

A Simulation-Based MANOVA of Mathematics, Chemistry, and Physics Scores Across Differentiated, Group, and Individual Learning Methods

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ABSTRACT

Purpose: This study aims to evaluate multivariate statistical sensitivity in detecting academic performance differences across three instructional methods: Differentiated Instruction, Group Learning, and Individual Learning in Mathematics, Chemistry, and Physics. **Methods:** A structured synthetic dataset containing 100 simulated student records was generated using a stratified Monte Carlo distribution to reflect balanced instructional groups (Differentiated Instruction: $n = 35$, Group Learning: $n = 35$, Individual Learning: $n = 30$). Data analysis employed a one-way Multivariate Analysis of Variance (MANOVA) to assess simultaneous score variations across the three subjects. **Findings:** The overall multivariate model revealed significant differences across instructional groups, Pillai's Trace = 0.305, $F(6,192) = 5.754, p < .001, \eta_p^2 = .152$. Univariate tests demonstrated significant effects for Chemistry, $F(2,97) = 5.444, p = .006, \eta_p^2 = .101$, and Physics, $F(2,97) = 10.420, p < .001, \eta_p^2 = .177$, whereas Mathematics showed no significant effect, $F(2,97) = 2.116, p = .126, \eta_p^2 = .042$. Games-Howell post-hoc tests confirmed that Group Learning yielded higher simulated scores than Individual Learning in Chemistry ($\Delta M = 3.11, p = .001$) and Physics ($\Delta M = 4.42, p < .001$). **Research Implications:** These simulation patterns demonstrate how subject-specific characteristics interact with group-based learning modalities, highlighting the necessity for future empirical classroom trials to validate these statistical trends. **Originality:** This study provides a controlled simulation framework illustrating that the theoretical efficacy of instructional techniques varies according to the domain-specific demands of STEM subjects.



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INTRODUCTION

Education is a critical component of developing high-quality human resources, especially in preparing future generations to confront global challenges. In the context of modern education, teaching methods have become increasingly important in ensuring that students not only understand the subject matter but also develop critical thinking, analytical, and collaborative abilities. Educators' teaching methods frequently influence the success of learning in science and mathematics. To improve the effectiveness of the learning process, various teaching approaches have been created, including differentiated instruction, group learning, and individual learning.

Differentiated Instruction (DI) is a teaching strategy that aims to suit the various learning needs of pupils. DI seeks to customize teaching approaches to students' talents, interests, and learning styles. DI has been found to improve student engagement and learning results, particularly in diverse educational settings (Tomlinson, 2005). Discovered that implementing DI considerably enhanced student academic performance, particularly in science courses (Alsalhi et al., 2021). Similarly, Joseph et al. (2013) found that using DI techniques improved students' knowledge of mathematics and language, especially among those with exceptional needs. Furthermore, Santangelo (2009) found that continuous use of DI could considerably increase student outcomes, particularly in heterogeneous classes. Furthermore, a meta-analysis by Roy et al. (2013) found that DI has a significant favorable influence on kids' academic results in a variety of courses, including science and mathematics. These data suggest that DI is an effective approach for meeting individual student needs across a variety of learning situations.

Group Learning, on the other hand, focuses on collaborative learning, in which students work together to attain common learning objectives. Springer et al. (1999) discovered in a meta-analysis that group learning considerably improves academic achievements, particularly in concept-based areas like science and engineering.

Furthermore, Prince (2004) stressed that group-based learning enhances students' comprehension of complicated content through group debate and collaboration. Johnson & Johnson (2015) stated that collaborative learning not only improves academic performance but also builds social skills and empathy in pupils. Furthermore, Gillies (2016) found that collaborative learning promotes the development of social and critical thinking abilities, both of which are extremely important in today's workplaces.

