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Integrating PLS-SEM and NVivo in Mixed-Methods Educational Research: A Comprehensive Evaluation of Quantitative and Qualitative Analytical Tools

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Abstract

Background/purpose. It revisits Partial Least Squares Structural Equation Modeling (PLS-SEM) as a robust tool for analyzing non-normal data and small samples, offering predictive modeling advantages. This study also compares the merits, practical applications, and added value of both tools in tackling complicated research issues, notably in education and social sciences, rather than reviewing their techniques. Simultaneously, it evaluates NVivo as a leading qualitative data analysis (QDA) tool, focusing on its effectiveness in organizing, coding, querying, and visualizing diverse qualitative datasets.

Materials/Methods. The study places both tools in real-world educational research settings to help researchers choose and utilize methodologies that align with their data and goals. This mixed-methods research employed two approaches. Method A utilized empirical data to assess PLS-SEM's performance using statistical metrics such as R^2, Q^2, and Composite Reliability. It compared PLS-SEM with MRA, CB-SEM, and Factor Analysis. Method B involved surveys, interviews, usability testing, and case studies to evaluate NVivo’s capabilities. NVivo was compared with ATLAS.ti, MAXQDA, and Dedoose on parameters like coding flexibility, usability, visualization, and collaborative features.

Results. The manuscript demonstrates how PLS-SEM can model latent concepts, such as student engagement, learning outcomes, and institutional support, while NVivo can analyze qualitative data, including interview transcripts, reflective diaries, and classroom discourse. NVivo outperformed competing QDA tools in advanced coding, data visualization, and integration features, with 72% of surveyed researchers preferring it for its effectiveness and usability. Usability testing revealed NVivo had a 30% higher task efficiency and a high user satisfaction score (8.5/10), despite a moderate learning curve. NVivo was particularly effective in thematic exploration and supported collaborative research.

Conclusion. PLS-SEM proves to be a robust and adaptable statistical method for complex quantitative research, especially when data quality or sample size is constrained. NVivo stands out as a versatile and user-friendly QDA tool, enhancing the rigor and efficiency of qualitative analysis. Together, these tools offer a methodological advancement for researchers undertaking mixed-methods studies, promoting more accurate, predictive, and interpretable research outcomes across disciplines.

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1. Introduction

In educational research, PLS-SEM is particularly useful for modelling complex constructs such as teacher self-efficacy, student engagement, learning motivation, and the effectiveness of digital learning tools (Huang, 2021). Researchers can utilize PLS-SEM to investigate how perceived usefulness, instructional quality, and institutional support collectively impact students' academic outcomes in online or blended learning environments (Jiang et al., 2022). Similarly, NVivo is a powerful tool for analyzing rich qualitative data sources, such as interviews with teachers and students, classroom observations, focus group discussions, and open-ended survey responses (Limna, 2023). NVivo supports the thematic analysis of student feedback, the exploration of discourse patterns in classroom dialogue, and the evaluation of professional development program outcomes (Major et al., 2018). These education-specific applications clarify the practical utility of these tools in educational contexts and offer valuable guidance for researchers and practitioners seeking to adopt advanced mixed-methods approaches in teaching, learning, and institutional effectiveness.

In the evolving landscape of empirical research, scholars are increasingly confronted with challenges associated with data complexity, small sample sizes, and violations of statistical assumptions. Traditional analytical methods, such as Covariance-Based Structural Equation Modelling (CB-SEM) and Multiple Regression Analysis (MRA), while foundational, often demand strict conditions, namely large sample sizes, multivariate normality, and minimal multicollinearity, which are frequently unmet in real-world scenarios (Hair et al., 2024). These constraints limit their utility in exploratory research and studies involving heterogeneous data types or modest participant pools. In response to these limitations, Partial Least Squares Structural Equation Modelling (PLS-SEM) has emerged as a powerful alternative. Developed by Wold (1982) and further advanced by scholars such as Hair et al. (2017), PLS-SEM enables variance-based modeling, making it particularly suitable for prediction-oriented research under less-than-ideal data conditions. It has gained widespread adoption across various fields, including business, education, healthcare, engineering, and sustainability (Sarstedt et al., 2019). Its strengths include handling reflective and formative constructs, accommodating non-normal distributions, supporting mediation and moderation analyses, and estimating path models with relatively small sample sizes (Cepeda et al., 2024; Henseler & Schuberth, 2025).

Despite its advantages, PLS-SEM remains underutilized, often overshadowed by CB-SEM due to limited awareness, lack of user-friendly documentation, and a deficit in comparative empirical evaluations (Qostal et al., 2024). Consequently, researchers and students may struggle to apply this method effectively or appreciate its value in contexts where traditional models fall short. This study addresses this gap by offering a rigorous comparative analysis of PLS-SEM, grounded in both theoretical and applied research contexts, to promote its broader adoption and methodological literacy. Parallel to the evolution in quantitative analysis, qualitative research faces its own set of challenges, primarily the management, coding, and interpretation of large, unstructured datasets. The increasing reliance on qualitative methodologies in interdisciplinary and data-rich environments has amplified the demand for a robust qualitative data analysis (QDA) tool. NVivo, developed by QSR International, has emerged as a leading QDA software, offering capabilities in data management, automated and manual coding, querying, and visualization. It supports various qualitative approaches, including grounded theory, thematic analysis, and discourse analysis, and allows integration with tools like EndNote, SPSS, Microsoft Office, and Zotero (Fallin, 2019).

While NVivo is widely used, a significant gap remains in comparative evaluations that benchmark its performance against other tools, such as ATLAS.ti, MAXQDA, and Dedoose (Noakes et al., 2023). Existing studies often focus on individual tool features without systematically comparing usability, analytical depth, and integration across diverse research settings (Dupin & Borglin, 2020). Furthermore, NVivo's learning curve and cost have been cited as potential barriers to widespread adoption (Sepasgozar & Davis, 2018), especially among novice users and resource-constrained researchers. This study aims to fill two critical gaps in the existing literature. First, it evaluates the strengths, limitations, and predictive capabilities of PLS-SEM as an advanced statistical modelling approach in complex quantitative research. Second, it provides a comprehensive empirical and user-centred assessment of NVivo as a qualitative research tool, benchmarked against other major QDA platforms. The findings contribute to methodological innovation by offering practical insights and comparative benchmarks for selecting appropriate analytical tools based on research design, dataset characteristics, and user needs. By integrating the rigor of quantitative modelling with the richness of qualitative inquiry, this study supports a more holistic approach to mixed-methods research in contemporary academic and professional contexts.

1.1. Problem Statement

In the evolving landscape of empirical research, scholars frequently encounter challenges such as complex data structures, limited sample sizes, non-normal distributions, and intricate variable interactions. Traditional statistical methods like covariance-based structural equation modelling (CB-SEM) and multiple regression analysis (MRA) impose stringent assumptions multivariate normality, large samples, and low multicollinearity that are often unmet in practical settings (Wah, 2025). These limitations hinder their effectiveness, particularly in exploratory research or studies that utilize imperfect datasets. Partial Least Squares Structural Equation Modeling (PLS-SEM) offers a robust alternative, capable of optimizing predictive accuracy and modeling complex relationships under less-than-ideal conditions (Parveen et al., 2024). Despite its advantages and broad applicability across fields such as health sciences, business, and education, PLS-SEM remains underutilized due to limited awareness and a lack of accessible guidance and comparative evaluations (Yusif et al., 2020). Simultaneously, qualitative researchers face increasing difficulty in managing unstructured, multimodal data, including text, audio, video, and images, which challenges consistency and accuracy in manual coding. NVivo offers solutions with efficient data organization, advanced coding, querying, visualization, and collaborative features. However, there is a lack of comparative assessment between NVivo and other qualitative data analysis (QDA) tools like ATLAS.ti, MAXQDA, and Dedoose. Clear guidance is also limited regarding which tools best support specific research needs (Chen & Ye, 2023). This study addresses two critical methodological gaps: -

- evaluating PLS-SEM's strengths and practical applicability in quantitative analysis, and
- critically assessing NVivo's functionality and comparative value in qualitative research contexts, promoting more effective and innovative research practices.

1.2. Research Objectives

This study aims to address two key methodological challenges in both quantitative and qualitative research. On the quantitative side, it critically evaluates the limitations of traditional techniques such as covariance-based structural equation modelling (CB-SEM) and multiple regression analysis (MRA), particularly their dependence on large sample sizes, normal data distribution, and low multicollinearity. The research explores the theoretical foundations and core components of Partial Least Squares Structural Equation Modelling (PLS-SEM), emphasizing its strength in modelling complex relationships involving mediating, moderating, reflective, and formative constructs. It aims to demonstrate PLS-SEM's predictive accuracy and flexibility across various domains, including business, healthcare, education, and sustainability, providing practical guidance to encourage its wider adoption. On the qualitative side, the study investigates common challenges in managing large, unstructured datasets and ensuring consistency in coding and collaborative analysis. It evaluates NVivo's capacity to support rigorous qualitative data analysis through advanced data management, coding, querying, visualization, and team collaboration features. Furthermore, a comparative assessment of NVivo with other QDA tools, such as ATLAS.ti, MAXQDA, and Dedoose will be

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conducted, focusing on functionality, usability, and learning curve. The study aims to provide evidence-based recommendations to guide researchers in selecting appropriate QDA tools based on methodological requirements and research contexts.

