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Intensifying quantitative data analysis and interpretation skills of senior high school students using Statistical Toolbox for Android

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Abstract

This study investigated the effectiveness of the Statistical Toolbox for Android (STA) in enhancing senior high school students' quantitative data analysis and interpretation skills, compared with the traditional use of calculators. Employing a two-group pre-test–post-test quasi-experimental design, the study involved two groups of students: one utilizing the STA application and the other using calculators. Instruction focused on core statistical procedures, namely the one-sample t-test, t-test for independent samples, one-way ANOVA, and Pearson's product-moment correlation. Pre-test results indicated that both groups initially demonstrated only beginning-level proficiency in quantitative analysis and interpretation. Following the intervention, post-test results revealed that all participants reached the proficient level. Statistical analysis showed a significant difference in favor of the calculator group in terms of quantitative data analysis skills, suggesting a higher computational efficiency with traditional methods. Conversely, the STA group obtained slightly higher mean scores in interpretation skills, although the difference was not statistically significant, indicating that both approaches were equally effective in fostering interpretation abilities. The findings suggest that while both calculators and STA contribute to skill development, calculators remain more effective for enhancing computational proficiency. Nevertheless, STA and similar mobile applications offer unique pedagogical value by facilitating engagement with complex statistical procedures and promoting digital literacy—skills increasingly vital in modern education. The results underscore the importance of aligning digital tool integration with specific learning objectives, and they highlight the need for further research into context-specific applications of mobile statistical tools in classroom settings.

Keywords: *interpretation skills, quantitative data analysis, Statistical Toolbox for Android (STA), statistics*

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1. Introduction

In today's data-driven world, the effective application of data analysis and interpretation empowers individuals and organizations to extract actionable insights, anticipate trends, and make evidence-based decisions. Such insights, grounded in an understanding of client expectations and societal needs, can guide strategic actions that enhance productivity and success across sectors. As technology continues to reshape education in transformative ways, both educators and students must learn to harness its potential to overcome barriers to learning and academic performance. Developing a technologically advanced education system is therefore essential to meet future demands (Raja & Nagasubramani, 2018).

Within this evolving digital landscape, statistical literacy has become an indispensable skill. Navigating today's data-rich environment requires proficiency in handling data, understanding probability, and distinguishing between valid signals and random noise. Foundational competencies in data collection, organization, and presentation, such as creating graphs, frequency tables, and pie charts, are integral components of statistical understanding (Gravemeijer et al., 2017). Statistical literacy enables learners to critically evaluate and interpret data, make independent judgments, and apply statistical reasoning in real-life contexts (Wing-yan, 2013). Hafiyusholeh (2015) further defines it as the ability to understand, analyze, and present data effectively through tables and graphs.

Despite its importance, many students find statistics one of the most challenging subjects (Fauzi & Fariantika, 2018; Leavy et al., 2013; Zhang, 2012). Studies have shown that difficulties in learning statistics often stem from abstract concepts, low comprehension, and negative attitudes or anxiety toward the subject (Burhan, 2013; Jatisunda et al., 2020; Mao et al., 2021; Sölpük, 2017). For instance, Burhan (2013) found that students performed poorly in inferential statistics, while Jatisunda et al. (2020) and Arifin and Aprisal (2020) observed gaps in statistical literacy among public administration and English majors, respectively. These findings emphasize the need to strengthen students' statistical competencies across disciplines.

The ability to analyze and interpret quantitative data is essential for learners to understand numerical information, recognize patterns, identify relationships, and draw evidence-based conclusions. For senior high school (SHS) students, cultivating these skills early enhances critical thinking, problem-solving, and preparedness for higher education and future careers in science, technology, business, and the social sciences. However, many SHS students struggle to acquire the statistical analysis skills necessary for meaningful research due to the limitations of traditional approaches, such as lectures and paper-based exercises, which often fail to capture interest and promote deep understanding (Garfield & Ben-Zvi, 2008; Chance et al., 2007).

To address these challenges, the integration of mobile statistical applications offers an innovative solution. Mobile learning technologies provide interactive, visual, and user-friendly environments that simplify complex concepts and allow real-time data manipulation. Gikas and Grant (2013) highlight that mobile learning promotes accessibility, flexibility, and learner-centered engagement, all critical features of modern, technology-oriented education. Similarly, Cheung and Slavin's (2013) meta-analysis found that technology integration significantly improved student achievement in mathematics compared to traditional methods, though its effectiveness depends on instructional design. Other studies have shown that mobile technologies enhance engagement and motivation (Lai et al., 2012) and support visualization, collaboration, and outdoor learning (Baya'a & Daher, 2009). Nonetheless, Fabian et al. (2016) caution that technological limitations can still hinder learning despite students' positive attitudes toward mobile tools.

