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Manual and Statistical analysis software packages techniques of quantitative data analysis in educational research: A comparative study

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Abstract

This study aimed to compare manual and software-based techniques for analyzing quantitative data in educational research. Specifically, it investigated whether using Chi-Square, paired sample t-tests, one-way ANOVA, and Pearson correlation would yield different results when analyzed manually versus using Statistical Package for the Social Sciences (SPSS) version 20. A comparative research design was employed, and datasets generated by the researcher were analyzed through both methods. Findings showed that both manual and SPSS analyses produced identical statistical results. However, the statistical analysis software method proved to be significantly faster than manual data analysis. Manual analysis offers greater flexibility and potentially deeper understanding; it is more time-consuming and susceptible to human error. In contrast, statistical software provides quicker and more accurate results and could handle complex computations, though it requires technical knowledge and may involve time to understand the syntax's when using and also may involve installation costs. The study concluded that both manual and statistical software-based techniques are accurate, but statistical methods offer greater efficiency. Researchers are encouraged to use either method for key statistical tests such as the t-test, Chi-Square, ANOVA, and Pearson correlation, depending on context and resources. Additionally, learning manual techniques may strengthen a researcher's understanding of statistical concepts and improve interpretation skills.

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1. Introduction

Quantitative data analysis involves the structured process of gathering and assessing measurable data. It relies heavily on statistical tools to interpret numerical data (Creswell, 2009). The primary goal for researchers using this method is to quantify theoretical concepts. Typically, such analysis is conducted by individuals skilled in either manual or computer-aided methods (Cowles, 2005). This approach provides two major benefits: it allows for the systematic organization, summarization, and presentation of observations known as descriptive statistics and it supports inference by enabling conclusions to be drawn from a sample representative of a larger population, forming the basis for inferential statistics. Data analysis, at its core, includes steps such as inspecting, cleaning, transforming, and modeling data to extract useful information and support sound conclusions (Brown, 2021). It spans multiple domains and employs a variety of methods (Pruneau, 2017). In the modern professional environment, data analysis plays a crucial role in data-driven decision-making and enhances organizational effectiveness (Xia & Gong, 2014). According to Akindutire (2013) quantitative data analysis relies on numerical values and is particularly effective in evaluations, as it yields results that are easy to interpret and visualize. Whether conducted manually or using computer software, the accuracy and quality of research interpretation largely depend on how well the data is analyzed (Abulela & Harwell, 2020; Kara, 2017).

Different analysis tools are used depending on whether the research is qualitative, quantitative, or mixed-methods. The selection of an analysis method is shaped by the research methodology, and analytical tools cannot compensate for flaws in study design. With the advancement of technology, computer software is increasingly replacing manual data analysis techniques. Researchers are encouraged to move from traditional tools like paper and calculators to more advanced software, which offers numerous advantages (Friese, 2019). However, while computers aid the analysis process, they cannot independently conceptualize data patterns (Creswell & Creswell, 2018; Holton, 2007). Researchers remain central to interpreting results and identifying relationships within the data (Soratto, Pires, & Friese, 2020). Statistical analysis software like SPSS, STATA, SAS, MINITAB, and open-source tools such as R, EPI-INFO, and CS-PRO is designed to efficiently process, analyze, and interpret numerical data. These tools enhance research quality by avoiding computational errors, offering predictive insights, and streamlining the statistical analysis process. Statistical software provides faster and more complex data analysis capabilities, from calculating means and standard deviations to running ANOVA and regression models. Still, accuracy depends on the quality of data and instructions given to the software hence the adage "garbage in, garbage out." Proper syntax and input are essential to avoid errors, especially with user-friendly modern interfaces like SPSS or SAS for desktop computers

Manual analysis, by contrast, requires hands-on computation. Though time-consuming, it deepens conceptual understanding. For instance, students who calculate statistical measures such as standard deviation by hand are more likely to comprehend the concepts of variability and distribution. This process also builds self-confidence and fosters active engagement and promotes better retention (Bruner, 1961). Moreover, manual computation strengthens fundamental quantitative skills. Performing calculations like ratios, deviations, and predictive values reinforces a student's numerical proficiency, which is crucial for disciplines like medicine and public health (Lowe & Lwanga, 1978).

