Ianna Journal of Interdisciplinary Studies, Volume 6 Number 3, Special Issue September 2024
DOI: https://doi.org/10.5281/zenodo.13188169 EISSN: 2735-9891

Can the Digital Software Method Outperform the Manual Method in Qualitative Data Analysis? Findings from a Quasi-experimental Research

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Abstract

Background: In the dynamic field of qualitative research, a contentious issue persists: Is digital software a more effective tool for research analysis than the manual method? To shed light on this debate, we undertook quasi-experimental research, focusing on our study's unique contribution to exploring the capabilities of both methods in analysing health datasets.

Objective: Our study aims to compare the effectiveness of qualitative analysis between researchers who are proficient in digital software and those skilled in the manual method. We seek to understand which method is more effective in various aspects of data analysis.

Methodology: We employed a quasi-experimental design and a purposive sampling approach to select our study participants. These participants (n=150) were then divided into two groups-those proficient in digital software and those skilled in the manual method. We then conducted an intervention, where participants analyzed a qualitative dataset using their preferred method. The data collected was then analyzed using quantitative measures, such as percentage, central tendency measures, and independent samples t-test.

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Results: The t-test result showed that statistically significant differences exist between the two groups across all indicators (all Ps<.0001). Specific observation of the mean scores revealed that for perceived efficiency (M=3.50 [SD=0.55]), productivity (M=3.40 [SD=0.60]), collaboration (M=3.55 [SD=0.50]), identification of complex themes (M=3.60 [0.45]), and visualisation techniques(M=3.60 [SD=0.45]), participants who used digital software scored higher than those who used manual method of data analysis. However, for perceived depth of analysis (M=3.50 [SD=0.55]), coding flexibility(M=3.45 [SD=0.50]), reflective quality(M=3.60 [SD=0.50]) and integration of contextual knowledge(M=3.55 [SD=0.45]), participants in the manual method group scored higher compared to those in the digital software group

Contribution: This study adds to burgeoning and existing knowledge on the need for a complementary approach to adopting and using digital tools and manual methods in conducting qualitative data analysis. Although using both methods can offer many benefits, it is crucial to use the advantages of one method to address the drawbacks of the other where possible. While these benefits should be observed when combining both methods, the challenges of both methods must be acknowledged.

Conclusion: This study crucially emphasises the complementary advantages of digital and manual qualitative data analysis methods.

Keywords: Qualitative data analysis, Digital software, Manual methods, Quasi-experimental research, Technology, Insights, Innovation.

Introduction

In the ever changing domain of qualitative research, there is a growing debate concerning whether digital software is more effective in conducting research analysis relative to the manual method. On the one hand, digital software for qualitative data analysis utilisesprogrammes such as Nvivo, QDA Miner, Dedoose, MAXQDA, Transana, Web QDA, HyperRESEARCH, Quirkos, Taguette, JMP, QualCoder, F4analyse, Delve, Ligre, and Excel. On the other hand, the manual method entails reading, underscoring, and codingdata by hand, using tools such as highlighter (i.e., Fluorescent pen), sticky notes, etc. Bryda and Costa (2023) have noted the burgeoning impact of digital technologies and their vast opportunities for researchers to redefine how qualitative researchers analyse data.Costa (2023) mentions that such digital tools can reproduce patterns and trends as well as generate data visualisation, which could offer insights into further research endeavours. Basit (2003) also stated how digital methods such as Nvivo and computer-assisted qualitative data analysis software (CAQDAS) could be effective and reliable in coding, retrieval and organisation of datasets but necessitating expertise, which can often neglect the in-depth and nuanced insights (i.e., feelings emanating from those offering the insights as well as why they feel the way they feel) that are inherent in qualitative data. Manual methods, on the other hand, offer these deeper insights but are arduous and have minimal consistency (Basit, 2003).

Similarly, Mattimoe et al. (2021) drew an analytical comparison between two PhD students who used different qualitative analysis methods (i.e., Nvivo and manual approaches) and found that the candidate who employed Nvivo in conducting qualitative data enjoyed a more efficient and

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organised coding experience with a straightforward audit trail, advantageous for organisingqualitative data which are naturally "messy" or disorganised. However, Mattimoe et al. (2021) revealed that a major disadvantage of this digital method is the risk of data quantification, which can in the long run defeat the sole and acknowledged purpose of conducting qualitative analysis. Regarding the candidate who conducted an analysis using the manual approach, Mattimoe et al. found that a more direct connection is formed between the researcher and the data in such a manner that themes can organically emerge. However, its time-consuming and arduous nature makes it exhausting when analysing a huge volume of data.

