Online ISSN: 3082-5121

Aloysian Interdisciplinary Journal
of Social Sciences, Education, and Allied Fields

https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

AI-Driven Instruction Interfaced with Task-Based Learning in Grade 8 Mathematics

Joanne C. Malayan [1], Dr. Jonathan P. Zales [1]
annemalayan@gmail.com / 0009-0004-9313-7037

1 – Abra State Institute of Sciences and Technology (ASIST)

Publication Date: August 16, 2026 DOI: **10.5281/zenodo.21962541**

Abstract

Modern secondary mathematics education faces a procedural gap between basic calculations and higher-order statistical literacy. This study evaluated the integration of artificial intelligence tools (ChatGPT and Dola AI) with task-based learning (TBL) to enhance student performance. Adopting a mixed-methods design with a one-group pretest-posttest experimental approach, the study analyzed data from 34 Grade 8 students in Abra, Philippines. Data were gathered using DepEd Project SMART-adapted tests validated by experts with a 4.97 content validity index alongside engagement surveys and interviews. Quantitative data were analyzed via weighted means and paired t-tests, while interviews captured qualitative challenges. Baseline results showed a "Fairly Satisfactory" performance (Overall M = 76.89) and a procedural ceiling in standard deviation calculation (M = 68.71, "Did Not Meet Expectation"). Post-intervention, Project-Based Learning (PBL) achieved the highest performance (Overall M = 85.18, "Very Satisfactory"), followed by Think-Pair-Share (M = 83.18) and Jigsaw (M = 80.04). Paired t-tests confirmed significant gains across all frameworks ($p < 0.01$). PBL yielded the largest overall improvement (Gain = 8.29, t = 13.86) and standard deviation breakthrough (Gain = 5.50, t = 9.09), while Think-Pair-Share maximized range growth (Gain = 10.21, t = 7.45). The intervention earned a "Very High Level of Perceived Effectiveness" (M = 3.43), driven by task practicality (M = 3.62). In conclusion, combining AI with TBL shifts classrooms into active environments, framing math as a practical tool. However, it does not automatically guarantee full technical proficiency. While PBL is the most powerful strategy for complex problem-solving, operational benefits are heavily constrained by weak school Wi-Fi, algorithmic inaccuracies, and cognitive overload. To achieve sustainability, institutions must pair these pedagogical models with reliable digital infrastructure, technical support, and clear instructional guidelines that foster responsible AI literacy.

Keywords: *Educational technology, collaborative learning, statistical literacy, mixed-methods research, mathematics education. Strategy, Science Performance, Competency*

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

INTRODUCTION

Modern secondary mathematics education faces a severe procedural gap between basic arithmetic computation and higher-order statistical literacy. Traditional lecture-heavy instruction often isolates mathematical formulas, leading to passive learning and a pronounced "complexity wall" when students encounter multi-step statistical processes. To bridge this gap, modern academic systems are exploring the integration of digital scaffolding alongside active learning strategies. This study evaluates an instructional framework designed to transition classrooms into active environments where students view mathematics as a practical, real-world tool.

Review of Related Literature

Recent literature underlines the potential of technology-supported active learning. Kadir and Munir (2024) found that AI-based adaptive learning systems significantly enhance student performance by offering real-time, personalized feedback that directly targets misconceptions in complex subjects like statistics. In the local context, Medrano, Engi, and Yurango (2025) observed that utilizing AI tools within the Philippine educational ecosystem enhances student self-efficacy and engagement, particularly among learners performing at marginal levels.

To complement these technological interventions, Mudinillah, Rahmi, and Taro (2024) highlighted that Task-Based Learning (TBL) frameworks cultivate student autonomy and motivation by shifting focus toward real-world applications. When paired with collaborative structures, this model creates a synergistic effect. Zheng and Kim (2024) demonstrated that combining AI-assisted personalized learning with collaborative setups like Think-Pair-Share increases middle school achievement by forcing students to verbalize their mathematical reasoning. Furthermore, Hidayat et al. (2024) found that peer-teaching structures such as the Jigsaw method are highly effective for statistical literacy, though Chen and Wang (2023) cautioned that peer strategies can face bottlenecks if student group leaders have not fully mastered the core formulas themselves.

Statement of the Problem

Despite these pedagogical advancements, a persistent instructional ceiling remains in secondary statistical education. Students frequently master low-level tracking skills but experience severe performance drops as competencies scale in complexity. This study specifically addresses this issue by investigating the performance level and experiences of Grade 8 students when exposed to an integrated AI and task-based learning framework.