Many statistical tools such as SPSS, R, MaxStat, STATA, SAS, XLSTAT, STATGRAPHICS, Microsoft Excel, WizardMac, MINTAB and others support educational researchers in performing a wide range of analyses. While manual analysis fosters understanding and skill-building, software tools offer speed, consistency, and advanced capabilities. The choice between these methods depends on the study's objectives, data collection instruments, and the researcher's expertise. Ultimately, the integrity of data analysis in educational research is shaped by a variety of factors such as the researcher's skills, appropriate methodological choices, ethical practices, and accurate data reporting (Silverman & Manson, 2003). With the availability of both manual and statistical tools, researchers can choose the most suitable approach based on their needs and competencies. This study aimed to compare these two methods of quantitative data analysis in educational research, evaluating their efficiency, reliability, and implications for research outcomes.

1.1. Statement of the Problem

There is an ongoing debate among scholars regarding the most reliable approach to quantitative data analysis. While some researchers support the use of statistical tools and statistical software due to their speed, accuracy, and ability to handle complex data (Field, 2018; Punch & Oancea, 2014) but other scholars still favor the use of manual techniques for their pedagogical value and perceived reliability (Muijs, 2010). Given the importance of accurate data analysis in producing valid research outcomes and supporting evidence-based decisions (Creswell & Creswell, 2018) choosing the most dependable method is essential. Although manual techniques such as hand calculations and basic calculators are commonly used in introductory research training, they are time-consuming and prone to error, especially with large datasets (Fraenkel, Wallen, & Hyun, 2019). On the other hand, despite the efficiency of software tools like SPSS, Excel, STATA, and R, their usage is often limited in developing countries due to factors such as inadequate access to technology, insufficient training, and low digital literacy levels of using this software (Komba, 2016). This presents a significant gap in understanding the comparative strengths, limitations, and user experiences of both methods. As the choice of data analysis technique can influence the quality and interpretation of research findings, there is a need for conducting a comparative study that critically evaluates the efficiency, accuracy, accessibility, and suitability of manual versus statistical data analysis techniques in educational research. Such a study will offer valuable insights for educators, researchers and students in selecting appropriate and effective strategies for research training and practice.

1.2. Objectives of the Study

The main objective of this study was to compare manual and statistical software-based techniques of quantitative data analysis in educational research. Specifically, the study aimed to:

i. Examine whether the results of Chi-square tests differ when using manual versus statistical software techniques
ii. Assess whether there is a difference in the outcomes of dependent t-test obtained from using manual or statistical software techniques
iii. Determine whether there is a difference in the results of one-way ANOVA obtained from using manual or statistical software techniques
iv. Determine whether there is a significant difference in Pearson correlation results when analyzed manually versus with statistical software.

1.3. Research Hypotheses

The following null hypotheses were formulated to guide the study.

H_{01}: There is no significant difference in Chi-square test results when using manual versus statistical software techniques of quantitative data analysis.

H_{02}: There is no significant difference in dependent t-test results obtained from using manual and statistical software techniques of quantitative data analysis.

H_{03}: There is no significant difference in One-way ANOVA results between manual and statistical software techniques of quantitative data analysis

H_{04}: There is no significant difference in Pearson correlation results when analysed manually versus with statistical software techniques of quantitative data analysis.

1.4. Theoretical Framework

This study is underpinned by two key theoretical frameworks: Cognitive Load Theory and Constructivist Learning Theory. Cognitive Load Theory was introduced by John Sweller, who explained that learning as a process involving the interaction between long-term memory, which holds information permanently, and working memory, which has limited capacity and handles conscious processing (Cooper, 1998; Sweller, 1988). Manual calculations of quantitative data analysis often place a heavy cognitive burden on learners because they involve multiple steps and the need to recall various statistical formulas. In comparison, statistical analysis tools reduces the mental strain by automating complex procedures and presenting outputs in a user-friendly format, allowing users to focus more on analysis and interpretation.

On the other hand, the Constructivist Learning Theory highlights that learners builds a new knowledge by connecting it to what they already know. This theory supports using both manual and digital analysis tools in educational research. Manual calculations help to solidify foundational concepts, while computer-based tools support the recognition of patterns and higher-order thinking. The researcher's engagement with both approaches reflects constructivist ideals, encouraging active participation, discovery, and critical reflection for deeper learning.