Furthermore, in an introduction to text mining as a feasible alternative to the ineffectiveness of manual analytical methods, particularly where a huge collection of datasets is involved, Hacking et al. (2023) conducted a quasi-experimental research comparing accuracy, consistency and expert feedback across text mining and manual coding. The authors found that there was an 80% similarity with respect to them and sentiments assignment relative to manual coding, indicating higher reliability. Nevertheless, according to expert feedback, limitations existed in both approaches (Hacking et al., 2023). The study concluded that even though text mining can be effective in qualitative data analysis, it often fails to capture the recognised essence of qualitative data analysis, which is to highlight its interpretivefunctions.

In addition, Morgan (2023)expanded the discourse by examining the effectiveness of ChatGPT in analysing qualitative data relative to the adoption of a manual method. Findings revealed that although ChatGPT has the capabilities to effortlessly offer basic, explanatory themes, it grapples with reproducing more critical and deeper-level analyses. This leads Morgan to summarise that the complete dependence on ChatGPT for qualitative data analysis could struggle to produce nuanced findings, which could be readily achievable when using manual methods.

Put together, these studieshighlight the contradictory nature of both analytical methods.However, Bryda and Costa (2023) and Morgan (2023) advised that combining both methods is more effective – a position which can be overwhelmingly challenging if researchers are faced with time constraints and tight deadlines. Gibbs et al. (2002) also questioned the capability of these digital methods to reproduce high-quality analysis or whether they merely provide assistance for human researchers who then conduct a much higher level analysis that these technologies are limited to perform. In addition, even though scholarly attention is expanding in this area, there is a paucity of recent research drawing comparisonsbased on user experience between those adopting the digital methods and others using the manual type. Significant research gaps require attempts to answer whether the digital software or application can outperform the manual methods in reproducing authentic and high-quality outputs. As a result, this current research offers insights into developing strategies that can be useful for qualitative researchers attempting to use any of these methods.Therefore, the study aims to compare the effectiveness of qualitative analysis between researchers who prefer and are prolific with digital software and those with preference and expertise in manual methods. The differences are evaluated explicitly across the following

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indicators: perceived efficiency, productivity, collaboration, identification of complex themes, visualisation techniques, perceived depth of analysis, coding flexibility, creativity in interpretation, reflective quality, and integration of contextual knowledge.

Method

Study Design

In this study, we adopted a quasi-experimental design to compare the effectiveness of qualitative data analysis with that of digital and manual software methods. The quasi-experimental design emerges as an appropriate approach, particularly in cases where randomisation is impossible (see Campbell & Stanley, 1963; Miller et al., 2020). Another justification for the choice of the design lies in its capability to contain the natural environments and multilayered interventions, according to Shadish et al. (2002). Overall, this research design permits a rigorous comparison while preserving ecological validity, which is fundamental for studies aiming to measure the impact of an independent variable on a dependent variable in real-world settings.

Recruitment

In recruiting participants, we used a purposive sampling approach, which is greatly efficient for identifying and selecting those with actual skills and experience pertinent to the research aim (Patton, 2015). In doing this, we targeted a pool of qualitative data analysts by contacting several professional networks and appropriate online media. We found that this strategy enabled us to reach a wide audience across different fields or subject areas, but we are experienced in conducting qualitative research. Participants needed at least three years of experience in undertaking qualitative research or analysis. Researchers or analysts with less than three years of experience in qualitative research or data analysis and who are not familiar with digital or manual methods were excluded from participating in the study.