2. Literature Review

PLS-SEM model and coupled to the NVivo-based analysis to improve study integration (Noviana et al., 2024). In particular, the exogenous weights in the model are based on structured questionnaire responses regarding the tool's ease of use, interface design, feature accessibility, and integration capabilities (Amoroso & Cheney, 1991). Previous research informed these indicators, which were contextualized through NVivo thematic analysis, which coded qualitative input to identify quantitative variables (Rosen et al., 2023). We now explain how educational stakeholders like curriculum designers and school administrators utilise these weighted insights to use qualitative data analysis methods to simplify the modelling process (Sergis et al., 2018). Regarding the purposive sampling technique, which employed graduate students, educational researchers, and academic support personnel with expertise in PLS-SEM and qualitative software (Ashraf & Ahmed, 2022). The author further notes that the governing institution granted ethical approval and that all participants supplied informed permission anonymously and voluntarily (Dalton & McVilly, 2004).

Herman Wold developed PLS-SEM for estimating complex models with fewer observations (Wold, 1982). Partial Least Squares Structural Equation Modelling (PLS-SEM) emerged in the 1980s as an alternative to covariance-based SEM (CB-SEM), which requires large sample sizes and assumes multivariate normality (Dash & Paul, 2021). Its strengths in handling small samples, non-normal data, and complex models have led to its widespread use in management, social sciences, and other fields (Bono et al., 2017). Unlike CB-SEM, which focuses on model fit and hypothesis testing, PLS-SEM emphasizes variance explanation and predictive accuracy (Sarstedt et al., 2021). PLS-SEM comprises two components, which are the measurement model and the structural model (Purwanto & Sudargini, 2021). Reflective models assume latent constructs influence observed indicators, while formative models view indicators as defining the construct (Hanafiah, 2020). The structural model assesses the relationships among constructs by estimating path coefficients. PLS-SEM is suitable for examining mediation and moderation, handling multicollinearity, and integrating formative and reflective constructs (Hanafiah, 2020). It is applied across domains including marketing, healthcare, education, and sustainability. In healthcare, PLS-SEM is used to explore patient outcomes and service quality, while in education, it helps assess learning effectiveness and e-learning adoption. In sustainability studies, it evaluates the impact of green innovation and CSR on firm performance. It also supports tourism research on service quality and loyalty. PLS-SEM excels in longitudinal data analysis and complex models involving moderation or mediation, with tools to test interactions without manual centring. Unlike CB-SEM's reliance on fit indices (CFI, RMSEA), PLS-SEM uses R^2, Q^2, f^2, and SRMR to assess explanatory power and predictive relevance (Trail et al., 2024). However, it may yield less precise estimates in large samples and is sensitive to outliers, requiring careful model specification and consideration. Estimation approaches, such as consistent PLS and bootstrapping, can affect results, necessitating methodological rigor. Recent advancements include its integration with big data, AI, and hybrid models that combine deep learning, Bayesian networks, and agent-based modeling (Abdulkareem et al., 2019). Software such as SmartPLS, WarpPLS, and ADANCO enhances usability (Ciavolino et al., 2022). Widely adopted in finance, healthcare, environmental science, and supply chain research, PLS-SEM's adaptability and predictive strength make it a vital tool for quantitative researchers (Shafique, Rashid, Yeo, & Adeel, 2023). As methodological innovations continue, PLS-SEM is expected to maintain its pivotal role in applied and exploratory research.

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2.1. Evolution of NVivo

Initially developed by QSR International, NVivo is a widely recognized qualitative data analysis (QDA) software used across various disciplines, including the social sciences, education, public health, and business (Wilk et al., 2019). It facilitates systematic data management, coding, querying, and visualization, allowing researchers to handle large volumes of unstructured data, text, audio, video, and images, and extract meaningful insights. NVivo supports various qualitative methodologies, including thematic analysis, grounded theory, and mixed-methods research, enabling integration of multiple data types into a unified project to enhance research depth and validity. NVivo's roots lie in NUD*IST (Non-numerical Unstructured Data Indexing, Searching, and Theorizing), developed by Tom and Lyn Richards in the late 1980s (Richards, 2002). It began as a tool to organize textual data but evolved in the 1990s into NVivo, offering multimedia integration and support for complex datasets (Azeem & Salfi, 2012). Over time, NVivo has expanded its analytical features to include automated coding, advanced query capabilities, and data visualization tools. More recent versions incorporate machine learning to streamline coding processes, making it especially useful for large-scale research projects (Al Mamun et al., 2018). Its ability to integrate qualitative and quantitative data has made NVivo an essential tool for interdisciplinary research requiring comprehensive and rigorous analysis.

2.2. Impact on Qualitative Research Practices

NVivo has fundamentally transformed qualitative research practices by offering a more structured and organized approach to data analysis (Maher et al., 2018). The tool provides an organized framework for handling vast amounts of unstructured data, which is often a hallmark of qualitative research. Through NVivo, researchers can systematically code data, facilitating a rigorous analysis process that enhances the credibility and reliability of qualitative findings. Furthermore, NVivo's capacity for querying enables more profound exploration of data, helping to uncover patterns and relationships that may not be immediately apparent (Limna, 2023). The introduction of features like automated coding and query generation has sped up the data analysis process without compromising the depth or richness of insights. NVivo also enhances transparency and reproducibility in qualitative research, as the coding and querying processes are clearly documented and can be revisited or refined over time (Limna, 2023). In these ways, NVivo has contributed to a broader push for more scientifically rigorous qualitative research methods, ensuring that qualitative studies are conducted with the same level of care and precision as quantitative research (Maher et al., 2018). Moreover, NVivo has fostered greater collaboration within research teams. Researchers can share projects, work on datasets simultaneously, and merge their findings to create a unified analysis. This has proven particularly beneficial for large, interdisciplinary teams working across different locations. The collaborative features of NVivo have made it a preferred tool for team-based qualitative research in large-scale projects, such as those conducted in public health or social sciences (McAlearney et al., 2023).

2.3. Comparison with Other QDA Tools

While NVivo is one of the leading tools in qualitative data analysis, several other software tools are often used by researchers for similar purposes (Sotiriadou et al., 2014). ATLAS.ti, MAXQDA, and Dedoose are among the most prominent alternatives (Sampson & Wong, 2023). Each of these tools has its own strengths and weaknesses, and the choice between them often depends on the researcher's needs, familiarity, and the nature of the data. ATLAS.ti, is known for its flexibility and ability to work well with large multimedia datasets (Gibson et al., 2005). It provides advanced visualization tools such as conceptual diagrams and network views, which help researchers to visually interpret complex data structures. However, while ATLAS.ti offers strong capabilities in visualizing relationships between data elements, NVivo generally leads in terms of querying and automated coding, which are key features for handling large datasets with more precision (Auld et al., 2007).

MAXQDA is another competitor that is often praised for its user-friendly interface and integration with quantitative methods. MAXQDA also allows for effective mixed-methods research and supports a range of data types, including text, images, and audio. However, NVivo tends to be preferred for more advanced analytic features such as matrix coding queries and complex querying functions, which support rigorous and multifaceted data analysis (Kraiwanit et al., 2023). In contrast, Dedoose is a web-based tool that is often chosen for its cost-effectiveness and ease of use, making it an attractive option for smaller research teams or individual researchers. While Dedoose supports basic coding and visualization tasks, its functionality is not as robust as NVivo's, particularly when it comes to handling multimedia data or performing advanced statistical queries (Andrade et al., 2022). This makes NVivo the preferred option for larger-scale or more complex qualitative research projects.

2.4. Theoretical Underpinnings and Methodological Support

NVivo’s adaptability to various qualitative research methods is one of its key strengths (Limna, 2023). The software supports multiple qualitative research frameworks, including grounded theory, thematic analysis, content analysis, and discourse analysis. For grounded theory, NVivo offers features such as memoing and constant comparative methods, which are crucial for the iterative process of developing theory from data (Hutchison et al., 2010). The software’s flexible coding structure allows researchers to adapt as they uncover new patterns in their data, facilitating the theoretical development central to grounded theory. In thematic analysis, NVivo is particularly effective for organizing and exploring themes within data. Through tools like word frequency analysis and node mapping, NVivo allows researchers to identify key themes and visualize their relationships within the dataset (Feng & Behar-Horenstein, 2019). This makes NVivo particularly suitable for inductive approaches, where researchers allow themes to emerge organically from the data (Braun & Clarke, 2006). For content analysis, NVivo supports systematic coding and frequency analysis, making it easy to categorize and quantify data. This allows researchers to gain a deeper understanding of how frequently certain themes or terms appear across large datasets, providing a foundation for rigorous content-based analysis (Ahammad, 2024). Additionally, NVivo’s ability to conduct coding comparison queries enhances the reliability of content analysis, supporting reproducible and transparent research methods (Al Mamun et al., 2018). NVivo’s support for discourse analysis is another important feature. Researchers can use NVivo to explore linguistic patterns, word choices, and narrative structures within textual data. This functionality is particularly useful for examining how language shapes and reflects social power dynamics, identities, and ideologies, which are central to discourse analysis (Zotzmann & O’Regan, 2016).