2. Methods

2.1. Research Design

This study adopted a self-experiential comparative design. The researcher systematically applied both manual and statistical software techniques to analyze quantitative data from various educational research problems. The aim was to compare the processes, efficiency, accuracy, and interpretation outcomes between the two approaches based on firsthand experience.

2.2. Nature of the Study

Rather than involving human subjects, the study focused on the researcher's practical application and reflection on each method. A variety of simulated educational research problems as a reflective of typical data analysis scenarios encountered in education were constructed and analyzed using both manual and statistical tools specifically SPSS in this study.

2.3. Data Sources

The data used in this study were secondary and simulated which were created to mirror a real-world quantitative dataset commonly used in educational research. These datasets included variables such as test scores and student performance metrics. Each dataset was carefully designed to enable the use of common statistical techniques such as Chi-square tests, t-tests, ANOVA and Pearson correlation.

2.4. Data Analysis Procedures

For the manual quantitative data analysis, the researcher conducted statistical computations by hand using appropriate formulae, statistical tables, and a scientific calculator. Each step was carefully documented to assess the complexity, time consumption, and likelihood of errors. For the statistical software approach, the same datasets were analyzed using SPSS Version 20.0 (SPSS Inc., Chicago, IL, USA), and the outputs were recorded and interpreted.

A comparative assessment was conducted based on several criteria: time required for analysis, ease of use, accuracy of results, quality of outputs (such as tables and charts), and clarity in interpretation. Datasets suitable for both manual and software-based techniques were prepared, and each method was applied to analyze the same data. The results of key statistical tests including Chi-square (χ^2), paired samples t-test, one-way ANOVA, and Pearson correlation were obtained from both manual calculations and SPSS were then compared to identify any differences in outcomes.

2.5. Evaluation and Comparison Criteria

The comparison was structured around the following key parameters: Efficiency (Time and steps required for completion), accuracy (Consistency of results across techniques), complexity (Cognitive load and required statistical knowledge), presentation quality (Clarity and professional appearance of outputs) and interpretation (Ease of interpreting and reporting results).

2.6. Ethical Considerations

Since the study did not involve human subjects or real personal data, there were no ethical risks. The simulated datasets were created purely for academic and comparative purposes.

3. Findings

3.1. Hypothesis One

Ho_1: There is no significant difference in the results of Chi-Square obtained from using manual or statistical SPSS Software Package of quantitative data analysis.

Problem 1: A sample of 870 trainees was subjected to different types of training classified as intensive, good and average and their performance was noted as above average, average and poor. The resulting data is presented in the table below. Use a 5 per cent level of significance to examine whether there is any relationship between the type of training and performance as shown below. Table 1 presents the distribution of performance levels across different types of training.

Table 1. Distribution of performance levels across different types of training.

Performance	Training			
	Intensive	**Good**	**Average**	**Total**
Above average	100	150	40	290
Average	100	100	100	300
Poor	50	80	150	280
Total	250	330	290	870

Table 2 presents a summary of the Chi-square test of independence results obtained from analyzing the data using manual techniques.

Table 2. Summary of Chi-square tests of Independence results using manual techniques of data analysis

Df	4	Since χ^2 calc. (105.65) > χ^2 critical (9.488), H_0 is rejected and H_a is accepted. Therefore, There is a statistically significant relationship between the type of training and performance at the 5% level of significance.
$\chi^2_{critical}$	9.488	
$\chi^2_{calculated}$	105.65	

The calculated chi-square value (105.65) is significantly greater than the critical chi-square value (9.488). This indicates that there is a statistically significant relationship between the variables being tested. Therefore, we conclude that there is enough evidence to reject the null hypothesis (H_0), which typically states that there is no significant association between the variables. In other words, the observed frequencies significantly differ from the expected frequencies, suggesting a meaningful relationship between the variables. Table 3 presents a detailed summary of the Chi-square test of independence results obtained from statistical software analysis.

Table 3. Summary of chi-square tests of Independence results using statistical SPSS software package of data analysis.