Given these trends, developing innovative digital tools, such as mobile applications, has become an educational priority. These applications make learning statistics more interactive and adaptive, providing opportunities for statistical computation, data visualization, and exploration of complex ideas through dynamic, real-time interfaces. Their accessibility aligns with students' digital habits, as smartphones and tablets are now widely available. Ariyanto et al. (2018) emphasized that mobile applications improve learning outcomes and foster better learning environments both inside and outside the classroom.

Considering these insights, this study seeks to enhance the quantitative data analysis and interpretation skills of senior high school students through the Statistical Toolbox for Android (STA), an innovative learning approach designed to promote statistical literacy and integrate digital technology in education. While prior studies have explored general challenges in teaching and learning statistics, there remains a notable gap in understanding the effectiveness of mobile statistical applications at the SHS level, particularly in developing both quantitative and interpretative skills.

2. Theoretical Framework

This study is anchored on three (3) major learning theories: (a) Jean Piaget's Theory of Cognitivism (1936–1950), (b) Piaget's Theory of Constructivism (1896–1980), and (c) Lev Vygotsky's Theory of the Zone of Proximal Development (ZPD) (1920). These theories collectively explain how learners acquire, process, and apply knowledge, providing a foundation for understanding the educational value of integrating digital tools, specifically a statistical mobile application, into classroom instruction.

Cognitivism emphasizes the mental processes involved in learning, such as how information is received, organized, stored, and retrieved by the brain. It views the mind as an information processor, similar to a computer, where learning is seen as an internal cognitive activity rather than a mere change in observable behavior (Clark, 2018). Cognitivism highlights that meaningful learning occurs when learners actively process and structure information, enhancing understanding and retention.

Constructivism, on the other hand, asserts that learners actively construct their own understanding of the world based on experiences and reflection. It is considered one of the most influential theories in education because it redefined the learning process as student-centered rather than teacher-centered. According to Bada and Olusegun (2015), constructivism emphasizes that learners generate knowledge and meaning through interactions with their environment, integrating new information with their prior knowledge (schemas). This approach encourages exploration, inquiry, and the development of higher-order thinking skills.

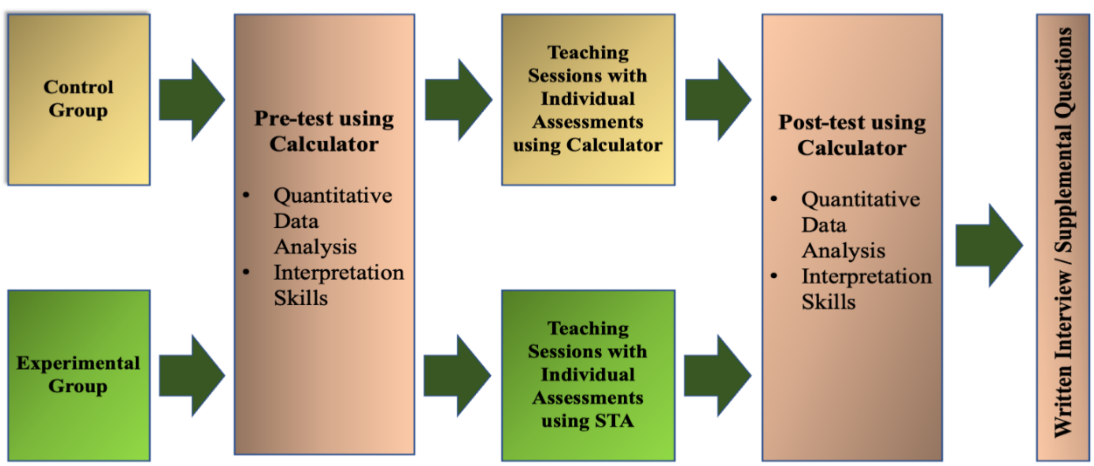
Vygotsky's Zone of Proximal Development (ZPD) complements Piaget's theories by emphasizing the social dimension of learning. The ZPD refers to the gap between what learners can accomplish independently and what they can achieve with guidance from teachers or collaboration with more capable peers. Through scaffolding, structured support provided during the learning process, students can perform more complex tasks and develop higher-order cognitive skills. Vygotsky argued that these interactions are crucial for stimulating cognitive development and fostering critical thinking and problem-solving abilities.