Sample

The sample size of participants was 150. With a 95 percent level of confidence (confidence interval - + 10%), an estimated rate of occurrence of the phenomenon at 50% (.5), and a permitted margin of error of.08 (8 percentage points), the researcher determined the 150 sample size for the study using the Cochran (1963, p. 75) Equation '1', which yields a representative sample for large populations, as follows:

$$n= \frac{[Z/_2]^2 \, (p\ q)}{e^2} \quad n= \frac{[Z/_2]^2 \, (P)(1-P)}{e^2}$$

Where: n= sample size, Z^2= confidence level, p= rate of occurrence or prevalence (the estimated proportion of an attribute that is present in a population), q= complement of p and e= margin of error. Therefore;

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$$n = \frac{[1.96]^2 0.5\,(1 - 0.5)}{0.08^2} \qquad n = \frac{3.8416\,(0.25)}{0.0064} \qquad n = 150.$$

Assignment

We assigned participants (n=150) into two groups (i.e., digital software versus manual methods) based on their self-reported proficiencyin usingeither of the qualitative data analysis methods. Seventy-fiveparticipants each were assigned to the group with a preference for digital software methods(such as Nvivo, ATLAS.ti, QDA Miner, MAXQDA, and Dedoose) and those who preferred the manual methods (such as highlighter [i.e., Fluorescent pen], sticky notes, etc). This non-random assignment aimed to take advantage of the internal validity by ensuring that we placed participants in groups where their expertise was put to the test (Bryman, 2016; Tashakkori& Teddlie, 2010).

Intervention

The study intervention entailed offering participants in the digital software groupaccess to use any of the following tools: Nvivo and ATLAS.ti, QDA Miner, MAXQDA, and Dedoose to conduct analysis on qualitative data. On the other hand, participants in the manual method groups were also instructed to use their traditional tools in analysing qualitative data given to them. We gave both groups public health study transcripts that were obtained from a recorded audio session of interviews and FGD (Focus Group Discussion). Using this intervention, we could compare the effectiveness of each analytical method across digital software and manual methods. The duration for which the groups conducted analysis was one week, during which manipulation checks were conducted, and analysis showed that participants were indeed exposed to the intended methods designed for each group.

Instrument of Data Collection

In order to determine the effectiveness of these two main types of qualitative analysis methods, we designed a questionnaire administered to participants after they had completed qualitative analyses using the tools they preferred. TheLikert-inspired questionnaire was designed based on key performance indicators obtained from our qualitative research experiences and from literature streams. We asked participants to rate their agreement on a4-point scale (1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree)regarding their analysis experience. The questionnaire was divided into subsections where items were presented under the following: perceived efficiency, productivity, collaboration, identification of complex themes, visualisation techniques, perceived depth of analysis, coding flexibility, creativity in interpretation, reflective quality, and integration of contextual knowledge.

A reliability statistic was conducted to measure the level of internal consistency within the data. Individually, results from each indicator reached an acceptable internal consistency level of above

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70%. For example, perceived efficiency (α=.82), productivity (α=.72), collaboration (α=.75), identification of complex themes (α=.80), visualisation techniques (α=.80), perceived depth of analysis (α=.73), coding flexibility (α=.80), creativity in interpretation (α=.92), reflective quality (α=.71), and integration of contextual knowledge (α=.82). The overall reliability result was also acceptable (α=.87).In conducting the study, we obtained an approval from the institutional review board of the University of Nigeria and all ethical issues were put into utmost consideration during and after the data collection phase.

Data Analysis

We conducted data analysis on the elicited data in this study using quantitative measures. To begin with, descriptive statistics were calculated to summarise the participants' demographic information across both groups. Furthermore, we conducted central tendency measures (mean and standard deviation) to highlight differences in the mean score of participants across the following indicators: perceived efficiency, productivity, collaboration, identification of complex themes, visualisation techniques, perceived depth of analysis, coding flexibility, creativity in interpretation, reflective quality, and integration of contextual knowledge. We further used an independent samples t-test to compare the differences between participants in the digital group and those in the manual group. Moreover, we computed effect size to measure the degree or magnitude of the differences between the two groups concerning the indicators above. The Cohen's (1988) guideline was used to measure the magnitude of the differences in ascertaining the practical significance of the observed differences that reached statistical significance. The results of the analysis conducted reached statistical significance at 5%.