Test	Value	Degree of freedom	Asymptotic Sig. (2-sided)	Exact sig. (2-sided)	Exact sig. (1-sided)
Pearson chi-square	105.65	4	0.000		
Likelihood ratio	100.27	4	0.000		
Fisher's exact test				0.000	0.000
Linear-by-linear association	28.57	4	0.000		
No. of valid cases	870				

The chi-square test results from both manual and statistical methods indicate a statistically significant association between the type of training and performance. In the manual analysis, the calculated chi-square value was 105.65, which exceeds the critical value of 9.488 at the 5% significance level (df = 4), leading to the rejection of the null hypothesis. Similarly, the statistical analysis using SPSS produced p-values of 0.000 for the Pearson

Chi-Square, Likelihood Ratio, Fisher's Exact Test, and Linear-by-Linear Association, all below the 0.05 threshold confirming statistical significance. These consistent findings provide strong evidence to reject the null hypothesis and support the conclusion that training type significantly influences performance. Overall, the chi-square test of independence confirmed a significant association, $\chi^2(4) = 105.65$, $p < 0.001$.

3.2. Comparison of Manual Vs. Statistical Software Results

Both the manual and statistical approaches revealed a statistically significant association between the variables. In the manual analysis, the null hypothesis was rejected because the calculated chi-square value (105.65) exceeded the critical value (9.488) at the 5% significance level. Similarly, the statistical analysis produced p-values of 0.000 for all tests Pearson Chi-Square, Likelihood Ratio, Fisher's Exact Test, and Linear-by-Linear Association confirming statistical significance.

The p-value represents the probability of observing the data if the null hypothesis is true, ranging between 0 and 1. It helps researchers decide whether to reject or retain the null hypothesis (Ali & Bhaskar, 2016). For instance, a p-value less than 0.01 indicate strong evidence to reject the null hypothesis as highly significant (see Table 4).

Overall, results from both methods consistently demonstrate a significant relationship between the variables, providing sufficient evidence to reject the null hypothesis (H_0) in favor of the alternative hypothesis (Ha), which asserts that the variables are significantly related.

Table 4. The p-value table.

p-value	**Evidence**	**Interpretation**	**Conclusion**
p<0.01	Overwhelming	Highly significant	Reject H_o
0.01<*p*<0.05	Strong	Significant	Reject H_o
0.05 <*p*<0.1	Weak	Not significant	Fail to reject H_o
p>0.1	None	No evidence	Fail to reject H_o

3.3. Hypothesis Two

H_{02}: There is no significant difference in the results of paired samples–t-test (Student's t-test) obtained from using manual or statistical software techniques of data management and analysis.

Problem 2: A school mathematics teacher decides to test the effect of using an educational computer package, consisting of geometric designs and illustrations, to teach geometry. Since the package is expensive, the teacher wishes to determine whether using the package will result in an improvement in the pupils' understanding of the topic. The teacher randomly assigns pupils to two groups; a control group receiving standard lessons and an experimental group using the new package. The pupils are selected in pairs of equal mathematical ability, with one from each pair assigned at random to the control group and the other to the experimental group. On completion of the topic the pupils are given a test to measure their understanding. Table 5 presents the paired performance scores for control and experimental groups across 10 matched pairs. Each pair represents corresponding observations between the two groups, possibly indicating the effect of an intervention or training technique on the experimental group.

Table 5. The paired performance scores for control and experimental groups across 10 matched pairs (N=10).

Pair	1	2	3	4	5	6	7	8	9	10
Control	72	82	93	65	76	89	81	58	95	91
Experimental	75	79	84	71	82	91	85	68	90	92

Assuming percentage marks to be normally distributed, investigate the claim that the educational computer package produces an improvement in pupils' understanding of geometry.

Table 6 presents a summary of independent and paired sample t-test results obtained through both manual calculations and analysis using the SPSS statistical software package.

Table 6. Summary of t-test results obtained from analyzing the data using manual and statistical SPSS Software Package of data analysis (N=10).

Manual	**Mean$_1$**	**Mean$_2$**	**Standard deviation**	**Standard error**	**Degree of freedom**	**Calculated t-value**	**t-critical**	

	80.20	81.70	5.72	1.81	9	0.830	2.262	
	80.20	81.70	11.87	3.75	9	-0.829	2.262	0.429
Statistical software	$Mean_1$	$Mean_2$	Standard deviation	Standard error	Degree of freedom	Calculated t-value	t-critical	p-value