In connection with these theories, the incorporation of a statistical mobile application into classroom instruction aligns with the principles of active and meaningful learning. From a cognitivist perspective, the mobile app enhances learners' mental processing by offering features such as real-time computations, data visualization, and sequential statistical operations that help organize and manage information effectively. From a constructivist viewpoint, the app provides interactive, student-centered experiences that allow learners to explore data, test hypotheses, and reflect on outcomes, facilitating the construction of new knowledge grounded in real-world applications. Furthermore, drawing from Vygotsky's ZPD, the app promotes scaffolding and collaborative learning by providing guided feedback, step-by-step solutions, and opportunities for peer interaction.

The paradigm in Figure 1 illustrates the procedural framework of the study. It shows that two groups of students underwent pre-testing and post-testing to assess their performance in solving statistical problems. Both groups participated in teaching sessions and assessments; however, while the control group utilized standard calculators, the experimental group used the Statistical Toolbox for Android (STA) mobile application.

Figure 1

Research paradigm



The paradigm shows the procedure for intensifying quantitative data analysis and interpretation skills of Senior High School students.

3. Methodology

3.1. Research Design

A two-group pre-test and post-test quasi-experimental design was employed in this study, utilizing a quantitative research approach. Stratton (2019) stated that the pre-test and post-test method is a common type of quasi-experimental design that provides the benefit of directionality. In this design, a dependent variable, such as knowledge or attitude, is measured before and after exposure to an independent variable, such as training or an informational session.

Two groups of students participated in this study. Both groups took the same pre-test and post-test after attending sessions on data analysis tools and interpretation. However, the main distinction lay in the intervention approach: the experimental group used a mobile-based statistical tool for data analysis, while the control group performed statistical calculations using a calculator. The results from both groups were collected, analyzed, and interpreted to determine whether the use of mobile-based statistical applications enhanced students' quantitative data analysis and interpretation skills compared to conventional methods.

3.2. Participants of the Study

Out of a total population of six hundred eighty-nine (689) Grade 11 students enrolled in Senior High School for the academic year 2023–2024, two sections from the Science, Technology, Engineering, and Mathematics (STEM) strand were selected through purposive sampling. The selection was based on their comparable academic standing, as all had successfully passed the same strand qualification examination administered during enrollment.

A total of seventy-three (73) students participated in the study, 37 students from Section A and 36 students from Section B. These sections were chosen to ensure homogeneity in prior academic achievement and strand admission requirements, thereby minimizing extraneous variability in the results. Purposive sampling was deemed appropriate for this study, as it required respondents to use mobile phones capable of running the Statistical Toolbox for Android (STA). Furthermore, students with a solid foundation in mathematical skills were selected to ensure that the intervention would be more effective and focused.

3.3. Instrumentation and Data Gathering Process

The study utilized two sets of research instruments: a written test and technology-based tools. The written test, composed of multiple-choice questions, consisted of two (2) parts. Part I involved identifying the appropriate statistical tool and performing the necessary computations, while Part II focused on assessing students' interpretation skills. The test included thirty-two (32) questions, each worth one point, covering four topics in the Statistics and Probability subject: the one-sample t-test, the t-test for independent samples, the one-way analysis of variance (ANOVA), and Pearson's r correlation. Student scores were categorized as Needs Improvement, Beginning, Developing, and Excellent. For the intervention, the experimental group used the STA mobile-based application, while the control group used calculators.

The validity of the research instruments was confirmed through expert validation within the institution. To further strengthen the validity of the questionnaire, the researcher sought assistance from four (4) internal validators and three (3) external validators, all of whom were experts in the field of mathematics. After expert validation, a pilot test was conducted among students of the same grade level (non-respondents). Item analysis, a crucial step for improving the reliability of the instrument, was performed based on the pilot test results. The researcher revised, replaced, or refined questions until they reached an acceptable level of difficulty and reliability. This careful process ensured the efficiency and accuracy of the research instrument in collecting essential data.

Upon approval of the research proposal, the researcher obtained consent from relevant authorities, including the research adviser, school principal, and other concerned officials. A pilot test was first conducted with non-target sections to ensure reliability. After analyzing the results and implementing necessary revisions, the final version of the instrument was administered. Subsequently, the researcher explained the purpose of the study to the selected participants.

Once permission was secured, the experiment was conducted with the two (2) student groups. Both groups took the same pre-test and post-test and were taught the same lessons (one-sample t-test, t-test for independent samples, one-way ANOVA, and Pearson's r correlation). However, their intervention strategies differed: the control group used calculators, while the experimental group used the STA mobile application. Both groups completed varied activities aligned with the same competencies.

To further support and validate the quantitative findings, the researcher collected qualitative data through a follow-up questionnaire administered via Google Forms. The follow-up aimed to explore students' personal experiences and perceptions while using STA. Questions focused on students' positive experiences, challenges encountered, and perceived effects of STA on their data analysis and interpretation skills. Students were also encouraged to suggest improvements to the application and reflect on how such modifications might enhance their learning experience.