Result

Table 1: Participant Demographic Characteristics

Characteristic	Digital Software Group (n=75)	Manual Methods Group (n=75)
Gender		
Male	38 (50.7)	36 (48.0)
Female	37 (49.3)	39 (52.0)
Area of Interest/Discipline		
Mass Communication	10 (13.3)	12 (16.0)
Sociology	15 (20.0)	13 (17.3)
Anthropology	13 (17.3)	14 (18.7)
Education	12 (16.0)	11 (14.7)
Public Health	14 (18.7)	13 (17.3)
History	11 (14.7)	12 (16.0)
Level of Experience in the use of Qualitative Methods		
- Inexperienced (less than 2 years)	22 (29.3)	20 (26.7)

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- Novice (2 to 3 years)	26 (34.7)	28 (37.3)
- Experienced (more than 3 years)	27 (36.0)	27 (36.0)

Information contained in Table 1 highlights the demographic characteristics of the participants across both groups (digital software vs. manual). As shown in the table, there were more males (50.7%) in the group digital software group but more females in the manual group (52.0%). Furthermore, as to participants' area of interest/discipline, participants with a speciality in Sociology accounted for the highest proportion (20.0%) in the digital software group. Also, those in Mass Communication, Anthropology, Education, Public Health and History accounted for 13.3%, 17.3%, 16.0%, 18.7% and 14.7% of categories in the area of interest/discipline among those in the digital software group, respectively. Equally, in the manual method group, participants with interest/discipline in Mass Communication, Sociology, Anthropology, Education, Public Health and History accounted for 16.0%, 17.3%, 18.7%, 14.7%, 17.3% and 16.0% of the total sample respectively.

Level of experience in the use of qualitative methods was analysed using percentages, and findings show that 29.3% of those in the digital software group were experienced, while some 34.7% were at the novice level, and those with the highest proportion of the sample were experienced (36.0%). In the same vein, of the 75 participants in the manual method group, 26.7%, 37.3%, and 36.0% were inexperienced, experienced and novice, respectively. Although those at the novice and experienced levels had the highest percentage in the manual group and digital software group, respectively, there appears to be a balanced distribution across both groups in terms of participants' level of experience.

Table 2: **T-test result comparing the mean of effectiveness of data analysis methods between digital software and manual methods groups**

Indicator	Digital Software Group Mean (SD)	Manual Methods Group Mean (SD)	t-test Result (t)	Cohen's d
Perceived Efficiency	3.50 (0.55)	2.90 (0.65)	5.60**	0.99
Productivity	3.40 (0.60)	2.85 (0.70)	4.85**	0.83
Collaboration	3.55 (0.50)	2.95 (0.60)	5.90**	1.06
Identification of Complex Themes	3.60 (0.45)	3.00 (0.55)	6.15**	1.15
Visualisation Techniques	3.70 (0.40)	2.80 (0.70)	7.25**	1.53
Perceived Depth of Analysis	3.00 (0.65)	3.50 (0.55)	-4.35**	-0.83

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Coding Flexibility	3.10 (0.60)	3.45 (0.50)	-3.75**	-0.63
Creativity in Interpretation	3.20 (0.55)	3.70 (0.45)	-4.90**	-0.96
Reflective Quality	2.95 (0.70)	3.60 (0.50)	-5.55**	-1.04
Integration of Contextual Knowledge	3.05 (0.65)	3.55 (0.45)	-4.45**	-0.87

Note: **p < 0.01

Data from Table 2 shows how researchers in both groups (digital software vs. manual methods) scored on the indicators, which measure the effectiveness of the methods they adopted in analysing the health research transcript they analysed. To effectively achieve this, we used an independent samples t-test to ascertain whether significant differences existed in the effectiveness of these methods across all the indicators between participants who used digital software and those who used manual methods. The t-test result showed that statistically significant differences exist between the two groups across all indicators (all Ps<.0001). We further conducted a Cohen's d effect size to ascertain the magnitude of the differences between both groups. Findings revealed that there were large effect sizes across the indicators used (as shown in Table 2). A closer look at the mean scores showed that for perceived efficiency (M=3.50 [SD=0.55]), productivity (M=3.40 [SD=0.60]), collaboration (M=3.55 [SD=0.50]), identification of complex themes (M=3.60 [0.45]), andvisualisation techniques(M=3.60 [SD=0.45]), participants who used digital software scored higher than those who used manual method of data analysis (See Table 2). However, for perceived depth of analysis (M=3.50 [SD=0.55]), coding flexibility(M=3.45 [SD=0.50]), reflective quality(M=3.60 [SD=0.50]) and integration of contextual knowledge(M=3.55 [SD=0.45]), participants in the manual method group scored higher compared to those in the digital software group (See Table 2).