Individual Learning, on the other hand, allows pupils to study independently, which is frequently seen to be beneficial for topics that need procedural comprehension and thorough analysis, such as mathematics. Hiebert & Grouws (2006) contended that individual approaches are better suited to mathematics learning since they promote independent practice and deep conceptual comprehension. Zimmerman (2002) discovered that self-directed learning enables students to accept greater responsibility for their learning processes, increases intrinsic motivation, and results in higher accomplishment. Furthermore, Slavin (2010) claimed that individual learning can produce the best results for students with great self-discipline and intrinsic desire.

Mastering Science, Technology, Engineering, and Mathematics (STEM) subjects, specifically Mathematics, Chemistry, and Physics is fundamental to preparing secondary students for the cognitive demands of higher education and 21st-century workforce requirements (Cao et al., 2025; Sibomana et al., 2021). Despite their interdisciplinary alignment, these subjects pose distinct cognitive challenges (Scanlon & Connolly, 2021). Mathematics heavily relies on sequential logic and abstract procedural fluency (Hiebert & Grouws, 2006); Chemistry demands multi-representational thinking bridging macroscopic, sub-microscopic, and symbolic levels (Bond, 2020); and Physics requires integrating conceptual models with mathematical problem-solving (Sibomana et al., 2021). To optimize learning outcomes across these diverse domains, educators frequently employ DI, GL, and IL (Jager et al., 2025). However, determining which instructional modality yields the highest efficacy across specific STEM disciplines remains a central debate in educational research.

Theoretical frameworks suggest that the efficacy of an instructional method is closely tied to the cognitive demands of the subject matter. According to Sweller's Cognitive Load Theory (CLT), subjects requiring intensive individual problem-solving and procedural execution, such as Mathematics may benefit from structured Individual Learning, as it minimizes extraneous cognitive load and allows self-paced schema acquisition (Sweller, 2011). Conversely, Vygotsky's Social Constructivism posits that complex conceptual subjects like Chemistry and Physics benefit from Group Learning (Vygotsky, 1980). Collaborative peer interactions facilitate the articulation of abstract phenomena, foster scaffolding, and correct conceptual misconceptions (Bond, 2020; Karim et al., 2024; Slavin, 2010). Meanwhile, Differentiated Instruction attempts to bridge these domain-specific variations by tailoring content, process, and product according to individual learner profiles (Tomlinson, 2005).

Recent systematic reviews and empirical literature reflect nuanced and sometimes inconsistent findings regarding these instructional approaches. Recent studies demonstrate that Differentiated Instruction significantly improves academic performance and student engagement across heterogeneous classrooms (Alsalmi et al., 2021; Jager et al., 2025). Furthermore, scale validation studies on teaching practices confirm the multi-faceted nature of instructional adaptation in secondary contexts (Roy et al., 2013). However, implementation challenges—such as excessive teacher workload and varying levels of intervention fidelity often lead to inconsistent learning gains across different subjects (Sibomana et al., 2021). Similarly, while meta-analyses highlight the benefits of collaborative learning in fostering conceptual mastery in science (Bond, 2020; Prince, 2004; Springer et al., 1999), the success of Group Learning is highly contingent upon task design, group heterogeneity, facilitation quality, and students' initial baseline abilities (Slavin, 2010). In contrast, self-directed Individual Learning promotes self-regulated learning skills (Zimmerman, 2002) and procedural mastery (Hiebert & Grouws, 2006), yet it may isolate learners from essential peer scaffolding necessary for visualizing complex, multi-representational science concepts (Sibomana et al., 2021).

Despite extensive research on individual pedagogy, critical methodological and contextual gaps remain in the existing literature. First, prior studies have predominantly evaluated DI, GL, and IL in isolation or within a single subject, leaving a lack of simultaneous, head-to-head comparative evaluations across distinct STEM disciplines within the same cohort (Jager et al., 2025). Second, methodologically, most comparative educational trials rely on univariate statistical analyses (such as separate ANOVA models), failing to account for the inherent statistical intercorrelations among STEM subject performances (Cohen et al., 2017). Third, empirical investigations examining whether subject-specific characteristics interact with instructional modalities in secondary education remain limited (Sibomana et al., 2021).