3.4. Data Analysis

After the study was conducted, the data were analyzed and assessed for normality using the Shapiro–Wilk test. Based on the results, appropriate statistical tools were applied. Descriptive statistics, including mean, standard deviation, and coefficient of variation, were used to analyze students' performance levels.

For inferential analysis, different statistical tests were used depending on the data distribution. For normally distributed data, the independent samples t-test was employed to compare the two groups; otherwise, the Mann–Whitney U test was used. To determine the significance of differences between pre-test and post-test scores, the paired samples t-test was applied for normally distributed data, while the Wilcoxon signed-rank test was used when normality was not assumed. Additionally, Pearson's r correlation was performed to examine the relationship between students' data analysis and interpretation skills.

3.5. Research Ethics

Participation in this study was entirely voluntary. Respondents were not compelled to take part in the sessions. All data collected from participants were treated with the utmost confidentiality. The researcher also sent formal communication to the rightful owners of the mobile-based statistical applications used in the study to request permission and acknowledge intellectual property rights (Bhandari, 2024).

4. Findings and Discussion

Table 1 presents the test of difference between the pre-assessment performance of students per topic. The results indicate that there were no significant differences between the students' performances before the intervention across the lessons or topics covered. This suggests that both groups began with comparable levels of understanding of the subject matter, indicating that their prior knowledge did not differ significantly. Such equivalence in baseline performance implies that any subsequent differences observed after the intervention can be more confidently attributed to the intervention itself rather than to pre-existing variances between the groups.

Attributing observed differences in results to the intervention, rather than to pre-existing variations, depends on the equivalence of baseline performance among groups in randomized controlled trials (RCTs). A well-balanced baseline enhances the internal validity of the study and enables researchers to conclude with greater certainty that any post-intervention changes are likely caused by the intervention itself. Various approaches aim to ensure baseline comparability to support this concept. Although perfect balance is not always achieved, proper random assignment is designed to equalize both known and unknown confounders across groups (Xu & Kalbfleisch, 2010).

Table 1

Difference of pre-test scores of the two groups in the different lessons

Topics	Groups	Mean	Computed value	p-value	Decision	Difference
One sample t-test	Control	1.744	555.5	0.218	Failed to reject Ho	Not Significant
	Experimental	2.118				
T-test for independent sample	Control	2.59	-1.23	0.223	Failed to reject Ho	Not Significant
	Experimental	3				
One-way analysis of variance	Control	2.949	-1.187	0.239	Failed to reject Ho	Not Significant
	Experimental	3.353				
Pearson's r correlation	Control	1.974	606	0.52	Failed to reject Ho	Not Significant
	Experimental	2.147				

Note: Level of significance; 5 %

The performances of all groups did not vary significantly, as both fell under the Beginning level. In the lessons on the one-sample t-test, t-test for independent samples, and Pearson's r correlation, both groups achieved a Beginning level of performance. Meanwhile, for the topic on one-way analysis of variance (ANOVA), the control group remained at the Beginning level, whereas the experimental group reached the Developing level. The standard deviation values across topics suggest a moderate level of variability in student scores within both groups. These values reflect differences in individual performance levels and indicate that students within each group were not homogeneous in their understanding of the topics prior to the intervention. This variability is important to consider, as it can influence how the effectiveness of the intervention is interpreted during the post-assessment phase.

The results imply that before the intervention, both groups possessed similar levels of understanding and skills in quantitative data analysis, with neither group demonstrating a distinct advantage. This establishes a comparable baseline, which is essential for accurately determining the effectiveness of the intervention applied to the experimental group during the post-assessment phase. Given the slight difference in baseline performance between the experimental and control groups, the experimental group may have a greater potential for improvement following the intervention. This notion aligns with previous studies emphasizing the importance of teaching strategies and learner characteristics in enhancing students' comprehension of statistical concepts.

Table 2 presents the test of difference between the post-assessment performance of students per topic. The results reveal significant differences in students' performance after the intervention in the lessons on the one-sample *t*-test and *t*-test for independent samples. Conversely, there were no significant differences in the post-assessment results for the topics on one-way analysis of variance (ANOVA) and Pearson's *r* correlation. This indicates that the impact of using a mobile-assisted statistical application versus a calculator varied depending on the topic.

The absence of significant variations in the post-assessment findings for the one-way ANOVA and Pearson's *r* correlation lessons suggests that the intervention did not yield observable improvements in these areas. Overall, the intervention enhanced student performance in the one-sample *t*-test and *t*-test for independent samples, while its effect on the one-way ANOVA and Pearson's *r* correlation was not statistically significant.