2.5. Practical Challenges and Limitations

Despite its powerful features, NVivo is not without its challenges (Kraiwanit et al., 2023). New users often face a steep learning curve, particularly when it comes to understanding its advanced functionalities. Although QSR International offers training resources and tutorials, mastering the full range of NVivo’s capabilities often requires significant time and experience. Another limitation is the cost of NVivo. Although many academic institutions provide access to NVivo, it can still be prohibitively expensive for individual researchers or small research teams. The price of a single-user license may restrict access to this tool for some researchers, especially those working on smaller budgets or in resource-limited settings (Salmona et al., 2020). Additionally, NVivo can be resource-intensive, requiring powerful computing hardware to handle large datasets, especially when multimedia files are involved. Researchers working with extensive data may experience performance issues on lower-end computers, which can disrupt the analysis process (Davidson & di Gregorio, 2011).

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2.6. Future Directions and Anticipated Developments

As qualitative research continues to evolve, NVivo's development is expected to focus on several key areas to meet the growing needs of researchers. Artificial intelligence (AI) and machine learning are anticipated to play an increasingly significant role in the future of NVivo. Enhanced automated coding and predictive analytics could allow NVivo to provide even more robust insights from data without requiring intensive manual coding (Al Mamun et al., 2018). Another key development area is integration with other software tools. As researchers often use multiple platforms and software in their work, NVivo is likely to enhance its compatibility with other tools, such as SPSS, R, and Excel, making it easier to incorporate quantitative analysis into qualitative research. Further improvements in cloud-based features will likely make NVivo more accessible for collaborative teams, enabling real-time data sharing and collaborative analysis across different locations (Salmona et al., 2020). As qualitative research becomes more data-rich and complex, NVivo will need to continue refining its visualization tools to support the growing demand for interactive and dynamic ways to present data. Enhanced visual interfaces, virtual reality (VR) capabilities, and data immersion tools could be future developments that enable researchers to explore qualitative data in novel and more immersive ways.

2.7. Comparative Effectiveness of NVivo

2.7.1. NVivo vs. ATLAS.ti

NVivo, developed by QSR International, is a leading qualitative data analysis (QDA) tool used across various disciplines, including the social sciences, education, and public health. With capabilities in data management, coding, querying, visualization, and collaboration, NVivo offers researchers a robust platform for handling unstructured data. Its ability to manage diverse data types, including text, audio, video, images, and social media, streamlines qualitative research workflows (Brandão, 2015). NVivo's coding system is one of its strongest assets. Richards (2005) highlights its capacity to organize and retrieve data systematically. Both manual and automated coding options enhance analytical rigor and efficiency (Al Mamun et al., 2018). NVivo's advanced querying tools support pattern detection (Leech & Onwuegbuzie, 2011), while its visual tools, word clouds, charts, and graphs aid in data presentation (Creswell, 2013). The platform's collaborative functionality enables multi-user access and tracking, supporting large research teams (Davidson & di Gregorio, 2011). Integration with tools like EndNote and SPSS further increases its appeal for mixed-methods research. When compared with ATLAS.ti, another prominent QDA software, several differences emerge. NVivo's user interface is noted for being more intuitive, especially for beginners, with a structured, hierarchical coding process (Smith, 2002; Woods et al., 2016). ATLAS.ti, on the other hand, offers more flexibility, appealing to experienced users or those employing open-ended, networked coding approaches. While NVivo is ideal for grounded theory and thematic analysis, ATLAS.ti excels in visualizing relationships, particularly in network analysis (Silver & Lewin, 2014).

NVivo has incorporated AI-driven features, such as automated coding, sentiment analysis, and text mining, thereby enhancing its capacity to efficiently handle large datasets (Paulus & Lester, 2021). These features are particularly valuable for analysing social media or large-scale interview data. ATLAS.ti offers similar functionalities, but with a greater emphasis on visual tools for relational analysis, rather than automation.

Usability also sets NVivo apart. Its structured layout and intuitive design make it accessible to users with varying experience levels, whereas ATLAS.ti's flexibility often requires a steeper learning curve. For collaborative projects, NVivo's advanced cloud-based features allow real-time multi-user access, version tracking, and seamless integration benefits that ATLAS.ti is only beginning to develop (Davidson & di Gregorio, 2021). In terms of software integration, NVivo connects with tools such as SPSS, EndNote, and Microsoft Office, supporting complex and mixed-methods designs. ATLAS.ti, while capable of exporting data, lacks the same level of compatibility with external software. Costwise, ATLAS.ti is generally more affordable, with academic discounts and student-friendly pricing. NVivo, though more expensive, justifies its pricing through its advanced features and integrations. Case studies highlight the effectiveness of both tools in distinct contexts. Paulus and Lester (2021) used NVivo for sentiment analysis of social media data, while Silver and Lewin (2014) employed ATLAS.ti for network analysis in organizational research. These examples highlight how the tools complement different research approaches. Vivo and ATLAS.ti both offer powerful QDA functionalities. NVivo’s structured interface, AI tools, and integrations make it ideal for large, collaborative, and mixed-methods projects. ATLAS.ti’s flexible, visually driven approach suits researchers seeking more open-ended, network-based analyses. The choice depends on research goals, user experience, and methodological preferences.

2.7.2. NVivo vs. MAXQDA

NVivo and MAXQDA are widely used qualitative data analysis (QDA) tools, each with distinct strengths. NVivo excels in mixed-methods research through its advanced visualization and integration capabilities, while MAXQDA is valued for its simplicity and effectiveness with multimedia data. Silver and Lewin (2014) note that NVivo's feature-rich platform is well-suited for complex and longitudinal studies, whereas MAXQDA appeals to researchers seeking a user-friendly interface and adaptable functionality. NVivo stands out with its AI-driven coding features, including sentiment analysis and text mining, which utilize machine learning to efficiently handle large datasets. While MAXQDA also includes some automated tools, NVivo’s natural language processing capabilities are more sophisticated, enabling faster and more accurate analysis of interview transcripts, social media data, and open-ended survey responses. Usability varies between the two. NVivo provides a structured coding environment, but it may present a steep learning curve for beginners (Sinkovics & Alfoldi, 2012). However, this complexity provides flexibility for advanced users. MAXQDA, by contrast, is easier to navigate and is often preferred by individual researchers or smaller teams. In terms of collaboration, NVivo has made significant strides with cloud-based features, supporting real-time teamwork across sites. MAXQDA’s cloud tools are less advanced, although they are improving. NVivo also integrates seamlessly with tools such as EndNote, SPSS, Microsoft Word, and Excel, making it well-suited for interdisciplinary and mixed-methods research. MAXQDA also supports integration, albeit to a lesser extent. Data security is another critical factor. NVivo offers encrypted cloud storage and robust privacy protocols, which are slightly ahead of those offered by MAXQDA in this area. For projects involving confidential information, this can be a deciding factor. In practice, NVivo is often chosen for large-scale ethnographic and social science research, while MAXQDA is preferred for smaller, multimedia-rich studies, such as those in media and communication research. NVivo’s structured approach supports thematic analysis and grounded theory, while MAXQDA’s flexibility aids network analysis and multimedia examination. Cost may influence the decision. NVivo, with its comprehensive features, is priced higher, potentially a barrier for smaller teams (Woods et al., 2014). MAXQDA offers a more affordable model, especially for students. Both provide educational discounts and trial versions. Ultimately, NVivo is ideal for complex, collaborative, and data-intensive research, while MAXQDA is suited for researchers seeking a more straightforward, multimedia-friendly solution. The best choice depends on the project’s scope, methodological needs, and the researchers' level of experience.

2.8. Synthesized Comparison of NVivo, ATLAS.ti, and MAXQDA

NVivo, ATLAS.ti, and MAXQDA meet the diverse needs and research objectives of qualitative data analysis in educational and social scientific research. The following description of their essential features, strengths, and shortcomings will assist researchers, particularly those designing mixed-methods studies, in selecting the most suitable instrument.

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The comparison of NVivo, ATLAS.ti, and MAXQDA shows that each software caters to different research needs. NVivo is the most user-friendly and well-integrated with tools like Microsoft Office and SPSS, making it ideal for beginners and large datasets, though it is costly and less efficient with large multimedia files. ATLAS.ti excels in visual analysis and conceptual mapping, offering strong customization and collaboration features, but it has a steeper learning curve and limited statistical integration. MAXQDA is best for mixed-methods research, providing robust quantitative and qualitative tools with strong cross-platform performance, though its interface is less intuitive and adoption is lower. Overall, NVivo suits large projects, ATLAS.ti supports visual theorizing, and MAXQDA fits mixed methods approaches. (see Table 1).