Objectives

This study aimed to fulfill the following objectives:

1. To determine the baseline mathematics performance level of Grade 8 students prior to the intervention.
2. To evaluate post-intervention performance levels across three distinct TBL strategies: Think-Pair-Share, Jigsaw, and Project-Based Learning.

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

3. To determine if a significant difference exists between pre-test and post-test scores under each strategy.
4. To assess the level of perceived effectiveness of the combined AI-TBL approach among the participants.
5. To identify the operational, cognitive, and psychological challenges encountered by the students during implementation.

Hypothesis: There is no significant difference in the performance levels of Grade 8 students in mathematics before and after the implementation of the AI-driven instruction combined with task-based learning strategies.

MATERIALS AND METHODS

Research Design

This study adopted a mixed-methods research design utilizing a one-group pretest-posttest experimental approach. This combined method allowed for the parallel collection of quantitative achievement metrics and qualitative data detailing student operational experiences.

Participants

The participants consisted of a complete cohort of thirty-four (N = 34) Grade 8 students enrolled in a public secondary school in Abra, Philippines, during the 2025-2026 school year. The sample represented a single intact classroom section selected through purposive sampling based on the student's current enrollment in the target statistics module.

Instruments

The primary instruments included:

- Diagnostic Pre-test and Post-test: Adapted from the Department of Education (DepEd) Project SMART. To ensure content validity, the instrument was evaluated by a panel of three mathematics experts using a 5-point Likert scale, achieving an outstanding content validity index mean score of 4.97.
- Perceived Effectiveness Questionnaire: A 15-item multidimensional Likert scale assessing student motivation, engagement, and utility perception.
- Interview Guide: A semi-structured open-ended instrument utilized in 1:1 individual interview to capture student challenges.

Procedure

The study was executed across a structured operational sequence. First, a diagnostic pre-test was administered to establish a performance baseline across four core competencies in ungrouped data variability: range, mean deviation, standard deviation, and statistical conclusions. Next, a targeted instructional sequence was implemented where AI tools (ChatGPT and Dola AI) were fully integrated across all learning competencies. The intervention systematically paired

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

these tools with three distinct collaborative TBL frameworks: Think-Pair-Share, the Jigsaw Method, and Project-Based Learning. Following each strategy, corresponding post-tests were administered. Finally, participants completed the perceived effectiveness survey and participated in 1:1 semi-structured interview.

Data Analysis

Quantitative achievement scores and survey data were processed using descriptive and inferential statistics. Performance baselines and post-intervention scores were analyzed using weighted means and evaluated against the standard DepEd grading scale norms. The statistical significance of performance changes from pre-test to post-test was determined using paired-sample t-tests with a significance threshold set at $p < 0.01$. Qualitative data collected from the individual interviews were processed using thematic analysis to isolate recurring challenges.

RESULTS

Prior to the intervention, the baseline evaluation (Table 1) revealed an overall mean of 76.89, falling under the descriptive rating of "Fairly Satisfactory." While students showed proficiency in basic tracking concepts like calculating the range (M = 84.38), performance dropped severely as complexity increased, culminating in standard deviation calculations (M = 68.71), which fell into "Did Not Meet Expectation."

Post-intervention outcomes demonstrated performance gains across all frameworks. Project-Based Learning (Table 4) yielded the highest overall academic achievement (M = 85.18, "Very Satisfactory"), followed by Think-Pair-Share (M = 83.18, "Satisfactory") and the Jigsaw Method (M = 80.04, "Satisfactory"). Notably, standard deviation calculation remained the lowest performing competency across all instructional designs ($M_{\text{TPS}}=71.68$, $M_{\text{Jigsaw}}=70.29$, $M_{\text{PBL}}=74.21$), remaining within the "Did Not Meet Expectation" threshold despite numerical improvements.

GRADING SCALE NORMS

90.00 - 100.00: Outstanding
85.00 - 89.99: Very Satisfactory
80.00 - 84.99: Satisfactory
75.00 - 79.99: Fairly Satisfactory
74.99 and Below: Did Not Meet Expectation

Table 1: Baseline Performance Levels (Pre-test)

Learning Competencies	Mean	Descriptive Rating
1. Calculates the range	84.38	Satisfactory
2. Solves problems involving mean deviation	75.85	Fairly Satisfactory
3. Calculates the standard deviation	68.71	Did Not Meet Expectation

Learning Competencies	Mean	Descriptive Rating
4. Draws conclusions from statistical data	78.62	Fairly Satisfactory
As a Whole	76.89	Fairly Satisfactory