Table 2

Difference of post-test scores of the two groups in the different lessons

Topics	Groups	Mean	Computed value	p-value	Decision	Difference
One sample t-test	Control	7.026	906	0.005	Reject Ho	Significant
	Experimental	6.176				
T-test for independent samples	Control	6.359	873.5	0.016	Reject Ho	Significant
	Experimental	5.735				
One-way analysis of variance	Control	5.205	1.594	0.115	Failed to reject Ho	Not Significant
	Experimental	4.647				
Pearson's r correlation	Control	4.795	601.5	0.49	Failed to reject Ho	Not Significant
	Experimental	5.176				

Note: Level of significance; 5 %

The effectiveness of the intervention on student performance therefore differed by topic, showing notable gains in the one-sample *t*-test and *t*-test for independent samples, but not in the one-way ANOVA or Pearson's *r* correlation. This difference highlights the nuanced nature of educational interventions, where the degree of impact may vary depending on the complexity of the concepts involved. The lack of statistically significant improvement in Pearson's *r* correlation and one-way ANOVA implies that these areas may require more comprehensive instructional strategies or innovative teaching methods to achieve measurable gains (Martins & Santos, 2018).

The results imply that in sessions 1 and 2, the control group obtained slightly higher scores than the experimental group. Specifically, in the sessions on the one-sample t-test and t-test for independent samples, the control group demonstrated excellent performance, while the experimental group also achieved an excellent level. However, in the sessions on one-way analysis of variance (ANOVA) and Pearson's r correlation, the experimental group recorded slightly higher mean scores than the control group.

The standard deviation values indicate that score distributions were relatively consistent between groups, although the experimental group exhibited slightly less variability in certain sessions. This suggests a more uniform understanding of the topics among students using the mobile-based application. The students' scores varied across different sessions during the experiment. It is noteworthy that during the earlier sessions on the one-sample t-test and t-test for independent samples, the control group performed marginally better than the experimental group. This suggests that traditional classroom instruction using calculators might have provided immediate benefits, particularly in understanding fundamental statistical concepts. Conversely, the experimental group slightly outperformed the control group in the later sessions, specifically in one-way ANOVA and Pearson's r correlation. This finding suggests that the mobile-based statistical application may have been more effective in supporting students' learning as the complexity of statistical concepts increased. Although the differences between groups remained relatively small, this outcome indicates that technology-assisted learning may be particularly advantageous when dealing with more advanced statistical topics.

Furthermore, since both groups achieved performance levels ranging from Proficient to Excellent, it can be inferred that the teaching sessions and strategies effectively supported students in analyzing and answering the questions in each session. As one student remarked, "*There weren't that many challenges because our teacher guided us on how to use the app*." Additionally, the third and fourth sessions required lengthy and meticulous computational procedures, wherein the use of a mobile-based statistical application proved beneficial. Several students expressed positive experiences, stating: "*For me, the positive experience of using STA is that it's really a trusted source for computation. When I tried to compare it with the scientific calculator, the answers were the same, but we could solve faster with STA.*"

"Using STA made it much easier and faster for me to compute answers compared to using a calculator. I have limited knowledge of calculators, and sometimes I get confused when using them. With STA, I can quickly get the results without struggling with complex calculations."

"It's really helpful, since I don't have to go through all the trouble just to solve something that can be solved immediately with one to three taps."

These responses highlight how the STA not only facilitated quicker computations but also enhanced student confidence and engagement in performing complex statistical analyses.

Table 3

Difference of pre-test and post-test scores of the two groups in the different lessons

Topics	Groups	Test taken	Mean	Computed value	p-value	Decision	Difference
One sample t-test	Control	Pretest	1.744	-5.303	< .001	Reject Ho	Significant
		Posttest	7.026				
	Experimental	Pretest	2.118	-5.086	< .001	Reject Ho	Significant
		Posttest	6.176				
T-test for independent samples	Control	Pretest	2.590	-5.273	< .001	Reject Ho	Significant
		Posttest	6.359				
	Experimental	Pretest	3.000	-8.079	< .001	Reject Ho	Significant
		Posttest	5.735				
One-way analysis of variance	Control	Pretest	2.949	-6.414	< .001	Reject Ho	Significant
		Posttest	5.205				
	Experimental	Pretest	3.353	-3.459	.002	Reject Ho	Significant
		Posttest	4.647				
Pearson's r correlation	Control	Pretest	1.974	-8.054	< .001	Reject Ho	Significant
		Posttest	4.795				
	Experimental	Pretest	2.147	-4.937	< .001	Reject Ho	Significant
		Posttest	5.176				

Note: Level of significance; 5 %

Table 3 presents the test of significant difference between the pre-test and post-test performance of students per topic, conducted separately for each group. The results reveal that all comparisons between pre-test and post-test scores across topics showed statistically significant differences, with p-values less than .05. This indicates that students' performance significantly improved after the intervention, regardless of group assignment. These findings suggest that the interventions implemented were highly effective in enhancing students' statistical skills, particularly in quantitative data analysis and interpretation.