At a 5% significance level ($\alpha = 0.05$) for a two-tailed test, the critical t-value is approximately 2.262, based on the t-distribution table. Since the computed t-value (0.83) is less than 2.262, we do not reject the null hypothesis. This implies that any observed improvement in students' performance using the educational computer package is not statistically significant and may simply be due to random variation. With 9 degrees of freedom, both manual and statistical t-values of 0.83 and -0.829 respectively are below the critical value, and their associated p-values (0.429) exceed 0.05. Thus, the null hypothesis (H_0) remains valid for both methods, indicating no significant difference between the control and experimental groups. The consistent results from both manual and software-based analyses suggest that the method of analysis did not affect the outcome. Therefore, the null hypothesis stating that there is no significant difference between the t-test results from manual and statistical approaches is upheld. These results imply that the difference in group means could be attributed to chance, and there is insufficient evidence at the 0.05 level to conclude that the computer-assisted instruction meaningfully improved pupils' understanding of geometry. Since the p-value is greater than 0.05, the result is not statistically significant, providing no strong indication that the educational software had a significant impact.

3.4. Hypothesis Three

H_{03}: There is no significant difference in the results of Analysis of Variance (ANOVA) obtained from using manual or statistical SPSS Software Package of quantitative data analysis.

Problem 3: Scores of three randomly selected groups of students in basics of research test are given below. Table 7 presents the scores obtained by three randomly selected groups of students in basics of research test.

Table 7. Scores of three randomly selected groups of students in basics of research test (N=11).

Group 1	15	20	12	10	9	7	6	11	18	14	5
Group 2	13	12	15	19	20	11	8	14	10	9	4
Group 3	18	16	13	9	8	4	20	18	12	7	10

Test the hypothesis at 5% significance level that the three groups do not belong to the same population.

Table 8. Summary of ANOVA results obtained from analyzing the data in Table using manual techniques of data analysis (N=11).

Source of variation (SV)	Sum of squares (SS)	Degrees of freedom(df)	Mean square (MS)	F-calculated	F- critical
Between groups (SSB)	3.8791	2	1.94	0.080	3.32
Within groups (SSW)	725.0900	30	24.17		
Total (SST)	728.9691	32			

Table 9. Summary of ANOVA results obtained from analyzing the data using statistical techniques of data analysis (N=11).

Source of Variation	Sum of squares	Degree of freedom	Mean square	F-statistic	F- critical	Sig.(p-value)
Between groups(SSB)	3.879	2	1. 939	0.080	3.32	0.923
Within groups(SSW)	725.091	30	24.170			
Total(SST)	728.970	32				

In the analysis of variance (ANOVA), the decision to reject or retain the null hypothesis depends on comparing the calculated F-statistic with the critical F-value. At the 5% significance level ($\alpha = 0.05$), with degrees of freedom between groups =2 and within groups =30, the critical F-value is approximately 3.32. When using the manual method, the computed F-value is 0.080, which is less than the critical value, leading to the conclusion that the null hypothesis cannot be rejected. This suggests there is no statistically significant difference between group means. Since $p > 0.05$, we fail to reject the null hypothesis; the group means are not significantly different (Table 8 and 9).

3.5. Hypothesis Four

H_{04}: There is no significant difference in the results of Pearson correlation obtained from using manual or statistical SPSS Software Package of data analysis.

Problem 4: A study is conducted involving 10 students to investigate the association between statistics and science tests. The question arises here; is there a relationship between the marks gained by the 10 students in statistics and science tests? [Note: marks are out of 30].

Table 10 presents the scores obtained by three randomly selected groups of students in statistics and science tests.

Table 10. Test scores of selected groups of students in statistics and science subjects (N=10).

Students	1	2	3	4	5	6	7	8	9	10
Statistics	20	23	8	29	14	12	11	20	17	18
Science	20	25	11	24	23	16	12	21	22	26

Table 11 presents the summary of Pearson correlation results obtained from analyzing the data in Table 10 using manual and statistical software techniques of data analysis.

Table 11. Summary of Pearson correlation results obtained from using manual and statistical software techniques of data analysis (N=10).

Manual	**$\sum X_1$**	**$\sum Y_1$**	**$\sum X_1 Y_1$**	**$\sum X_1^2$**	**$\sum Y_1^2$**	**Calc. r_1**
	172	200	3667	3308	$\sum$4252	0.765
Statistical software	$\sum X_2$	$\sum Y_2$	$\sum X_2 Y_2$	$\sum X_2^2$	$\sum Y_2^2$	Calc. r_2
	173	200	3688	3349	4552	0.765

The data presented in Table 11 can be interpreted as follows:

1. Correlation Coefficient (r): The calculated Pearson correlation coefficient (r) for both manual and statistical analysis is 0.765, indicating a strong positive correlation between the two variables being analyzed (e.g., test scores, time spent, performance metrics, etc.). This means that as one variable increases, the other tends to increase as well.