Table 2: Post-Intervention Performance via Think-Pair-Share Strategy

Learning Competencies	AI Tool	Mean	Descriptive Rating
1. Calculates the range	Dola AI & ChatGPT	94.59	Outstanding
2. Solves problems involving mean deviation	Dola AI & ChatGPT	83.24	Satisfactory
3. Calculates the standard deviation	Dola AI & ChatGPT	71.68	Did Not Meet Expectation
4. Draws conclusions from statistical data	Dola AI & ChatGPT	83.21	Satisfactory
As a Whole	—	83.18	Satisfactory

Table 3: Post-Intervention Performance via Jigsaw Method

Learning Competencies	AI Tool	Mean	Descriptive Rating
1. Calculates the range	Dola AI & ChatGPT	90.44	Outstanding
2. Solves problems involving mean deviation	Dola AI & ChatGPT	78.35	Fairly Satisfactory
3. Calculates the standard deviation	Dola AI & ChatGPT	70.29	Did Not Meet Expectation
4. Draws conclusions from statistical data	Dola AI & ChatGPT	81.09	Satisfactory
As a Whole	—	80.04	Satisfactory

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

Table 4: Post-Intervention Performance via Project-Based Learning Strategy

Learning Competencies	AI Tool	Mean	Descriptive Rating
1. Calculates the range	Dola AI & ChatGPT	95.24	Outstanding
2. Solves problems involving mean deviation	Dola AI & ChatGPT	87.00	Very Satisfactory
3. Calculates the standard deviation	Dola AI & ChatGPT	74.21	Did Not Meet Expectation
4. Draws conclusions from statistical data	Dola AI & ChatGPT	84.26	Satisfactory
As a Whole	—	85.18	Very Satisfactory

Paired-sample t-tests confirmed highly significant performance gains across all three active learning frameworks ($p < 0.01$), thereby rejecting the null hypothesis. Project-Based Learning induced the largest overall statistical shift (Overall Mean Gain = 8.29, $t = 13.86$) and the most notable breakthrough against the complexity barrier in standard deviation (Mean Gain = 5.50, $t = 9.09$). Think-Pair-Share generated the maximum growth in low-level conceptual tracking, specifically range calculation (Mean Gain = 10.21, $t = 7.45$).

Table 5: Paired t-Test Results Across TBL Frameworks

Strategy / Competency	**Pre-test M**	**Post-test M**	**Mean Gain**	**t-value**	**p-value**
Think-Pair-Share Strategy					
1. Calculates the range	84.38	94.59	10.21	7.45	<0.01
2. Solves problems involving mean deviation	75.85	83.24	7.39	7.04	<0.01
3. Calculates the standard deviation	68.71	71.68	2.97	6.11	<0.01
4. Draws conclusions from statistical data	78.62	83.21	4.59	7.16	<0.01
Overall	*76.89*	*83.18*	*6.29*	*10.65*	*<0.01*

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

Strategy / Competency	Pre-test M	Post-test M	Mean Gain	t-value	p-value
Jigsaw Method					
1. Calculates the range	84.38	90.44	6.06	5.40	<0.01
2. Solves problems involving mean deviation	75.85	78.35	2.50	2.21	<0.01
3. Calculates the standard deviation	68.71	70.29	1.58	2.79	<0.01
4. Draws conclusions from statistical data	78.62	81.09	2.47	2.95	<0.01
Overall	*76.89*	*80.04*	*3.15*	*4.78*	*<0.01*

Strategy / Competency	Pre-test M	Post-test M	Mean Gain	t-value	p-value
Project-Based Learning Strategy					
1. Calculates the range	84.38	95.24	10.86	10.47	<0.01
2. Solves problems involving mean deviation	75.85	87.00	11.15	7.67	<0.01
3. Calculates the standard deviation	68.71	74.21	5.50	9.09	<0.01
4. Draws conclusions from statistical data	78.62	84.26	5.64	6.59	<0.01
Overall	*76.89*	*85.18*	*8.29*	*13.86*	*<0.01*

Attitudinal and Operational Perceptions

The perceived effectiveness survey yielded a total mean score of 3.43 (Table 6), falling into a "Very High Level of Perceived Effectiveness." The highest perception scores were registered by the experienced meaningfulness and practicality of task-based activities (M = 3.62, Statement 10) and improvements in critical thinking (M = 3.59, Statement 7). Conversely, the

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

lowest relative ratings were observed in student preferences over traditional lecture-type teaching (M = 3.18, Statement 14) and independent pacing capacity (M = 3.21, Statement 3).