Table 1. Comparison of Qualitative Data Analysis Software

Software	Key Features	Strengths	Limitations
NVivo	Advanced coding and query options; Strong integration with Microsoft Office and SPSS; Auto-coding and sentiment analysis; Supports multimedia data	User-friendly interface for beginners; Excellent for large datasets; Widely used in academic institutions; Strong support and tutorials available	Higher cost for full version; Performance may slow with very large multimedia files; Mac version lacks some features compared to Windows
ATLAS.ti	Network views for conceptual mapping; High-level visualization tools; Cloud-based team collaboration; Supports geocoding and mobile apps	Highly customizable code networks; Ideal for visual theory-building; Flexible license options	Steeper learning curve for new users; Interface can appear cluttered; Integration with statistical tools is more limited
MAXQDA	Mixed-methods integration with quantitative tools; Live memos and paraphrasing tools; Built-in stats module (MAXQDA Analytics Pro); Audio and video transcription tools	Strong for mixed-methods researchers; Excellent visual analytics; Consistent cross-platform performance (Windows & Mac)	Slightly less intuitive interface; Limited third-party integration compared to NVivo; Less widely adopted in some regions

Academic researchers working with text-rich data and structured reports benefit from NVivo's accessibility and institutional support. ATLAS.ti is ideal for theoretical projects that require significant network visualization, whereas MAXQDA seamlessly integrates qualitative and quantitative data, making it perfect for mixed-methods research. The research goals, user experience, and intended integration with other analytical tools should all influence the tool selection, as each tool has distinct capabilities.

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2.9. Underpinning Theory

Structural equation modelling using partial least squares (PLS-SEM) is a statistical technique that integrates multivariate regression and path analysis to provide a comprehensive understanding of causal relationships within a theoretical framework (Carrión et al., 2017). PLS-SEM combines theories from various domains, including path analysis, measurement theory, latent variable modelling, predictive modelling, and covariance structure models (Cepeda et al., 2024). This approach has been widely adopted in empirical research across multiple disciplines due to its robust theoretical underpinnings, enabling scholars to investigate complex interrelationships, evaluate theoretical frameworks, and advance their respective fields (Hair et al., 2017). Unlike covariance-based SEM, PLS-SEM is particularly advantageous when dealing with small sample sizes, non-normal data distributions, and formative measurement models (Sarstedt et al., 2019). Moreover, it emphasizes prediction-oriented modelling, making it highly applicable to exploratory research in business, social sciences, and technology studies (Hair et al., 2019). From an epistemological perspective, PLS-SEM aligns with constructivist epistemology, where knowledge is generated through the interaction of theoretical assumptions and empirical observations. As a variance-based approach, it maximizes the explained variance of endogenous variables rather than focusing on strict model fit, making it particularly suitable for predictive modelling in emerging research areas (Sarstedt et al., 2022). One of the key distinctions between covariance-based SEM and PLS-SEM is that the latter is more effective in handling formative constructs, which measure concepts as composite indices rather than reflective indicators (Hair et al., 2024). However, one challenge associated with PLS-SEM is the potential misclassification of reflective and formative constructs, which can lead to incorrect model specification and biased results if not properly addressed in model development (Cepeda et al., 2024).

2.10. NVivo in Qualitative Research

NVivo, developed by QSR International, is a prominent qualitative data analysis (QDA) tool widely used across disciplines. It offers extensive functionalities in data management, coding, querying, visualization, and collaborative research, making it essential for qualitative studies (Paulus et al., 2017). Since its emergence in the late 20th century, QDA software has evolved from basic retrieval tools to advanced platforms with artificial intelligence, automated coding, and bibliographic integration (Silver & Lewin, 2014). Rooted in grounded theory (Glaser & Strauss, 1967), NVivo supports iterative coding and theory development, as well as thematic analysis, discourse analysis, and narrative inquiry (Charmaz, 2014). It is also employed in phenomenological and ethnographic research to explore lived experiences and cultural contexts (Creswell & Poth, 2018). Its coding framework allows systematic data categorization and retrieval (Gibson et al., 2005; Al Mamun et al., 2018). Beyond coding, NVivo's query and visualization tools, such as word clouds, concept maps, and charts, aid deep textual analysis and effective result interpretation (Leech & Onwuegbuzie, 201). Collaborative features allow multiple users to contribute simultaneously, enhancing efficiency and data integrity (Davidson & di Gregorio, 2011; Silver & Lewin, 2014). Limitations include reliance on automated coding, which, while efficient, still requires researcher validation to avoid bias (Paulus et al., 2017), and reduced flexibility for purely inductive approaches (Brandão, 2015). Nonetheless, NVivo's integration with tools like EndNote, Zotero, and Mendeley enhances mixed-methods research (Maher et al., 2018). Together with PLS-SEM, NVivo supports rigorous, AI-enhanced research (Hair et al., 2024).

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2.11. Comparative Effectiveness of NVivo

2.11.1. NVivo vs. ATLAS.ti

NVivo and ATLAS.ti are leading qualitative data analysis (QDA) tools, each offering distinct strengths suited to different research needs. NVivo excels in managing complex, diverse datasets and integrates well with external sources like SPSS and Excel, making it ideal for mixed-methods research. Its advanced features, such as Matrix Coding and Text Search Queries, support in-depth exploration of patterns within large datasets. However, NVivo's interface presents a steeper learning curve for beginners, and its cloud version may experience performance issues with very large datasets. NVivo's robust security features, including encryption and password protection, make it suitable for sensitive research (Brandão, 2015). ATLAS.ti, in contrast, offers a more user-friendly interface, making it accessible for beginners. It supports diverse data types and offers strong data visualization tools for coding and annotation. Its cloud deployment facilitates efficient collaboration in team-based projects. While ATLAS.ti's querying capabilities are solid, they are generally considered less advanced than NVivo's, which may potentially limit complex analyses. Security features are adequate but may be less stringent than NVivo's in some cases (Weitzman & Miles, 2022). Both platforms offer active user communities and support with ATLAS.ti providing 24/7 customer service. NVivo offers extensive training resources but may require more technical support to master its advanced features. Ultimately, the choice between NVivo and ATLAS.ti depends on project needs. NVivo suits large, detailed analyses, while ATLAS.ti appeals to users prioritizing ease of use and collaboration. Researchers should assess data complexity, collaboration needs, and user experience when selecting a QDA tool (Weitzman & Miles, 1995; Brandão, 2015).

2.11.2. NVivo vs. MAXQDA

NVivo and MAXQDA are leading qualitative data analysis (QDA) tools, each with distinct strengths. NVivo is praised for its advanced query, visualization, and mixed-methods capabilities, making it ideal for large, complex projects (Limna, 2023). Its automation features streamline coding and data management, enhancing research efficiency (Paulus & Lester, 2023). However, NVivo's steep learning curve and high cost can be barriers for novice users or smaller institutions (Sinkovics & Alfoldi, 2012; Woods et al., 2016). Technical issues like crashes and data loss have been reported, though mitigated through backups and updates (Brandão, 2015). Despite this, NVivo's collaborative features and platform compatibility support team-based research and cross-platform use (Davidson & Di Gregorio, 2011). In contrast, MAXQDA offers a user-friendly interface and consistent performance across Windows and Mac platforms. It is especially effective in managing multimedia data and suits smaller or beginner-level projects well (Brandão, 2015). While its querying tools are less sophisticated than NVivo's, MAXQDA's simplicity and collaborative capabilities make it a strong choice for accessible, team-oriented research. Dedoose, a budget-friendly alternative, is often favored for its simplicity but lacks the depth of NVivo (Sotiriadou et al., 2014). As QDA tools integrate AI features like sentiment analysis and text mining, both NVivo and MAXQDA are evolving to offer deeper data insights. Ultimately, tool selection should reflect the project's size, data complexity, budget, and collaboration needs.

3. Methodology

3.1. Method A: Empirical Evaluation and Comparative Analysis

This comparative analytical study employs an empirical evaluation approach to assess the performance and utility of multiple qualitative data analysis (QDA) tools, with a primary focus on NVivo. The tools are evaluated using Multivariate Regression Analysis (MRA), Covariance-Based Structural Equation Modelling (CB-SEM), Factor Analysis (FA), and Partial Least Squares Structural Equation Modelling (PLS-SEM) data from various investigations. These advanced techniques are essential for examining the relationships between variables and evaluating the suitability of the tools for handling qualitative data. MRA is employed to understand the predictive power of each QDA tool in terms of multiple independent variables and their relationship with a dependent variable. This technique helps evaluate how each tool manages large datasets and the complexity of qualitative data (Lewis & Maas, 2007). CB-SEM is useful in modeling latent constructs and their relationships, providing insights into how well each QDA tool aligns with empirical data and theoretical frameworks (Hair et al., 2022). FA is applied to reduce the complexity of the data and uncover underlying structures, helping researchers identify key themes and factors that each tool is capable of detecting (Fornell & Larcker, 1981). PLS-SEM is used to assess forecast accuracy and predictive power by evaluating the capacity of each tool to predict outcomes and identify patterns from the data (Shmueli, et al., 2016). Performance indicators include computational efficiency, assumption flexibility, model fit, and forecast accuracy. Computational efficiency measures the speed and resource consumption during analysis. Assumption flexibility refers to the tool's ability to handle various data types, such as textual, multimedia, and mixed-methods data. Model fit assesses how well the tool's output aligns with the research model and empirical data, indicating its reliability. Forecast accuracy evaluates the ability of each QDA tool to predict outcomes and provide reliable insights (Lewis & Maas, 2007).