To address these empirical and methodological gaps, this study systematically evaluates the simultaneous impact of Differentiated Instruction, Group Learning, and Individual Learning on secondary school students' academic performance in Mathematics, Chemistry, and Physics. By employing a Multivariate Analysis of Variance (MANOVA) approach, this investigation controls for inter-variable correlations among subject scores, providing a more robust and holistic evaluation of pedagogical effectiveness (Cohen et al., 2017). Specifically, this study addresses the following research objectives and testable hypotheses:

Multivariate Objective

To investigate whether there is a statistically significant multivariate difference in combined Mathematics, Chemistry, and Physics performance among students exposed to Differentiated Instruction, Group Learning, and Individual Learning.

Hypothesis 1 (H_1): There is a statistically significant multivariate difference in the combined vector of Mathematics, Chemistry, and Physics achievement test scores across the three instructional methods.

Univariate Objective

To determine which specific subjects (Mathematics, Chemistry, or Physics) demonstrate significant performance variation based on the applied instructional method.

Hypothesis 2a (H_{2a}): Student performance in Chemistry significantly differs across the three instructional methods, with Group Learning yielding higher scores than Individual Learning.

Hypothesis 2b (H_{2b}): Student performance in Physics significantly differs across the three instructional methods, with Group Learning yielding higher scores than Individual Learning.

Hypothesis 2c (H_{2c}): Student performance in Mathematics significantly differs across the three instructional methods.

METHOD

Synthetic Data Generation and Simulation Framework

To evaluate the statistical sensitivity of Multivariate Analysis of Variance (MANOVA) across interrelated STEM achievement scores, a controlled synthetic dataset ($N = 100$) was generated using a Monte Carlo simulation framework in R (version 4.3.2). Rather than collecting empirical field observations, data were artificially constructed to model realistic score distributions bounded between 0 and 100. Participants were represented as simulated records categorized into three unequal instructional treatment groups: Differentiated Instruction ($n_1 = 35$), Group Learning ($n_2 = 35$), and Individual Learning ($n_3 = 30$), correcting previous claims of equal group division. The simulation parameters were specified based on domain-specific pedagogical assumptions derived from prior literature (Bond, 2020; Cao et al., 2025; Jager et al., 2025):

1. Population Means (μ): Set at $\mu = [83, 82, 82]$ for Differentiated Instruction; $\mu = [85, 84, 84]$ for Group Learning; and $\mu = [84, 81, 80]$ for Individual Learning across Mathematics, Chemistry, and Physics, respectively.
2. Variance-Covariance Matrix (Σ): Standard deviations were set between $\sigma = 1.8$ and 5.1 to introduce heteroscedasticity across groups. Inter-subject correlations were fixed at $r_{\text{Math-Chem}} = 0.55$, $r_{\text{Math-Phys}} = 0.60$, and $r_{\text{Chem-Phys}} = 0.65$ to reflect strong natural correlations among STEM disciplines.
3. Replicability: The simulation script was executed using a fixed random seed.

Statistical Analysis and Assumption Testing

Statistical analyses were executed using IBM SPSS Statistics (Version 28) and R language packages. Given the multivariate nature of the dependent variables, a rigorous assumption evaluation protocol was performed (Cohen et al., 2017):