2. Consistency across methods: Despite slight variations in the raw sums ($\sum X$, $\sum XY$, $\sum X^2$, $\sum Y^2$), both methods yielded the exact same correlation coefficient ($r = 0.765$). This suggests that both manual and statistical software techniques were accurately and consistently applied in calculating the Pearson correlation.

3. Implications: The identical results demonstrate no significant difference between the two methods in terms of outcome. It supports the validity and reliability of using statistical software for data analysis, offering the same level of accuracy as manual computation, but likely with greater efficiency and speed.

In conclusion**,** both manual and statistical methods yielded the same Pearson correlation coefficient ($r = 0.765$), showing a strong positive relationship between the variables under study. The similarity in results validates the effectiveness of software tools in performing accurate statistical analysis and confirms that either method can be reliably used depending on context and researcher preference.

4. Discussions

The results obtained for Chi-square tests was not different at all from both techniques of analysis. This means that both approaches yielded the same Chi-square results, although during the process of computation, more time was spent calculating manually, as it took just some few minutes to enter the data into SPSS, while it took just a few seconds for the software to analyze the data. Both methods produced the same Chi-square value (105.65), meaning the manual calculation was accurate. However, the statistical method provided multiple test statistics (e.g., Likelihood Ratio, Fisher's Exact, Linear-by-Linear Association), p-values with higher precision (e.g., 0.000), and additional insights like asymptotic and exact significance values. The statistical technique also yielded the answer very much faster than manual, saving a lot of time and energy as opposed to the manual technique. This finding is in line with Owan and Bassey (2018) who found that**,** both methods yielded identical results for the statistical tests conducted. However, the statistical technique was notably faster and more efficient.

The research findings revealed that the calculated t-values from both manual (0.83) and statistical (-0.829) methods are less than the critical value and the corresponding p-values (0.429) are greater than 0.05, the null hypothesis (H_0) is not rejected in either case.

The findings of this study revealed that the ANOVA results obtained from both manual and statistical techniques were identical, indicating no difference in the outcomes produced by either method. However, a notable distinction was observed in the efficiency and level of detail. The statistical technique, using SPSS, generated the ANOVA results within seconds and included exact p-values and critical values ($p = 0.923$ at 30 degrees of freedom) features not easily obtainable through manual calculation, which took over 50 minutes to complete.

Similarly, both approaches produced the same Pearson correlation coefficient ($r = 0.765$), indicating a strong positive relationship between the variables. This consistency in results validates the reliability of both methods, confirming that either can be used depending on the research context and preference. While manual methods may encourage deeper engagement with data, statistical software enhances speed, accuracy, and output clarity. Ugochukwu, Falaiye, Mhlongo, and Nwankwo (2024) found that digital tool users scored higher in efficiency, productivity, and collaboration, whereas manual method users demonstrated strengths in analytical depth and contextual integration.

Although computers have significantly improved the data analysis process, there remains a need to continuously develop and systematically apply advanced, state-of-the-art techniques in educational research. As Tchibozo (2009) noted, embracing modern methodologies represents the new frontier in data analysis. Similar sentiments have been echoed in psychological research by Blanca, Alarcón, and Bono (2018) and they continue to remain relevant today.

5. Conclusion

The following main conclusions can be made from the research presented in this article:

The results of this study indicate that there is no significant difference between the outcomes generated by manual and statistical software techniques when conducting statistical tests such as the Chi-square, Pearson correlation, paired sample t-test, and one-way ANOVA. While statistical data analysis tools are notably faster and more efficient than manual methods, both approaches proved to be reliable and trustworthy. Regardless of the method employed, data analysis plays a critical role in uncovering insights from datasets, enabling researchers to draw conclusions, inform decision-making, and expand existing knowledge.

The techniques discussed in this study can assist educational researchers in maximizing the value of empirical data to produce well-substantiated, generalizable findings and recommendations. This makes the discussion a practical resource for those new to computer-based data analysis. The broader use of statistical software is likely to enhance the quality and clarity of research reporting in education.