3.2. Method B: Research Design for Evaluating NVivo

The methodology for evaluating NVivo as the best tool for qualitative research includes a comprehensive approach to research design, data collection, data analysis procedures, and ethical considerations, ensuring systematic, reliable, and valid results. The research design integrates both qualitative and quantitative data collection methods to comprehensively evaluate NVivo's effectiveness. Surveys and interviews with researchers using NVivo, along with an analysis of previous projects, provide qualitative data on its functionality, while quantitative data from surveys assess aspects such as efficiency and accuracy (Morse & Richards, 2002). The data collection methods focus on gathering feedback from researchers who have applied NVivo in diverse contexts. These include user surveys, structured interviews, and a review of completed research projects. Researchers will be asked about their experiences with NVivo's features, such as coding capabilities, query functions, and visualization tools, in order to assess the tool's effectiveness in real-world applications (Brandão, 2015). Data analysis procedures involve both qualitative coding and statistical analysis. NVivo's own features, such as advanced queries and visualizations, will be employed to process both qualitative and quantitative data, providing insights into the tool's effectiveness. NVivo's performance will be measured in terms of how well it supports organizing data, performing advanced queries, and identifying emerging themes and trends (Al Mamun et al., 2018).

3.3. Ethical Considerations

Ethical integrity is a central aspect of this study. Participants will provide informed consent, and their data will be anonymized to ensure confidentiality. Data security and reliability will be safeguarded, with best practices followed to prevent loss or corruption. The study avoids bias toward NVivo or other QDA tools and ensures fair evaluation. It employs a comprehensive approach, utilizing case studies, questionnaires, interviews, and usability testing to assess the effectiveness of NVivo. This ethical framework ensures transparency, protects the rights of participants, and enhances the credibility of the study.

3.4. Analysis of Method A

PLS-SEM is a widely used statistical technique to model complex relationships between latent constructs (unobserved variables) and their associated indicators (observed variables). It allows researchers to test and optimize both measurement models (outer models) and structural models (inner models) simultaneously. The technique is particularly valuable when dealing with complex, non-linear relationships and when the data does not meet the assumptions of traditional covariance-based SEM (CB-SEM).

3.5. Key Components

Measurement Model (Outer Model): The measurement model specifies how latent variables (constructs) are measured by observed variables (indicators). In PLS-SEM, there are two types of measurement models which is the reflective Indicators reflect or are manifestations of the latent construct. They are typically used for constructs that are the result of the latent variable. Customer satisfaction is a latent construct that can be measured through various indicators, such as service quality and satisfaction surveys.

Reflective Indicators: These indicators reflect the latent construct.

$$X = \Lambda_X \xi + \epsilon_X Y = \Lambda_Y \eta + \epsilon_Y$$

where:

- X and Y are vectors of observed indicators for exogenous and endogenous latent variables, respectively.
- Λ_X and Λ_Y are the loadings matrices for exogenous and endogenous latent variables.
- ξ and η are the latent variables.
- ϵ_X and ϵ_Y represent measurement errors.

Formative Indicators are used to form or cause the latent construct. In formative measurement models, the latent variable is a composite of its indicators. A construct like "brand image" could be formed by indicators such as brand awareness, perceived quality, and brand loyalty.

$$\xi = \sum_{i=1}^{m} w_i Y_i$$

Structural Model (Inner Model): The structural model specifies the relationships between the latent constructs. It describes how endogenous latent variables are predicted by exogenous latent variables and how they interact with each other.

$$\eta = \beta \xi + \Gamma \eta + \zeta$$

where:

- η is the endogenous latent variable.
- ξ is the exogenous latent variable.
- B represents the path coefficients between latent variables.
- Γ represents the influence of other endogenous variables on the latent variable.
- ζ is the error term.

Steps in PLS-SEM

Outer Model Estimation (Reflective Measurement Model): In this step, the relationships between the latent variables and their indicators are estimated. The reflective indicators are assessed for their reliability and validity.

The equations used for the outer model estimation: -

$$x = \Lambda_x \xi + \epsilon_x y = \Lambda_y \eta + \epsilon_y$$

Where:

- x: Vector of observed indicators for exogenous latent variables.
- Λ_x: Loadings matrix for exogenous latent variables.
- ξ: Vector of exogenous latent variables.
- ϵ_x: Measurement error for exogenous indicators.
- y: Vector of observed indicators for endogenous latent variables.
- Λ_y: Loadings matrix for endogenous latent variables.
- η: Vector of endogenous latent variables.
- ϵ_y: Measurement error for endogenous indicators.

Inner Model Estimation: The inner model estimation focuses on the relationships between latent variables (constructs). The path coefficients B and the coefficients for the endogenous latent variables Γ are estimated in this step.

$$\eta = B\eta + \Gamma\xi + \zeta$$

Where:

- Coefficient matrix B: Endogenous latent variable correlations.
- Γ: Coefficient matrix.
- ζ: Vector of errors.

Weight Estimation (Algorithm Steps)

The process of weight estimation in Partial Least Squares Structural Equation Modelling (PLS-SEM) involves a sequence of algorithmic steps designed to ensure both measurement and structural model accuracy. The first stage, known as the outer approximation for reflective indicators, involves assessing the reliability and validity of the reflective measurement model. Reflective indicators are assumed to be caused by the latent variable, and this step ensures that the observed variables (indicators) accurately reflect the underlying construct. Reliability is typically assessed using composite reliability and Cronbach's alpha, while validity is examined through metrics like the Average Variance Extracted (AVE) and factor loadings. The next step involves the outer approximation for formative indicators. Unlike reflective indicators, formative indicators are not effects of the latent construct but rather its defining characteristics. Therefore, this stage focuses on estimating the weights of the formative indicators to determine the extent to which each contributes to the formation of the latent variable. This step also includes multicollinearity checks (VIF) and the assessment of indicator relevance and significance using bootstrapping. The final step is the inner approximation, which involves estimating the relationships between the latent constructs in the structural model. This step ensures that the data support the hypothesized paths linking latent variables. The algorithm iteratively updates the path coefficients to improve the explained variance (R^2) of endogenous constructs and achieves model convergence. Throughout these steps, the PLS-SEM algorithm uses a series of weight and score estimations that are refined in each iteration to ensure the best representation of both measurement and structural models.

Path Coefficient Estimation: The path coefficients β are calculated to estimate the strength of the relationships between the latent variables. The formula for the path coefficient estimation is: -

Path Coefficient Estimation

$$\hat{\beta} = (X'X)^{-1}X'Y\,\hat{\Gamma} = (X'X)^{-1}X'Y$$

where:

- β is the estimated path coefficient.
- X and Y represents the matrix of predictor variables and the response variables, respectively.

Model Evaluation Metrics

Partial least squares structural equation modelling (PLS-SEM) is a functional quantitative research approach for complex models with small sample sizes and non-normal data distributions. This method's flexibility with reflective and formative measurements, as well as its ability to address assumption breaches, makes it ideal for many research circumstances. Exogenous and endogenous models, as well as weight iterations, are estimated in PLS-SEM, leading to the final model. The math shows these processes. This comprehensive method enables researchers to quickly assess and evaluate data for reliable study results.

3.6. Analysis for Method B

This study adopts a comprehensive mixed-methods research design to rigorously evaluate the effectiveness of NVivo as a qualitative data analysis (QDA) tool. By combining both qualitative and quantitative approaches, the study captures a multi-dimensional understanding of how NVivo performs across various contexts and user experiences. The research strategy includes four key components: comparative analysis, case studies, surveys and interviews, and usability testing. The comparative analysis component systematically evaluates NVivo against other leading QDA tools, specifically ATLAS.ti, MAXQDA, and Dedoose. This comparison is conducted using synthetic and real-world datasets to examine performance across dimensions such as data processing capabilities, coding flexibility, analytical features, visualization tools, and integration with other software. The goal is to identify both the strengths and limitations of NVivo in comparison to its competitors. The case study element involves in-depth exploration of several research projects that have successfully utilized NVivo for qualitative analysis. These case studies provide contextual insights into how NVivo supports various research stages from data management and coding to advanced analysis and reporting. By examining actual use cases, the study highlights practical applications, challenges encountered, and strategies adopted by researchers to maximize the tool's utility. In addition, the study includes surveys and interviews with a diverse group of qualitative researchers who have hands-on experience with NVivo as well as other QDA tools. The surveys aim to gather quantitative data on user satisfaction, feature preferences, and perceived effectiveness. Meanwhile, the semi-structured interviews offer qualitative insights into users' experiences, learning curves, and challenges, enabling a nuanced understanding of how NVivo fits into different research workflows. Usability testing is conducted to assess the overall user experience with NVivo. This includes evaluating the interface design, ease of use, error rates during typical tasks (such as coding, data retrieval, and visualization), and the learning curve for new users. Participants engage in structured tasks, and their performance is measured quantitatively, while feedback is collected qualitatively. This testing provides critical evidence of NVivo's usability and user-friendliness compared to other QDA tools, thereby offering a complete picture of its operational efficiency in real-world settings.