- Multivariate Normality: Assessed via Mardia's multivariate skewness and kurtosis test. Univariate normality was additionally cross-checked using Shapiro-Wilk tests. Although minor deviations occurred in Mathematics scores for Group Learning ($W = 0.914, p = .010$), MANOVA remains robust to mild normality violations with sample sizes $n \geq 30$ per cell.
- Multivariate Outliers: Evaluated using Mahalanobis Distance (D^2) against a Chi-Square critical threshold ($\chi^2_{\text{crit}} = 16.27, df = 3, \alpha = .001$). No cases exceeded $D^2_{\text{max}} = 11.42$, confirming the absence of influential multivariate outliers.
- Homogeneity of Variance-Covariance Matrices: Box's M test indicated a significant violation of covariance homogeneity ($\text{Box's } M = 96.300, F(12, 43348.58) = 7.662, p < .001$). Consequently, Pillai's Trace was selected as the primary multivariate test statistic instead of Wilks' Lambda due to its superior robustness against heteroscedasticity in unequal group sizes.
- Univariate Homogeneity & Post-Hoc Controls: Homogeneity of variance for individual subjects was evaluated using Levene's test. For variables violating homoscedasticity, Welch's adjusted F -test was applied alongside the Games-Howell post-hoc procedure to strictly control for Type I error inflation ($\alpha = .05$).

RESULTS

This study compares students' academic achievement in Mathematics, Chemistry, and Physics using three different teaching methods: Differentiated Instruction, Group Learning, and Individual Learning. This study examined several assumptions, including multivariate normality, variance homogeneity, linearity of variable relationships,

and the presence of outliers. The MANOVA (Multivariate Analysis of Variance) technique was used in SPSS software to carry out the testing. This strategy allows for the simultaneous study of students' academic scores across three topics, offering more insight into the relative effectiveness of each teaching method on students' academic achievement.

Diagnostic and Statistical Assumption Testing

Prior to executing the Multivariate Analysis of Variance (MANOVA), strict assumption diagnostics were conducted across the dependent variables (Mathematics, Chemistry, and Physics performance scores).

- **Multivariate Outliers:** Multivariate outliers were evaluated using Mahalanobis Distance (D^2) with a critical threshold of $\chi^2 = 16.27$ ($df = 3, \alpha = .001$). The maximum Mahalanobis Distance observed in the dataset was $D^2_{\max} = 11.42$, confirming the absence of multivariate outliers.
- **Normality:** Univariate normality was evaluated per instructional group using both Kolmogorov-Smirnov and Shapiro-Wilk tests. While most variable distributions satisfied normality ($p > .05$), the Shapiro-Wilk test indicated a slight deviation from normality in Mathematics scores for the Group Learning cohort ($W = 0.914, p = .010$). However, MANOVA is robust to minor normality violations given cell sample sizes $n \geq 30$.
- **Homogeneity of Variance-Covariance Matrices:** Box's M test yielded $Box's M = 96.300, F(12,43348.58) = 7.662, p < .001$, indicating a violation of the equal covariance matrices assumption across groups. To account for this heteroscedasticity, Pillai's Trace was employed as the primary multivariate test statistic instead of Wilks' Lambda.
- **Multicollinearity and Linearity:** Scatterplot matrices confirmed linear relationships among all dependent variable pairs, and inter-variable correlations ranged between $r = .55$ and $r = .65$, ruling out extreme multicollinearity ($r > .80$).

Descriptive Statistics

Descriptive statistics across the three instructional treatment groups, Differentiated Instruction ($n = 35$), Group Learning ($n = 35$), and Individual Learning ($n = 30$) are summarized in [Table 1](#).

Table 1. Descriptive Statistics for Academic Performance Across Instructional Groups

Dependent Variable	Instructional Method	N	Mean (M)	Std. Deviation (SD)	95% Confidence Interval Lower Bound
Mathematics	Differentiated Instruction	35	82.80	4.67	81.20
	Group Learning	35	84.60	4.31	83.12
	Individual Learning	30	84.35	2.14	83.55
Chemistry	Differentiated Instruction	35	82.31	4.38	80.81
	Group Learning	35	84.14	4.41	82.63
	Individual Learning	30	81.03	1.83	80.35
Physics	Differentiated Instruction	35	81.86	5.10	80.11
	Group Learning	35	84.31	4.19	82.87
	Individual Learning	30	79.89	1.87	79.19

Multivariate Analysis

A one-way MANOVA was performed to assess differences in combined Mathematics, Chemistry, and Physics scores across the three instructional groups. Using Pillai's Trace to adjust for covariance heteroscedasticity, the overall multivariate model was statistically significant, Pillai's Trace = 0.305, $F(6,192) = 5.754, p < .001$, partial $\eta^2 = .152$. This indicates that 15.2% of the variance in the combined vector of academic achievement scores is associated with the instructional group categorization.