The consistent improvement across topics highlights the effectiveness of integrating technology into statistics instruction as a means to support and improve students' learning outcomes. The potential of digital technologies in mathematics education has been well-documented, with several studies showing that technological interventions using virtual learning objects can enhance mathematical skills, particularly in problem-solving and computational tasks (Cóndor-Herrera & Ramos-Galarza, 2021).

Table 4

Differences in the pre-test and post-test scores in quantitative data analysis and interpretation skills

Skills	Test Taken	Groups	Mean	Computed value	p-value	Decision	Difference
Quantitative Data Analysis Skills	Pretest	Control	4.128	-2.056	0.043	Reject Ho	Significant
		Experimental	5.059				
	Posttest	Control	13.410	-0.84	< .001	Reject Ho	Significant
		Experimental	11.618				
Interpretation Skills	Pretest	Control	5.128	3.602	0.404	Failed to Reject Ho	Not Significant
		Experimental	5.559				
	Posttest	Control	9.974	593	0.436	Failed to Reject Ho	Not Significant
		Experimental	10.118				

Note*: Level of significance; 5 %*

Table 4 presents the test of significant difference between the pre- and post-assessment results in terms of the quantitative and interpretation skills of the two groups. The results show significant differences between the pre-test and post-test quantitative skills of the control and experimental groups, indicating that the two groups did not start the intervention with the same level of proficiency in quantitative skills. In contrast, no significant difference was found between the groups in their interpretation skills, either before or after the intervention. This suggests that the intervention had a comparable impact on enhancing students' interpretation abilities across both groups. As highlighted in several studies, including Sánchez-Almeida et al. (2021), factors such as the difficulty of the content and students' prior knowledge may have influenced these results.

Table 5

Differences between the two groups in their pre-test and post-test scores

Test taken	Group	Mean	t	p-value	Decision	Difference
Pretest	Control	9.256	-2.464	0.016	Reject Ho	Significant
	Experimental	10.912				
Posttest	Control	23.385	2.008	0.048	Reject Ho	Significant
	Experimental	21.735				

Note: *Level of significance: 5%*

Table 5 presents the test of significant differences between the pre-assessment and post-assessment levels of students from both groups. The results show a significant difference between the pre-test scores of the two groups, leading to the rejection of the null hypothesis. Likewise, a significant difference was also observed between their post-test performances, indicating that the null hypothesis should again be rejected.

This finding suggests that the significant difference in post-assessment scores between the two groups may be attributed to the type of intervention each received. The traditional calculator-based approach used by the control group may have been more effective in enhancing students' quantitative data analysis skills compared to the STA, a mobile-based approach utilized by the experimental group. It is also possible that the control group's familiarity and continued use of calculators throughout the sessions contributed to their performance on the post-assessment, suggesting that this factor may have influenced the observed difference. While the mobile-based intervention shows potential, the effectiveness of calculator use in supporting learning outcomes remains noteworthy.

Moreover, mobile applications such as StatHand and Calculadora Estadística y Probabilidad allow students to access statistical tools anytime, thereby improving engagement and learning flexibility (Romero et al., 2019; Allan et al., 2015). Research further indicates that students using mobile applications tend to perform better in statistical tasks and demonstrate greater accuracy in data interpretation compared to those using conventional methods (Benedictos, 2022; Said et al., 2019).

Table 6 presents the test of significant differences between the pre-assessment and post-assessment levels of students in both the control and experimental groups. The results reveal significant differences between the pre-test and post-test scores of both groups, leading to the rejection of both null hypotheses.

Table 6

Differences between the pre-test and post-test scores of the two groups

Groups	Test Taken	Mean	Computed value	p-value	Decision	Difference
Control	Pretest	9.256	-18.564	< .001	Reject Ho	Significant
	Posttest	23.385				
Experimental	Pretest	10.912	-16.787	< .001	Reject Ho	Significant
	Posttest	21.735				

Note: *Level of significance: 5%*

The finding indicates that both the control and experimental groups demonstrated notable improvement from pre-test to post-test, suggesting that both instructional strategies, traditional classroom-based teaching and the statistical mobile-based application, were effective in enhancing students' quantitative data analysis and interpretation skills. Furthermore, the comparison between mobile-based applications and conventional classroom instruction in improving students' quantitative and interpretative abilities suggests that both approaches can be beneficial, albeit through different mechanisms. Mobile applications such as StatHand and other statistical software facilitate faster data analysis and decision-making processes, thereby enhancing students' attitudes and performance in statistics (Romero et al., 2019; Benedictos, 2022; Allan et al., 2015). Conversely, traditional classroom instruction provides a structured learning environment that fosters these skills through direct engagement and guided teaching.