When results from manual and SPSS analysis closely align, it is typically a good indication that no major errors have occurred. Minor discrepancies may be attributed to differences in decimal precision, rounding methods, or variations in formulas (e.g., using sample versus population calculations).

To maintain consistency, it is important to clearly state whether sample or population standard deviation is being used and to retain at least four decimal places in intermediate steps during manual computations. Although manual analysis can be accurate for simpler statistical tasks, statistical methods generally offer more comprehensive output and reduce the likelihood of human error. Manual techniques can be time-consuming and require solid statistical skills, particularly when working with large datasets, such as those with 870 valid cases. In contrast, software tools like SPSS, Excel, or R enable faster, more efficient analysis, handle large volumes of data effortlessly, and minimize manual effort and calculation mistakes. Therefore, for extensive analyses or multiple tests, statistical methods offer a clear advantage in terms of speed, efficiency, and accuracy.

5.1. General Insights from Comparative Studies

Accuracy: When used appropriately, both manual and statistical techniques can produce reliable and accurate results.

Efficiency: statistical methods greatly enhance the speed and ease of data analysis, particularly when working with large datasets.

Practicality: Modern research increasingly favors statistical tools due to their suitability for performing complex statistical procedures.

Conclusion: Although manual data analysis can be dependable, statistical approaches offer notable benefits in terms of efficiency, speed, and capacity to manage complex data. As such, they are generally the preferred option for conducting quantitative analysis in contemporary research contexts.

5.2. Recommendations

Based on aforementioned findings this study recommends as follow:

i. Students in higher learning institutions must be trained with practical application of statistical packages in analyzing data because research project/study at the end of a discipline should be based on pure or applied field work that solve existing problem in our society.
ii. Researchers should be the research analyst for their research findings and seize from giving their research data out for another to analyze.
iii. The recommendation that hand computations be employed in educational research is based primarily on the resulting enhancement of the learning process, as indicated previously, and less on the anticipation that students will deal with statistical problems by hand in their professional lives. However, the fact that everyone uses quantitative skills in one way or another throughout their lives provides an added benefit to the requirement of hand computation.
iv. Lengthy computations should be avoided; these include large data sets or heavy calculations (such as computing the sums of squares for a three-way factorial ANOVA) that do not have a compensating yield of descriptive enlightenment. If the type and extent of hand computations are poorly conceived, then those computations can be counterproductive, becoming frustrating and tedious to the student.

v. While manual methods help develop foundational understanding, statistical methods (like SPSS, Excel, R, or Python) are clearly more accurate, faster, and efficient especially crucial when dealing with large samples or when high precision is needed in academic or professional research.
vi. For research and academic analysis, especially with a large sample size like N=870, the statistical method is both more accurate and more efficient. Manual methods are great for learning and verification, but statistical tools are preferable for practical research work.
vii. This study collectively suggest that while statistical methods enhance efficiency and are well-suited for handling large datasets, manual methods offer depth and nuanced understanding, particularly valuable in qualitative research. A balanced approach, leveraging the strengths of both methods, is often recommended based on the specific requirements of the research.

5.3. Suggestions for Further Research

Other statistical techniques, such as Analysis of Covariance (ANCOVA), linear regression, and similar methods, were not examined in this study. As a result, the conclusions drawn might have differed had these additional methods been included. Moreover, the study focused solely on SPSS version 20 for statistical data analysis, without considering other software tools like MS-EXCEL, SAS, STATA, R, Minitab, or JMP. It remains uncertain whether these other software packages would produce comparable or divergent results. Therefore, further research is recommended to incorporate a broader range of statistical techniques and alternative data analysis software to provide more comprehensive insights.

5.3.1. Best Practices for Students and Researchers

i. Manual computation is most appropriate when the goal is to develop a deeper understanding of statistical concepts, particularly during the learning phase. It is also suitable when working with small datasets where calculations are manageable and can reinforce comprehension of how statistical formulas operate.
ii. Statistical tools are preferable when dealing with large datasets that require efficient processing. They are also ideal when accuracy is critical, time is limited, or when visual outputs such as graphs and reports are needed for interpretation and presentation purposes.