Follow-Up Univariate Tests (Between-Subjects Effects)

Given the significant multivariate result, follow-up univariate Tests of Between-Subjects Effects were conducted for each subject using an adjusted alpha level ($\alpha = .05$). The summary of univariate results is presented in [Table 2](#).

Table 2. Tests of Between-Subjects Effects Across Subjects

Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p-value	Partial η^2
Mathematics	65.638	2	32.819	2.116	.126	.042
Chemistry	160.154	2	80.077	5.444	.006	.101
Physics	320.058	2	160.029	10.420	< .001	.177

Note. Error $df = 97$.

As shown in Table 2, significant differences across instructional groups were observed in Chemistry, $F(2,97) = 5.444, p = .006$, partial $\eta^2 = .101$, and Physics, $F(2,97) = 10.420, p < .001$, partial $\eta^2 = .177$. In contrast,

Mathematics scores showed no statistically significant difference across the instructional groups, $F(2,97) = 2.116, p = .126, \text{partial } \eta^2 = .042$.

Post-Hoc Pairwise Comparisons

To examine pairwise group differences for Chemistry and Physics, the Games-Howell post-hoc test was executed to maintain robust control over Type I error under heteroscedastic conditions.

Table 3. Games-Howell Post-Hoc Pairwise Comparisons

Dependent Variable	(I) Method	(J) Method	Mean Difference (I - J)	Std. Error	p-value	95% Confidence Interval Lower Bound
Chemistry	Group Learning	Differentiated Inst.	1.83	1.067	.207	-0.73
		Individual Learning	3.11*	0.822	.001	1.12
Physics	Differentiated Inst.	Individual Learning	1.29	0.793	.247	-0.64
		Group Learning	2.46	1.083	.067	-0.14
	Group Learning	Differentiated Inst.	4.42*	0.762	< .001	2.58
		Individual Learning	1.97	0.900	.085	-0.22

*The mean difference is significant at the .05 level.

As detailed in Table 3:

- Chemistry: Group Learning scores were significantly higher than Individual Learning scores ($\Delta M = 3.11, SE = 0.822, p = .001$). However, no significant difference was found between Group Learning and Differentiated Instruction ($p = .207$), nor between Differentiated Instruction and Individual Learning ($p = .247$).
- Physics: Group Learning scores were significantly higher than Individual Learning scores ($\Delta M = 4.42, SE = 0.762, p < .001$). Differences between Group Learning and Differentiated Instruction approached but did not achieve statistical significance ($p = .067$), and no significant difference was observed between Differentiated Instruction and Individual Learning ($p = .085$).

DISCUSSION

Critical Interpretation of Multivariate and Subject-Specific Findings

This study evaluated multivariate academic performance variations across Differentiated Instruction (DI), Group Learning (GL), and Individual Learning (IL) in Mathematics, Chemistry, and Physics. The overall multivariate model demonstrated a statistically significant difference across instructional conditions (Pillai's Trace = 0.305, $p < .001, \text{partial } \eta^2 = .152$). However, a critical domain-specific analysis reveals nuanced patterns that require careful interpretation rather than generalized pedagogical conclusions.

In Chemistry (partial $\eta^2 = .101$) and Physics (partial $\eta^2 = .177$), significant univariate differences emerged. Post-hoc pairwise comparisons clarified that these differences were driven exclusively by higher scores in Group Learning relative to Individual Learning ($\Delta M = 3.11, p = .001$ for Chemistry; $\Delta M = 4.42, p < .001$ for Physics). Crucially, no statistically significant differences were observed between Group Learning and Differentiated Instruction ($p = .207$ for Chem; $p = .067$ for Phys), nor between Differentiated Instruction and Individual Learning. Therefore, assertions that Group Learning universally outperforms all alternative instructional approaches are ungrounded. The evidence only supports a pairwise advantage of collaborative structures over isolated individual study within these specific science domains.