Table 7

Relationship between students' data analysis skills and interpretation skills

Variable	R-value	p-value	Decision	Relationship
Quantitative Skills vs Interpretation Skills	.272	0.020	Reject Ho	Significant

Note*: Level of significance: 5%*

Table 7 presents the test of a significant relationship between students' quantitative data analysis skills and their interpretation skills. The results reveal a significant relationship between these two competencies, indicating that students' interpretive abilities strongly influence their capacity to analyze numerical data. Conversely, students who excel in quantitative data analysis also tend to demonstrate higher proficiency in interpreting statistical outcomes. This finding underscores the importance of integrating both computational and critical thinking components in teaching statistics, as strengthening analytical skills can enhance students' ability to interpret statistical results meaningfully.

Understanding and solving mathematical problems depend considerably on verbal skills, as these enable reasoning and knowledge application. Ugi and Askandar (2021) emphasized that students with stronger verbal reasoning skills tend to perform better in mathematics, highlighting the role of verbal thinking in mathematical contexts. Similarly, Lozzia et al. (2008) noted that verbal reasoning, as measured through analogies, reflects the cognitive processes essential for problem-solving and is positively associated with mathematical performance.

Student reflections further illustrate this relationship. One student shared, "*It (STA) positively impacts my interpretation skill because not only does it make analysis easier, but it also gives a clear result.*" Another commented, "*STA became my reference for interpretation because the app also provides a conclusion, and it brought positive changes*." Similarly, a student remarked, "*Using the STA makes me understand things better and clearer since I don't have to recall formulas that just distract me when I don't remember them correctly*."

Table 8

Differences in quantitative data analysis and interpretation skills between the two groups

Skills	Groups	Mean	Computed Value	p-value	Decision	Difference
Quantitative Skills	Control	13.410	3.602	< .001	Reject Ho	Significant
	Experimental	11.618				
Interpretation Skills	Control	9.974	593	0.436	Failed to Reject Ho	Not Significant
	Experimental	10.118				

Note*: Level of significance: 5%*

Table 8 presents the test of significant differences between students' quantitative data analysis skills and interpretation skills. The results reveal a significant difference in students' abilities to analyze and compute quantitative data, but no significant difference in their data interpretation skills. This suggests that while the interventions produced varying levels of improvement in students' quantitative analysis skills, their ability to interpret data remained consistent across both groups. Therefore, both instructional approaches appear equally effective in enhancing interpretation skills. However, in developing quantitative competencies, one approach may be more effective than the other.

Research by García-García et al. (2019) comparing students from Mexico and Chile found that, although students were capable of performing basic data comparisons, many struggled with statistical interpretation, particularly in identifying trends and performing arithmetic computations. This indicates that students may require more focused instruction on interpreting statistical data, rather than solely on computation. The study further shows that while university students from Mexico and Chile generally achieved level 2 (comparative) in knowledge of statistical tables, they had difficulty identifying increases or decreases and performing arithmetic operations. This underscores the distinction between interpretative and computational skills, emphasizing that proficiency in one does not necessarily guarantee proficiency in the other. Consequently, a balanced approach in teaching statistics is essential to enhance both understanding and analytical skills, enabling students to accurately analyze and interpret statistical data.

Students' reflections support this finding. One student stated, "*Since it provides the right answers for the computed value and provides information on whether the data you selected is rejected or accepted (null hypothesis), I must say that it did help me interpret the data in a positive way*." Another added, "*STA became my reference for my interpretation because the app also provides a conclusion, and it brought positive changes*."

Table 9

Test of difference between post-performances of students as affected by pre-performances and group

Cases	Sum of Squares	F	p-value	Difference
Pretest	7.338	0.596	0.443	Not Significant
Group	56.356	4.574	0.036	Significant
Residuals	862.511			

Note: Type III Sum of Squares

Table 9 presents the test of differences in post-performance of students as influenced by pre-performance and group membership. The results reveal a significant difference in post-assessment performance based on the group to which students belonged, but no significant difference when the effect of pre-performance was considered. This indicates that students' post-assessment performance was largely determined by their assignment to either the control or experimental group, highlighting the efficacy of the intervention. The lack of a notable effect from pre-performance suggests that prior knowledge or skill level did not significantly influence the outcomes. Therefore, the observed differences in post-performance are primarily attributable to the intervention itself rather than students' initial abilities.