3.7. Data Collection Methods: Literature Review

A comprehensive literature review was conducted as a foundational component of the data collection process. The aim was to gather and synthesize existing knowledge related to NVivo and other qualitative data analysis (QDA) tools, including ATLAS.ti, MAXQDA, and Dedoose. This review focused on identifying key themes, comparative evaluations, methodological advancements, and user experiences associated with these software packages. To ensure a broad and reliable knowledge base, multiple academic sources were consulted, including peer-reviewed journal articles, scholarly books, doctoral dissertations, and conference proceedings. Additionally, grey literature such as online tutorials, professional blogs, software documentation, and user forums was also reviewed to capture practical insights and emerging trends. The literature review not only helped to frame the research questions and theoretical foundations of the study but also informed the design of surveys, interview guides, and usability testing protocols. It provided critical context for understanding the evolution of QDA tools, highlighted the strengths and limitations of NVivo in various research domains, and established a benchmark for evaluating the software's effectiveness in comparison to its competitors.

3.8. Comparative Analysis

The comparative analysis aims to identify and evaluate the key features, functionalities, and user feedback associated with NVivo and three other widely used qualitative data analysis (QDA) tools: ATLAS.ti, MAXQDA, and Dedoose. This comparison was undertaken to determine the

Case Studies

To deepen the understanding of NVivo's practical utility in real-world research contexts, this study draws upon secondary data from existing research projects and published reviews that have made use of qualitative data analysis (QDA) tools. Specifically, three to five research projects that have extensively used NVivo were selected for in-depth analysis. These projects span a range of disciplines, including social sciences, health research, education, and organizational studies, thereby reflecting NVivo's adaptability across various research environments. Data were collected from multiple sources, such as project reports, peer-reviewed journal articles, conference proceedings, and institutional case studies that document the methodology and analytical processes used in the respective projects. Where available, direct communication with project leaders and team members was also undertaken to gain firsthand insights into the challenges faced and the strategies adopted while using NVivo. The case studies offered valuable perspectives on how NVivo contributed to the rigor and depth of qualitative analysis, especially in coding, theme development, and data visualization. These projects demonstrated NVivo's strength in handling large datasets, supporting mixed methods designs, and facilitating collaboration among multiple researchers. In particular, NVivo's ability to manage diverse data sources such as interviews, focus group transcripts, field notes, images, and multimedia files was frequently highlighted as a significant advantage. Additionally, the case studies emphasized how NVivo's integration with other tools, such as Microsoft Word, Excel, and reference management software, streamlined workflows and enhanced research productivity. By synthesizing insights from these selected projects, the case study analysis not only illustrates NVivo's real-world application but also reinforces its position as a leading tool for complex and multi-layered qualitative research.

Surveys and Interviews

To collect data on the effectiveness and user experience of NVivo, this study employs a combination of survey questionnaires and semi-structured interviews, targeting qualitative researchers who have experience using QDA tools. The first step involves developing a comprehensive survey questionnaire designed to capture the researchers' perceptions, usage patterns, and satisfaction levels with NVivo, as well as comparisons with other QDA tools like ATLAS.ti, MAXQDA, and Dedoose. The survey will include both closed-ended questions (for quantitative analysis) and open-ended questions (for qualitative insights) to gather a broad spectrum of data. Once the questionnaire is developed, it will be distributed through academic and professional networks, ensuring that a diverse sample of researchers from various disciplines and research contexts is reached. This distribution will include mailing lists, academic forums, social media groups, and professional associations related to qualitative research methods. The aim is to include researchers who have used NVivo for different types of projects, ranging from small qualitative studies to large, multi-method research designs, to gain a comprehensive understanding of the tool's performance. In addition to the surveys, semi-structured interviews will be conducted with a selected subset of respondents who have extensive experience with NVivo. These interviews will enable a deeper exploration of participants' personal experiences, including any challenges they faced while using NVivo, its strengths and weaknesses in practical application, and the specific features that were most beneficial or problematic. Semi-structured interviews will offer flexibility, allowing the interviewer to probe deeper into particular aspects of NVivo's functionality and gather detailed accounts of how the software fits into the research workflow. The combination of surveys and interviews will provide both quantitative and qualitative data, offering a holistic view of NVivo's effectiveness and usability from the perspective of actual users in the field. The findings will contribute to understanding the strengths, limitations, and potential improvements of NVivo as a tool for qualitative research.

Usability Testing

To evaluate the user experience and interface of NVivo, this study will incorporate usability testing, aimed at assessing how effectively and efficiently users can navigate and use the software for qualitative data analysis. The first step involves recruiting a diverse group of participants, ensuring that individuals with varying levels of experience in qualitative research are included. This will encompass both novice users, who may have limited exposure to QDA tools, as well as experienced researchers who are well-versed in using qualitative analysis software. The diversity in experience levels will help capture a wide range of perspectives on NVivo's usability. The usability testing sessions will involve participants performing a series of specific tasks designed to test the core functionalities of NVivo. These tasks could include coding data, running queries, visualizing results, and creating reports, all of which are integral components of the software's functionality. By having participants engage with the software directly, the study can identify areas where users encounter difficulties, such as complex features or inefficient workflows. Participants will be observed as they complete these tasks, and their actions will be recorded to provide insight into their interaction with the software. Data collection during usability testing will focus on several key metrics, including task completion time, error rates, user satisfaction, and overall usability. Task completion time will measure how long it takes participants to complete each assigned task, providing an indicator of NVivo's efficiency. Error rates will track mistakes made by participants, which can reveal issues with the software's interface, instructions, or functionality that might confuse users. User satisfaction will be assessed through post-test questionnaires, where participants rate their overall experience, highlighting aspects they found intuitive or challenging. Overall usability will be evaluated using established usability metrics, such as the System Usability Scale (SUS), which provides a numerical score reflecting the ease of use and effectiveness of the software. By conducting usability testing with a diverse group of users, this study aims to provide a detailed understanding of how NVivo performs in real-world, practical scenarios. The results will help identify areas where NVivo excels and where it might need improvement, offering valuable feedback for both users and the developers of the software.

Data Analysis Procedures

This study employs a mixed-methods approach to evaluate NVivo's effectiveness, integrating both qualitative and quantitative data analysis procedures. NVivo is central to the qualitative analysis, supporting the coding and examination of interviews, case studies, and survey responses. The software enables researchers to identify recurring themes, patterns, and key insights, while its robust coding features help uncover relationships within the data. An iterative coding process enhances depth, ensuring nuanced perspectives are captured. NVivo systematically organizes qualitative data, laying the foundation for meaningful interpretation and theory development. For the quantitative analysis, statistical tools such as SPSS or R are used to conduct descriptive and inferential analyses. Descriptive statistics offer an overview of data characteristics, while inferential tests (e.g., t-tests, ANOVA) compare NVivo's performance with other qualitative data analysis (QDA) tools. These tests help quantify NVivo's strengths and limitations and triangulate findings from the qualitative analysis. Benchmarking is also employed to evaluate NVivo alongside ATLAS.ti, MAXQDA, and Dedoose. A SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis identifies the unique features and performance of each tool. NVivo's strengths, such as its broad data format support and advanced query options, are highlighted alongside areas for improvement. Usability testing assesses NVivo's interface and user experience using metrics like task completion time, error rates, and user satisfaction scores. Feedback is collected through surveys to evaluate ease of use, functionality, and design. By combining qualitative insights, statistical validation, and usability feedback, this study provides a comprehensive evaluation of NVivo's capabilities as a QDA tool.

Data Description

While NVivo is primarily a qualitative data analysis (QDA) software and doesn't inherently involve mathematical formulations, it can be integrated with quantitative methods to provide comprehensive mixed-methods research. Here's how NVivo's functionalities can be presented with some mathematical components:

Variables and notation

1. X_1: Data Management Capability
   - x_{11}: Ease of organizing data
   - x_{12}: Import/export functions
2. X_2: Data Analysis Capability
   - x_{21}: Coding capabilities
   - x_{22}: Query functions
3. X_3: Visualization Tools
   - x_{31}: Word clouds
   - x_{32}: Mind maps
   - x_{33}: Models
4. X_4: Collaboration Features
   - x_{41}: Team projects

- x_{42}: Sharing and exporting reports

5. X_5: User Experience
   - x_{51}: Interface usability
   - x_{52}: Customer support
6. Y: Overall Effectiveness Score of NVivo

Utility Function

The overall effectiveness score (Y) of NVivo can be modelled as a weighted sum of the key variables X_i: $Y = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5$

Where:

- α_i represents the weight assigned to each category X_i.
- Each X_i is a weighted sum of its components x_{ij}.

Data Management Capability (X_1):

$$X1 = \beta 11 x11 + \beta 12 x12$$

Where β_{ij} are weights assigned to each sub-component x_{ij}.

Statistical Analysis

To determine the weights α_i and β_{ij}, we can use methods such as multiple regression analysis or factor analysis. Here is a step-by-step approach:

1. Data Collection: Collect data on the performance of NVivo in each category Xi from a sample of qualitative researchers.
2. Normalization: Normalize the data to ensure all variables are on a comparable scale.
3. Regression Model: Fit a multiple regression model to estimate the weights α_i and β_{ij}:

   $Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \epsilon$ Where α_0 is the intercept and ϵ is the error term.
4. Estimation: Use statistical software to estimate the coefficients α_i and β_{ij}.
5. Validation: Validate the model using techniques such as cross-validation or bootstrapping to ensure its robustness.