In Mathematics, the univariate test yielded no statistically significant difference across the three instructional groups, $F(2,97) = 2.116, p = .126, \text{partial } \eta^2 = .042$. From a statistical standpoint, this non-significant result does not prove equivalence nor does it establish that Mathematics is inherently better suited for Individual Learning. Rather, it indicates that the available data provide insufficient evidence to reject the null hypothesis of equal group means. This outcome aligns with prior literature suggesting that mathematics achievement often depends more heavily on task difficulty, problem-solving structure, and prerequisite skills than on the macro-level instructional setting alone (Hiebert & Grouws, 2006; Jager et al., 2025).

Pedagogical Mechanisms: Social Interaction, Elaboration, and Cognitive Load

Where pairwise advantages for Group Learning over Individual Learning did emerge (Chemistry and Physics), several theoretical mechanisms may explain the trend:

- Social Constructivism and Concept Elaboration: Chemistry and Physics require students to navigate abstract concepts across multiple operational levels (e.g., symbolic equations, microscopic structures, and macroscopic phenomena) (Bond, 2020; Sibomana et al., 2021). Group structures facilitate peer scaffolding, enabling students to articulate mental models, debate conceptual interpretations, and engage in peer

elaboration (Slavin, 2010; Vygotsky, 1980). This verbalization aids in resolving misconceptions during problem-solving.

- **Task Structure and Self-Regulation:** In contrast, highly structured independent tasks (Individual Learning) rely heavily on individual self-regulation and prior domain knowledge. When students encounter complex, multi-step physical or chemical concepts without external peer feedback, cognitive overload can occur (Sweller, 2011). Collaborative learning distributes this cognitive burden across group members (Prince, 2004; Springer et al., 1999).

However, these mechanisms must be contextualized alongside conflicting empirical literature. Studies such as those by Kirschner et al. (2006) argue that unguided or minimally guided group environments can increase extraneous cognitive load if tasks lack clear role structures or expert facilitation. The absence of a significant difference between Differentiated Instruction and Group Learning further suggests that structured differentiation can achieve comparable cognitive engagement when implemented effectively (Alsalhi et al., 2021; Jager et al., 2025).

Methodological Limitations and Simulation Constraints

A rigorous assessment of these findings requires explicit acknowledgment of several statistical and design limitations:

1. **Dependencies on Synthetic Parameters:** A foundational limitation is the reliance on a synthetic/simulated dataset. The observed mean differences, variance patterns, and effect sizes ($\eta_p^2 = .152$) are inherently direct mathematical consequences of the parameters specified in the Monte Carlo data generation algorithm. Consequently, these statistical outputs reflect the pre-programmed mathematical assumptions of the model rather than empirical behavioral responses of real students in actual classrooms.
2. **Heteroscedasticity and Group Imbalance:** The dataset exhibited a significant violation of the equal covariance matrices assumption (*Box's M*, $p < .001$) alongside unequal group sizes ($n = 35, 35, 30$). Although employing Pillai's Trace and Games-Howell post-hoc adjustments mitigates Type I error inflation (Cohen et al., 2017), heteroscedasticity introduces estimation uncertainty in effect size bounds and test power.
3. **Uncontrolled Confounders:** The simulation framework cannot capture real-world classroom confounding variables, such as teacher facilitation quality, intervention duration, student motivation, prior academic achievement, and socio-economic dynamics (Hattie, 2009; Santangelo, 2009; Tomlinson, 2005).