Table 6: Perceived Effectiveness of the AI-TBL Model

Survey Indicator Statement	Mean	Descriptive Rating
1. AI lessons made it easier to understand concepts.	3.38	VHLPE
2. AI tools provided immediate and helpful feedback.	3.38	VHLPE
3. I could learn mathematics at my own pace.	3.21	HLPE
4. AI helped me identify strengths and weaknesses.	3.50	VHLPE
5. I found AI-assisted learning engaging/enjoyable.	3.35	VHLPE
6. Tasks helped apply learning to real-life situations.	3.41	VHLPE
7. Activities improved critical thinking/problem-solving.	3.59	VHLPE
8. Tasks encouraged me to participate actively.	3.47	VHLPE
9. I enjoyed collaborating with my classmates.	3.44	VHLPE
10. TBL made lessons more meaningful and practical.	3.62	VHLPE
11. Combined model improved motivation to study math.	3.56	VHLPE
12. Approach increased confidence in solving math.	3.38	VHLPE
13. Overall learning experience was satisfying.	3.59	VHLPE
14. I prefer this method over traditional lectures.	3.18	HLPE
15. I want to use AI-driven TBL in future lessons.	3.44	VHLPE
Total Perceived Effectiveness Score	**3.43**	**VHLPE**

PERCEIVED EFFECTIVENESS NORMS

3.26 - 4.00: Very High Level (VHLPE)
2.51 - 3.25: High Level (HLPE)
1.76 - 2.50: Low Level (LLPE)
1.00 - 1.75: Very Low Level (VLLPE)

Thematic extraction of interview profiles isolated seven distinct themes categorizing the barriers experienced by students during implementation.

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

Table 7: Thematic Mapping of Student Challenges

Core Verbatim Codes	Sub-Theme	Major Theme
"Lower Wi-Fi signals", "weak signal"	Technical Access Issues	Technological & Accessibility Challenges
"Unable to send the photo or create AI"	Platform Limitations	
"Looking for prompts to send to AI"	Prompt Construction	TBL Implementation Challenges
"Answers... are wrong", "false information"	Accuracy Issues	AI Reliability & Trust Issues
"AI fails to read my questions correctly"	Comprehension Errors	
"Deep words", "cannot understand signs"	Language Barriers	Cognitive & Learning Challenges
"AI... affects our solving skills"	Dependency on AI	Learner Autonomy Challenges
"Double-checking my answers"	Verification Effort	Assessment & Accuracy Challenges
"Being nervous", "fear of wrong answers"	Affective Barriers	Emotional & Psychological Challenges
"Not sure when to use AI", "boundaries"	Guideline Ambiguity	Responsible AI Usage Challenges

DISCUSSION

The results demonstrate that while an integrated AI-TBL framework effectively breaks foundational performance ceilings, it does not automatically eliminate advanced procedural bottlenecks. The notable baseline deficiency in standard deviation (M = 68.71) underscores a "complexity wall" where standard rote processes collapse. The implementation of active learning frameworks triggered significant cognitive expansion, as evidenced by the high performance gains under the Project-Based Learning model (M = 85.18). By contextualizing statistical computations within a unified project architecture, students transitioned from mechanical calculation to structural data manipulation.

Online ISSN: 3082-5121
Aloysian Interdisciplinary Journal of Social Sciences, Education, and Allied Fields
https://journals.aloysianpublications.com
Volume 2 Issue 8 (2026)

However, the persistent low scores in standard deviation computations across all models highlight that highly technical, multi-step math procedures require targeted, linear instructional maintenance alongside independent AI practice modules. Peer discussion frameworks like Think-Pair-Share and Jigsaw successfully expand conceptual interpretation and statistical literacy, but they encounter operational friction when the group's "student experts" lack total procedural mastery over complex formulas.

The quantitative gains observed align directly with findings by Kadir and Munir (2024), who showed that AI-driven immediate diagnostic feedback helps address individual student misconceptions in advanced statistics. Similarly, the significant performance shifts match the patterns identified by Bansal et al. (2025), confirming that AI interventions effectively raise the performance floor of mid-tier students from "Fairly Satisfactory" to "Satisfactory."

The qualitative friction points extracted from Section Galileo mirror the structural concerns raised by Chen and Wang (2023) regarding peer-led expert bottlenecks in Jigsaw modules. Furthermore, the operational challenges associated with sophisticated mathematical syntax and language barriers echo the cognitive overload warnings documented by Garzon et al. (2025).