Example Calculation

Assume we have collected data and estimated the following weights (for illustration purposes):

- $\alpha_1 = 0.2$
- $\alpha_2 = 0.3$

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- $\alpha_3 = 0.25$
- $\alpha_4 = 0.15$
- $\alpha_5 = 0.1$

And for Data Management Capability (X_1):

- $\beta_{11} = 0.6$
- $\beta_{12} = 0.4$

If we have the following normalized scores for a specific evaluation:

- $x_{11} = 0.8$
- $x_{12} = 0.7$
- $X_2 = 0.85$
- $X_3 = 0.9$
- $X_4 = 0.75$
- $X_5 = 0.6$

We calculate X_1 as:

$$X_1 = 0.6 \times 0.8 + 0.4 \times 0.7 = 0.48 + 0.28 = 0.76$$

Then, the overall effectiveness score Y is:

$$Y = 0.2 \times 0.76 + 0.3 \times 0.85 + 0.25 \times 0.9 + 0.15 \times 0.75 + 0.1 \times 0.6$$

$$Y = 0.152 + 0.255 + 0.225 + 0.1125 + 0.06 = 0.8045$$

This score indicates the overall effectiveness of NVivo based on the weighted performance in each category.

This mathematical formation demonstrates a structured approach to evaluating NVivo's effectiveness as a qualitative research tool. By assigning weights to different performance categories and their components, researchers can quantitatively assess NVivo's capabilities and systematically compare them with other tools.

Result of Method A

Comparing factor analysis (FA), variance-based structural equation modelling (CB-SEM), multiple regression analysis (MRA), and PLS-SEM can help you choose the finest quantitative research statistical methodologies simulated and accurate experiment results. Model applicability, anticipated accuracy, assumption dependability, and computational efficiency are evaluated. Many regression analyses statistically analyse many independent variables and a dependent variable. MRA fits basic linear correlations well. Linear models' anticipated precision is reliable. Resilience to Assumptions: Considering multi-collinearity and related assumptions. The computational efficiency of processing small and medium-sized data sets is excellent. Covariance-based structural equation modelling Fits theory-based models with complex linkages. Big sample numbers and normality assumptions suggest good precision for models. This method relies on multivariate normality and requires a large sample size. Processing big datasets is computationally intensive. Factor analysis is a sound methodology for data reduction and study. It influences model suitability, mainly for latent idea identification; precision N/A. Robustness assumes linear correlations between variables. Highly efficient for medium-to-large datasets. Partial Least Squares: PLS-SEM can fit complex models even with limited samples. This allows model fit flexibility and modification. The expected accuracy is high for models with multiple dependent variables and indirect effects. Resistance to assumptions, capable of handling odd data and tiny samples, and efficient for medium-sized datasets while scalable to large datasets with sufficient computational resources.

Formulation

The study utilizes specific metrics and mathematical formulations for model fit, predictive accuracy, and robustness to assumptions.

- Multiple Regression Analysis (MRA):

– Model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Fit Metric: Coefficient of Determination (R^2)

- Assumption Testing: Variance Inflation Factor (VIF) for multicollinearity, Durbin-Watson statistic for autocorrelation.
- Covariance-Based Structural Equation Modelling (CB-SEM):
- Mathematical Model:

$$\Sigma(\theta) = \Lambda\Phi\Lambda' + \Theta_\epsilon$$

- Fit Metrics: Chi-Square (χ^2), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA).
- Assumption Testing: Mardia's test for multivariate normality.
- Factor Analysis (FA):
- Model:

$$X = \Lambda F + \epsilon$$

- Fit Metric: Eigenvalues and explained variance.
- Assumption Testing: Bartlett's Test of Sphericity, Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy.
- Partial Least Squares Structural Equation Modelling (PLS-SEM):

- Model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

- Fit Metrics: Average Variance Extracted (AVE), Composite Reliability (CR), Predictive Relevance (Q^2).
- Assumption Testing: No strict assumptions about data distribution, can be tested using bootstrapping.

This study systematically evaluates NVivo against other widely used qualitative data analysis (QDA) tools ATLAS.ti, MAXQDA, and Dedoose using both synthetic and real-world datasets to ensure objectivity and relevance across diverse research contexts. Synthetic datasets are crafted to simulate complex qualitative data with known structures, allowing precise comparisons of thematic coding, pattern recognition, and sentiment analysis. Real-world datasets from social sciences, business, education, and healthcare test each tool's ability to extract meaningful insights from actual interviews, focus groups, and survey responses. The evaluation focuses on three criteria which is model fit and predictive accuracy, robustness to assumptions, and computational efficiency. For model fit, tools are assessed on how accurately they reflect the embedded meaning and structure in both simulated and real data. Robustness is examined by using challenging datasets that violate common assumptions such as unstructured language, inconsistent terminology, and small samples to determine each tool's adaptability and reliability under non-ideal conditions. Real-world datasets with incomplete responses and mixed media further test flexibility. Computational efficiency is measured by evaluating processing time, memory usage, stability, and responsiveness during tasks like data import, coding, querying, and reporting. This includes performance on datasets ranging from a few documents to thousands of entries, such as social media posts and lengthy interviews. By combining synthetic precision with real-world complexity and evaluating performance across key methodological dimensions, this analysis provides a rigorous comparison. It guides researchers in selecting the most suitable QDA software based on analytical needs, data characteristics, and project scale.

Comparative Analysis

The comparative analysis of NVivo and other leading qualitative data analysis (QDA) tools ATLAS.ti, MAXQDA, and Dedoose revealed distinct advantages and trade-offs. NVivo excelled in data processing capacity, advanced coding, multimedia support, visualization, and collaboration. It accommodates diverse data formats including text, audio, video, images, and social media, making it well-suited for complex, multidisciplinary research. ATLAS.ti stands out for its network visualization tools and flexible coding, ideal for relational or conceptual mapping. MAXQDA offers strong integration of qualitative and quantitative data, with features like code frequency tables and lexical searches, supporting mixed-methods research. However, neither matches NVivo's automation features, such as sentiment analysis and auto-coding, which are increasingly essential for handling large datasets. Dedoose, while user-friendly and affordable, is better suited for smaller projects or beginners. Its web-based interface supports real-time collaboration but lacks the advanced analytical depth of NVivo, ATLAS.ti, or MAXQDA. A major strength of NVivo is its Collaboration Cloud, enabling real-time teamwork, version tracking, and user-specific access control beneficial for distributed research teams. NVivo also integrates seamlessly with Microsoft Office, SPSS, EndNote, Zotero, and SurveyMonkey, enhancing workflow efficiency in literature reviews, surveys, and data reporting. While MAXQDA and ATLAS.ti offer some interoperability, NVivo's broader compatibility across platforms provides greater research flexibility. Overall, NVivo offers a comprehensive, flexible, and collaborative environment ideal for medium to large-scale projects involving complex data structures and interdisciplinary approaches. While ATLAS.ti and MAXQDA remain strong alternatives with unique strengths, NVivo's extensive data support, AI-enhanced automation, and integration capabilities give it a competitive edge in modern qualitative research.

Case Study 1: Educational Research

NVivo has been widely used in educational research, particularly in analysing qualitative data related to teaching and learning experiences. A recent study by Wahyuddin (2023) utilized NVivo to examine how high school teachers adapted to distance learning during the COVID-19 pandemic. The software effectively managed large volumes of textual data from teacher interviews, discussion forums, and classroom recordings, allowing for the identification of key themes such as student engagement strategies, pedagogical adaptation, and challenges related to technology integration. NVivo's word frequency analysis and thematic coding enabled researchers to categorize responses systematically, revealing that teachers faced significant challenges in student participation and technological accessibility. The software's visualization tools, including word clouds, mind maps, and cluster analysis, provided an intuitive representation of recurring themes, facilitating a more comprehensive understanding of distance learning's impact on educators. Such findings align with broader educational research that emphasizes the necessity of digital literacy training for educators and students (Kier & Johnson, 2022).

Case Study 2: Healthcare Research

NVivo is increasingly being employed in healthcare research, particularly in studies requiring an in-depth analysis of patient experiences, caregiver narratives, and medical professional interviews. In a recent qualitative study on palliative care by Hannon et al. (2017), NVivo was used to analyse data from caregiver diaries and in-depth interviews with terminally ill patients. The software's advanced coding framework allowed researchers to extract meaningful insights from emotionally rich data, identifying critical themes such as emotional support, pain management, and caregiver burden. The ability to perform cross-case comparisons using NVivo's matrix coding function enabled researchers to examine variations in palliative care experiences across different demographic groups. Additionally, NVivo's collaborative coding features ensured consistency and reliability in qualitative analysis, as multiple researchers could validate coding schemes and interpretations. This approach strengthens the credibility of qualitative healthcare research, supporting the integration of patient-centred insights into healthcare policy and practice (Vennedey et al., 2020).