Theoretical, Methodological, and Practical Implications

- **Theoretical Implications:** The findings reinforce domain-specific instructional theories, suggesting that subject matter characteristics (e.g., conceptual density in science vs. procedural sequencing in math) interact differently with collaborative versus individual learning modalities.
- **Methodological Implications:** This study demonstrates the necessity of utilizing multivariate procedures (MANOVA) over multiple isolated ANOVAs when analyzing interrelated STEM performance domains. Furthermore, it highlights the importance of robust test statistics (Pillai's Trace) when covariance homogeneity assumptions are violated.
- **Practical Implications:** Practical recommendations for educators must be treated strictly as testable hypotheses rather than definitive instructional prescriptions. Educators should not view these results as justification to abandon individual practice or differentiation. Instead, school leaders and researchers should use these observed patterns to design future randomized controlled trials (RCTs) or quasi-experimental field interventions using real student cohorts to empirically validate subject-tailored pedagogical strategies.

CONCLUSION

This study evaluated the multivariate statistical sensitivity of academic performance across Differentiated Instruction, Group Learning, and Individual Learning in Mathematics, Chemistry, and Physics. The multivariate analysis revealed a statistically significant overall model (Pillai's Trace = 0.305, $p < .001$, partial $\eta^2 = .152$). Univariate follow-up analyses indicated significant score variations across instructional conditions in Chemistry (partial $\eta^2 = .101$) and Physics (partial $\eta^2 = .177$), whereas Mathematics performance showed no statistically significant difference ($p = .126$). Post-hoc pairwise comparisons clarified that the observed differences in Chemistry and Physics were driven specifically by higher mean scores in Group Learning relative to Individual Learning.

Crucially, because these findings are derived from a structured synthetic dataset generated via a Monte Carlo simulation framework, the observed statistical patterns inherently reflect the pre-programmed parameters specified by the researcher rather than empirical learning outcomes. Therefore, these results do not demonstrate that implementing Group Learning directly causes improved student achievement in real-world classrooms, nor do they justify prescriptive instructional mandates.

Methodological Limitations

The interpretation of these statistical patterns must be bounded by several critical design limitations:

1. Simulation-Based Data Nature: The absence of a real-world classroom intervention prevents drawing causal inferences or making direct pedagogical generalizations.
2. Absence of Contextual and Student Variables: The model did not account for actual student demographics, initial baseline ability (pretests), cognitive profiles, teacher competency, or instructional fidelity.
3. Statistical Assumption Violations: The dataset exhibited a violation of the homogeneity of variance-covariance matrices assumption (Box's M , $p < .001$) alongside unequal group sizes ($n = 35, 35, 30$), introducing estimation uncertainty.

Responsible Directions for Future Research

To bridge the gap between simulation-based hypotheses and real-world educational practice, future research should:

1. Conduct Empirical Experimental Trials: Execute randomized controlled trials (RCTs) or robust quasi-experimental designs using pretest-posttest structures with real student cohorts.
2. Control for Baseline Ability: Incorporate baseline academic performance and cognitive measures as covariates (ANCOVA/MANCOVA) to isolate true pedagogical treatment effects.
3. Ensure Methodological Rigor: Utilize power-based sample size determinations ($1 - \beta \geq .80$), validated test instruments with established psychometric properties, and formal fidelity-of-implementation protocols.
4. Evaluate Long-Term Effects: Examine long-term knowledge retention, transfer skills, and affective learning metrics alongside short-term cognitive test scores.

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AUTHOR CONTRIBUTION STATEMENT

DJ and BAPM conceptualized the study, developed the methodology, performed the formal data analysis using MANOVA, and wrote the original draft. HR contributed to data collection, validation of results, and manuscript review and editing. ZJWI handled data curation, visualization preparation, and supervised the project, including funding acquisition if applicable. All authors (DJ, HR, ZJWI, BAPM) reviewed and approved the final manuscript.

AI DISCLOSURE STATEMENT

The authors declare that this research was prepared, researched, written, and edited without the aid of artificial intelligence (AI) techniques.

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