Discussion of Findings

This study attempted to compare the effectiveness of qualitative analysis between researchers who preferred and were prolific with digital software and those with preference and expertise in using the manual method. In doing these, several findings emerged, and we submit that these findings contribute to the current debate about the effectiveness of digital software against manual methods in analysing qualitative data. To begin with, findings showed that those who used digital software reported higher scores in terms of perceived efficiency than researchers using manual methods. This outcome is in alignment with previous studies suggesting that digital tools were more effective in coding and organisation processes and, in the long run, saving time and effort that manual methods involve (Bryda& Costa, 2023). The perceived efficiency noted in digital tools

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like Nvivo and MAXQDA can thus be attributed to the capabilities of computerisingiterative activities and working with large datasets.

Findings also indicated that digital software was highly collaborative and used visualisation approaches. This aligns with the view of Mattimoe et al.(2021), stating that in using digital software, teamwork features are facilitated in actual time during coding, theme development and other process in situations where the researchers are not physically present together. In addition, the visualisation capabilities observed among those who used digital software offer explanations for the reason why manual methods might not be able to develop visual outputs (Costa, 2023).

Also, the higher performance level of digital tools in developing complex themes, which was found in the present study, extends previous knowledge and suggests that such tools have the capability to improve the depth of analysis that a researcher intends to attain. The findings are related to the ideas projected by Basit (2003), indicating that digital tools can enhance how nuanced and deep-level analysis might be developed in qualitative analysis during research.

On the flip side, and expectedly, the manual method scored impressively higher compared to digital methods in our present findings, particularly in the contexts of the depth of analysis, coding flexibility and reflective quality. These findings are in agreement with results from the study of Basit (2003), which found and also argued that manual tools offer the researcher the leverage to interact with the data more in-depth, leading to a state where the analyst arrives at multiple explanations in the experiences and emotions portrayed by those who participate in their study. Equally, the concrete immersion into the data, which is the hallmark of manual coding – text highlight, note taking, and tangible management and organisation of data can allow the researcher to become more reflective and interpretative during analysis.

Moreover, the use of the manual method was more favoured with respect to creativity in interpretation and incorporation of contextual knowledge. This is consistent with the argument of Morgan (2023), who maintained that a researcher’s insights, intuition and suspicion play a crucial part in data interpretation. On this basis, we argue that manual tools can be advantageous due to their capacity to enhance flexibility in coding and interpretation. In all, such flexibility can assist researchers to arrive at a more nuanced and detailed explanation of data.

Overall, the findings from the current study showcase the complementary characteristics embedded in both digital and manual methods. Although digital methods are being championed as superior and effective both within and outside the academic environments, the efficacy of the manual methods of data analysis has also been emphasised as a result of their capabilities to generate in-depth insights into a phenomenon. A major pathway to take as a researcher in this area is always to combine both methods. This duality resonates with the recommendations of previous authors, indicating that a balanced technique is required in order to benefit from the advantages of both methods (Bryda& Costa, 2023; Morgan, 2023) while also using the advantages of one method

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to address the drawbacks of the other where possible. While these benefits should be observed when combining both methods, the challenges of both methods must be acknowledged.

Limitation

As is common with many types of research, the present study is not without its limitations. First, our non-random assignment of participants, predicated upon self-reported expertise, might have led to selection bias as participants might have not been truthful concerning their skill level and experience. Further, a sample size of 150 is small, and also the adoption of a non-probability sampling procedure may affect the interpretation of the results in terms of generalizability/external validity. Dependence on self-reported measures after intervention might have brought about response bias. We did not also ascertain participants' scores before the intervention was administered. Finally, the one-week intervention for performing qualitative analysis might not be reflective of what might take place realistically, where timelines could be longer or shorter. This might have impacted on the depth and quality of the outcome. Regardless, future research can develop ways to address these limitations to validate the findings further.

Conclusion

This study places crucial emphasis on the complementary advantages that are common with both digital and manual methods of qualitative data analysis. It is established that while manual approaches provide deeper, more flexible, more introspective insights, digital tools excel in efficiency, collaboration, and complicated theme identification. A well-rounded strategy that makes use of the benefits of both approaches is advised in order to provide thorough and complex qualitative research results.

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