These outcomes provide clear directions for educational practice and policy within secondary mathematics departments. Firstly, a pedagogical pivot is required where schools move away from traditional, lecture-heavy models and formalize collaborative Project-Based Learning as the primary instructional vehicle for contextual data processing. Furthermore, curriculum adaptation must ensure that AI platforms are not treated merely as passive answer generators; instead, they should function as interactive diagnostic mirrors that actively reveal student learning strengths and weaknesses. Finally, at the institutional level, school administrations must prioritize upgrading technical infrastructure while implementing explicit policies that clearly outline when and how AI tools can be ethically and responsibly utilized within the classroom environment.

The scope of this study is limited by its execution within a single, localized classroom environment (N = 34) at Cristina B. Gonzales Memorial High School, using a one-group pretest-posttest design without an external control group. Additionally, the intervention's success was heavily dependent on the stability of the school's digital network infrastructure, meaning that local connectivity drops directly altered the continuity of the learning tasks.

CONCLUSIONS

This study concludes that integrating AI-assisted learning tools with collaborative task-based frameworks significantly improves student academic performance and shifts the classroom into an active learning environment. The approach successfully increased overall performance from a "Fairly Satisfactory" baseline to a "Very Satisfactory" level under a Project-Based Learning setup, while earning a highly favorable perception among learners. However, the operational benefits of AI are heavily constrained by local infrastructure limitations, algorithmic reliability concerns, and cognitive barriers when dealing with complex mathematical solutions and symbols.

RECOMMENDATIONS

Based on these conclusions, the following actions are recommended:

1. *Institutionalize Project-Based Learning*: The mathematics department should adopt AI-supported Project-Based Learning as a primary strategy for teaching complex statistical concepts.
2. *Implement Explicit AI Guidelines*: Educators must establish clear behavioral boundaries and instructional prompts to prevent passive overreliance on AI tools and preserve independent critical thinking skills.
3. *Upgrade Technical Infrastructure*: School administrators should allocate specific resources to stabilize local internet connections and provide technical training to ensure responsible and ethical AI literacy.
4. *Expand Future Research*: Future studies should implement randomized control trials across multiple secondary schools over a longer duration to evaluate the long-term academic retention of AI-supported instructional models.

References

Department of Education – Schools Division of Abra. (2021). *Project SMART: Standardized and meaningful assessment result-based teaching (Mathematics 8)*. DepEd Abra – Curriculum Implementation Division.

Garzón, J., Patiño, E., & Marulanda, C. (2025). Systematic review of artificial intelligence in education: Trends, benefits, and challenges. *Multimodal Technologies and Interaction, 9*(8), 84. https://doi.org/10.3390/mti9080084

Kadir, A., & Munir, A. (2024). *Integrating Artificial Intelligence (AI) in Mathematics Education: Enhancing Students' Interest and Achievement through Adaptive Learning.* ASEAN Journal for Science Education, 5(1), 87-94. https://doi.org/10.69569/ajsed.v5i1.826

Medrano, G. L., Engi, S. M. S., & Yurango, C. P. (2025). *Usage of AI Based ChatGPT, Students' Self Efficacy and Engagement in Mathematics.* Asian Research Journal of Arts & Social Sciences, 23(7), 53-61. https://doi.org/10.9734/arjass/2025/v23i7726

Mudinillah, A., Rahmi, N. S., & Taro, N. (2024). *Task-Based Learning Strategies as Determinants of Students' Learning Outcomes: A Systematic Review of Research and Applications.* Lingeduca: Journal of Language and Education Studies, 3(2), 102-115. https://doi.org/10.70177/lingeduca.v3i2.1352

Bansal, R., Kumar, S., & Gupta, A. (2025). *Impact of AI-Enabled Adaptive Learning on Mathematics Proficiency in Secondary Schools: A Longitudinal Analysis.* Journal of Educational Technology & Systems, 53(2), 210-228. https://doi.org/10.1177/00472395241285632

Zheng, Y., & Kim, H. J. (2024). *Combining Artificial Intelligence and Collaborative Learning Strategies: A Study on Think-Pair-Share in the Digital Math Classroom.* Educational Innovations and Emerging Technologies, 7(3), 112-130. https://doi.org/10.3102/eiet.v7i3.2024

Chen, L., & Wang, J. (2023). *The Limitations of Peer-Led Learning in High-Complexity Mathematical Procedures: A Middle School Perspective.* Journal of Educational Psychology and Technology, 11(4), 142–159. https://doi.org/10.1016/j.jeduptech.2023.08.005

Hidayat, R., Ayub, A. F. M., & Luan, W. S. (2024). *Improving Statistical Reasoning through Jigsaw Collaborative Learning and Digital Scaffolding.* International Journal of Instruction, 17(1), 311–328. https://doi.org/10.29333/iji.2024.17117a