References

Abulela, M. A., & Harwell, M. M. (2020). Data analysis: Strengthening inferences in quantitative education studies conducted by novice researchers. *Educational Sciences: Theory and Practice*, *20*(1), 59-78. https://doi.org/10.12738/jestp.2020.1.005

Akindutire, A. (2013). Usage of mobile phone: Deception. *Deviance and Fraud (A case study of Ambrose-Alli)*.

Ali, Z., & Bhaskar, S. B. (2016). Basic statistical tools in research and data analysis. *Indian Journal of Anaesthesia*, *60*(9), 662-669.

Blanca, M. J., Alarcón, R., & Bono, R. (2018). Current practices in data analysis procedures in psychology: What has changed? *Frontiers in Psychology*, *9*, 2558. https://doi.org/10.3389/fpsyg.2018.02558

Brown, M. S. (2021). Transforming unstructured data into useful information. In Big data, mining, and analytics. In (pp. 227–246): CRC Press. https://doi.org/10.1201/b16666-14.

Bruner, J. S. (1961). The act of discovery. *Harvard Educational Review*, *31*, 118-202.

Cooper, G. (1998). *Research into cognitive load theory and instructional design at UNSW*. Sydney: University of New South Wales.

Cowles, M. (2005). Computerized accounting systems: Benefits and challenges. *Journal of Accounting Education*, *23*(3), 123–135.

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches* (3rd ed.). Thousand Oaks, CA: Sage.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Thousand Oaks, CA: SAGE Publications.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Thousand Oaks, CA: SAGE Publications.

Fraenkel, J. R., Wallen, N. E., & Hyun, H. H. (2019). *How to design and evaluate research in education* (10th ed.). New York: McGraw-Hill Education.

Friese, S. (2019). *Qualitative data analysis with ATLAS.ti* (3rd ed.). London: SAGE.

Holton, J. A. (2007). The coding process and its challenges. In A. Bryant, & K. Charmaz (Eds.), The Sage handbook of grounded theory. In (pp. 265-289). Thousand Oaks, CA: Sage.

Kara, H. (2017). *Mixed methods data analysis*. Retrieved from https://helenkara.com/2017/03/23/mixed-methods-data-analysis

Komba, W. L. M. (2016). Challenges of integrating ICT in education in Sub-Saharan Africa: A review. *International Journal of Education and Development using ICT*, *12*(2), 80–92.

Lowe, C. R., & Lwanga, S. K. (1978). *Health statistics: A manual for teachers of medical students*. Oxford: Oxford Medical Publications.

Muijs, D. (2010). *Doing quantitative research in education with SPSS* (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Owan, V. J., & Bassey, B. A. (2018). Comparative study of manual and computerized software techniques of data management and analysis in educational research. *International Journal of Innovation in Educational Management*, *2*(1), 35-46.

Pruneau, C. A. (2017). The multiple facets of correlation functions. In Data analysis techniques for physical scientists. In (pp. 526–576): Cambridge University Press. https://doi.org/10.1017/9781108241922.013.

Punch, K. F., & Oancea, A. (2014). *Introduction to research methods in education* (2nd ed.). Thousand Oaks, CA: SAGE Publications.

Silverman, S., & Manson, M. (2003). Research on teaching in physical education doctoral dissertations: A detailed investigation of focus, method, and analysis. *Journal of Teaching in Physical Education*, *22*(3), 280-297. https://doi.org/10.1123/jtpe.22.3.280

Soratto, J., Pires, D. E. P. d., & Friese, S. (2020). Thematic content analysis using ATLAS. ti software: Potentialities for researchs in health. *Revista Brasileira De Enfermagem*, *73*, e20190250. https://doi.org/10.1590/0034-7167-2019-0250

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive science*, *12*(2), 257-285.

Tchibozo, G. (2009). Applications in data analysis for educational research. In (Vol. 7, pp. 364-367): SAGE Publications Sage UK: London, England.

Ugochukwu, E. C., Falaiye, T., Mhlongo, N. Z., & Nwankwo, E. E. (2024). Accounting for digital currencies: A review of challenges and standardization efforts. *International Journal of Science and Research Archive*, *11*(1), 2438-2453.

Xia, B. S., & Gong, P. (2014). Review of business intelligence through data analysis. *Benchmarking: An International Journal*, *21*(2), 300-311. https://doi.org/10.1108/BIJ-08-2012-0050