The influence of group membership on post-assessment outcomes demonstrates the effectiveness of interventions in educational settings. Several studies have shown that students in experimental groups consistently outperform their counterparts in control groups, implying that targeted interventions can enhance learning outcomes. Specifically, the absence of a significant impact from pre-performance scores suggests that prior knowledge or skill level did not play a decisive role in the observed improvements.

Experimental groups often demonstrate the efficacy of instructional treatments by showing statistically significant gains in post-test scores compared to control groups. For example, a study on career advising found that the intervention led to improvements in self-assessed knowledge and skills, even when pre-test scores had little influence on results (David et al., 2022). Similarly, other research indicates that pre-test performance does not consistently correspond with post-test gains, highlighting that prior knowledge is not necessarily a determining factor in the effectiveness of educational interventions (Martins & Santos, 2018; Pal & Bhati, 2024).

5. Conclusion

The findings of the study lead to several conclusions. Initially, there were no significant differences between the groups prior to the intervention, indicating that participants began with comparable baseline levels in the subject matter. Following the intervention, significant differences were observed between the groups in certain statistical tests, such as t-tests, but not in others, such as one-way ANOVA and Pearson's r correlation. This suggests that the effectiveness of the interventions varied depending on the specific topic or analytical method employed.

Both groups demonstrated significant improvement from pre-test to post-test, highlighting the overall effectiveness of the instructional strategies in enhancing students' statistical skills, particularly in quantitative data analysis and interpretation. Notably, differences in quantitative skills between groups emerged, whereas interpretation skills did not differ significantly. This implies that both interventions were equally effective in improving interpretation abilities, but varied in their impact on quantitative competencies. The observed improvements in pre- to post-test scores across both groups support the conclusion that both teaching methods, traditional classroom instruction and the STA application, were successful in enhancing students' abilities. This conclusion is further reinforced by the rejection of both null hypotheses, confirming that significant learning gains occurred.

Additionally, a strong relationship was identified between students' quantitative data analysis and interpretation skills, suggesting that proficiency in one skill reinforces the other. However, while a significant difference was found in students' quantitative analysis skills post-intervention, their interpretation abilities remained consistent across both groups, indicating that the effectiveness of the interventions may depend on the type of skill being assessed. Lastly, post-intervention performance varied by group, demonstrating the impact of the interventions, although these differences were not always apparent when controlling for pre-intervention performance.

Based on these results, several recommendations are proposed to enhance the teaching and learning of statistics. Educational institutions are encouraged to continue using calculators to develop students' quantitative skills while integrating statistical mobile-based applications for solving complex or lengthy problems. These tools have proven effective in strengthening students' interpretive abilities. Teachers, in turn, should adopt a balanced instructional approach that emphasizes both analytical thinking and computational proficiency, ensuring comprehensive skill development and addressing individual student strengths.

Moreover, differentiated instruction based on topic complexity should be implemented. Since the effectiveness of interventions varies by statistical topic, teachers should tailor their methods to match the difficulty and nature of specific content. Schools should also provide enrichment activities for high-performing students and remedial programs for those struggling with foundational concepts, thereby bridging gaps in prior knowledge and promoting more equitable learning outcomes.

Professional development programs for teachers should incorporate training on the effective use of mobile-based statistical tools, equipping educators with the skills to maximize the educational potential of technology. Future research is encouraged to explore technology-assisted learning across diverse student demographics and statistical topics to gain deeper insights into the long-term impact of mobile learning tools.

Teachers should also foster collaborative learning environments that integrate both traditional and digital tools, promoting peer-to-peer problem-solving and engagement with data analysis and interpretation. Finally, curriculum developers are urged to revise statistics curricula by incorporating technology-driven modules and real-world data analysis tasks. Such updates would provide students with hands-on experience and better prepare them for practical applications of statistical knowledge.

It is important to note that this study was conducted in a single school, focused on one content area, and involved only two sections of Grade 11 senior high school students enrolled in statistics and probability during the second semester of the academic year 2024–2025. Therefore, the results may not be broadly generalizable to other grade levels, schools, or educational contexts. Future research could expand the sample to include multiple schools, different grade levels, and diverse academic settings to determine whether the observed effects are consistent across various student populations.

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Institutional Review Board Statement

This study was conducted in accordance with the ethical guidelines set by the Department of Education. The conduct of this study has been approved and given relative clearances by the Schools Division of Laguna.

Declaration

The author declares the use of Artificial Intelligence (AI) in writing this paper. In particular, the author used Quillbot and ChatGPT in summarizing key point and paraphrasing ideas. The author takes full responsibility in ensuring proper review and editing of contents generated using AI.

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