Case Study 3: Market Research

NVivo has also gained traction in market research, particularly in analysing consumer sentiment from social media, focus groups, and customer feedback. A study by Modi & Zhao (2021) explored the public perception of a newly launched sustainable fashion brand by analysing thousands of social media comments and customer reviews. NVivo's auto-coding capabilities expedited the data processing, allowing researchers to focus on interpretation rather than manual data categorization. The software's sentiment analysis tools helped classify customer opinions into positive, neutral, and negative categories, identifying key areas of satisfaction and concern. Additionally, NVivo's advanced search functions enabled researchers to detect patterns in customer preferences, highlighting common themes such as affordability, product durability, and ethical sourcing. These insights were instrumental in guiding the brand's future marketing strategies and product development. The study confirmed previous findings that qualitative data analysis tools like NVivo enhance efficiency in processing unstructured consumer data, offering companies valuable insights into consumer behaviour (Aziz et al., 2023). These case studies illustrate NVivo's versatility across various disciplines, demonstrating its capability to streamline qualitative data analysis, enhance thematic exploration, and improve research reliability. The growing adoption of NVivo in education, healthcare, and market research underscores its significance as a powerful tool for qualitative researchers seeking to extract meaningful insights from complex datasets. As NVivo continues to evolve, integrating AI-driven analytical tools and enhanced visualization features, it is expected to further improve qualitative research methodologies, making data interpretation more accessible and impactful.

Surveys and Interviews

The survey and interview components of this study provided critical insight into user experiences and perceptions regarding NVivo's performance in qualitative data analysis. Among the 150 qualitative researchers surveyed, a significant 72% indicated a preference for NVivo over competing QDA tools, citing its comprehensive feature set and user-friendly interface as primary reasons for their choice. Users appreciated NVivo's streamlined workflows, particularly for tasks related to programming, auto-coding, and data visualisation. These functions were described as intuitive, even for users with limited technical backgrounds. Furthermore, 75% of respondents reported that NVivo enhanced the overall quality of their data analysis process, with many pointing to improved analytical clarity, easier access to coded data, and time savings as major advantages. Despite acknowledging the platform's somewhat steep learning curve, the majority of the 20 experienced qualitative researchers interviewed concluded that the investment in learning NVivo was justified. They emphasized that the software's sophisticated capabilities such as robust data organisation, thematic analysis, and integration with external data sources contributed substantially to the depth and reliability of their qualitative research findings.

Usability Testing

Usability testing, conducted with a sample of 30 participants ranging from novice to advanced users, further validated NVivo's advantages in terms of interface design and task efficiency. The results showed that NVivo outperformed ATLAS.ti and MAXQDA by an average of 30% in completing core programming and coding tasks, including categorising text, running queries, and generating visual reports. Participants using NVivo made significantly fewer errors when performing data encoding and retrieval operations, which underscores the software's intuitive design and effective user guidance features. Visualisation tools in NVivo, such as word trees, mind maps, and cluster analysis diagrams, received especially positive feedback. Participants assigned an average satisfaction score of 8.5 out of 10 for NVivo's visualisation capabilities and ease of use, highlighting the program's ability to simplify complex analytical tasks through visually engaging outputs. These findings suggest that NVivo not only supports rigorous data analysis but also improves user confidence and reduces cognitive load during the research process.

Threshold Values for Validity and Reliability

To ensure methodological rigor in evaluating NVivo as a qualitative data analysis tool, threshold values for validity and reliability were established. For validity, the Content Validity Index (Dalton & McVilly, 2004) assessed the relevance of NVivo's features, with scores ≥0.80 indicating that 80% of expert reviewers found the analytical tools meaningful (Polit & Beck, 2006). Construct Validity was measured using Average Variance Extracted (AVE), where values >0.50 signified that NVivo's functions such as thematic saturation, coding coherence, and pattern recognition captured the intended constructs effectively (Fornell & Larcker, 1981). Criterion Validity employed Pearson correlation coefficients to compare NVivo-generated coding outputs with established external coding frameworks; strong positive correlations suggested alignment with qualitative research standards. For reliability, Cronbach's Alpha values ≥0.70 indicated acceptable internal consistency across coding categories (Hair et al., 2022). Test-retest reliability was evaluated using the Intraclass Correlation Coefficient (ICC), showing that repeated analyses produced stable results over time. Inter-rater reliability measured using Cohen's Kappa, with values >0.75, demonstrated substantial agreement between independent coders, affirming NVivo's support for consistent collaborative analysis (Landis

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& Koch, 1977). These thresholds confirm NVivo's ability to support valid, reliable, and reproducible qualitative research outcomes in line with established standards in the field.

Summary of Threshold Values

Content Validity Index (Dalton & McVilly): ≥ 0.80

Construct Validity (AVE): ≥ 0.50

Criterion Validity (Pearson's r): ≥ 0.70

Internal Consistency (Cronbach's Alpha): ≥ 0.70

Test-Retest Reliability (ICC): ≥ 0.75

Inter-Rater Reliability (Cohen's Kappa): ≥ 0.70

These threshold values ensure that NVivo meets high standards of validity and reliability, making it a robust tool for qualitative research. By adhering to these benchmarks, researchers can confidently use NVivo, knowing that it provides accurate and consistent support for qualitative data analysis.

4. Discussion

This study examined the practical uses and methodological compatibility of PLS-SEM and NVivo in cross-disciplinary research, focussing on education and social science. New researchers typically misinterpret the integration and advantages of both technologies despite their widespread usage. The author covers how these technologies suit education research goals and when and why we should employ them rather than using technical approaches. PLS-SEM is essential for modelling education latent concepts, including teacher effectiveness, student engagement, learning motivation, and institutional support, due to its capacity to handle complicated models and small samples. However, NVivo excels in organising and interpreting rich, unstructured data from interviews, focus groups, classroom discussions, and open-ended survey responses essential sources in qualitative educational research. For educational fieldwork researchers interested in Microsoft Office integration and auto-coding, NVivo is suggested over ATLAS.ti or MAXQDA. PLS-SEM is better than CB-SEM for research projects or small sample sizes, typical in master's theses and grant-funded experimental experiments. Educational researchers who engage with real-world challenges and varied data kinds need this change from abstract debate to practical tool selection recommendations. The conversation has evolved from technical to contextual instruction, which is influential.

The strengths of statistical methods lie in their alignment with research objectives, data characteristics, and theoretical underpinnings. Multiple Regression Analysis (MRA) is commonly used for predictive linear correlation, assessing the impact of independent variables on a dependent variable. However, MRA assumes linearity, homoscedasticity, and normality, limiting its applicability in complex or non-normal data scenarios (Hair et al., 2024). Covariance-Based Structural Equation Modelling (CB-SEM) is valuable for validating theoretical models and testing hypotheses using large datasets. It is particularly useful in confirmatory factor analysis (CFA), enabling researchers to examine measurement models before structural relationships. A major strength of CB-SEM is its capacity to estimate complex relationships while accounting for measurement error (Byrne, 2013). Nonetheless, it requires large sample sizes and assumes multivariate normality, which may not always be practical (Kline, 2023). Factor Analysis (FA) supports structural identification and latent variable exploration. Exploratory Factor Analysis (EFA) uncovers potential factor structures, while CFA confirms theoretical constructs (Fabrigar & Wegener, 2012). FA reduces dimensionality, ensuring observed variables accurately reflect latent constructs. Partial Least Squares Structural Equation Modelling (PLS-SEM) is ideal for predictive modelling in small samples or non-normal data. Unlike CB-

SEM, which emphasizes theory testing, PLS-SEM prioritizes prediction and model flexibility (Sarstedt et al., 2023). Its application spans business, social sciences, and healthcare, where modelling complex relationships is critical. However, researchers must carefully evaluate the validity and reliability of PLS-SEM results to ensure analytical robustness.

4.1. Reliability and Validity in PLS-SEM

Reliability in PLS-SEM ensures that latent constructs yield consistent and stable measurements. Cronbach's alpha, commonly used for assessing internal consistency, is acceptable above 0.70 but assumes equal factor loadings, which is often unrealistic (Henseler et al., 2015). Composite reliability (CR) overcomes this by considering individual loadings, offering a more accurate assessment; values above 0.70 indicate acceptable reliability (Hair et al., 2022). Validity ensures constructs measure intended theoretical concepts. Convergent validity is confirmed when factor loadings exceed 0.70, indicating indicators assess the same underlying construct (Fornell & Larcker, 1981). The Average Variance Extracted (AVE) further supports this, with values ≥0.50 reflecting strong convergent validity (Sarstedt et al., 2023). Discriminant validity ensures constructs are distinct. The Fornell-Larcker criterion requires that the square root of each construct's AVE be greater than its correlations with others. Additionally, the Heterotrait-Monotrait (HTMT) ratio offers a more rigorous test, with HTMT values <0.85 indicating good discriminant validity (Henseler et al., 2023). Recent advancements in PLS-SEM include predictive modelling techniques such as PLS Predict, improving predictive power and generalizability (Shmueli et al., 2016). Integration with machine learning has enhanced model performance, particularly with large or complex datasets. Bayesian methods are also emerging to provide more robust parameter estimation (Rigdon et al., 2010). While CB-SEM is preferred for theory testing in large-sample studies, PLS-SEM is increasingly valued for predictive, exploratory analysis under less stringent data conditions. Researchers must remain current with methodological innovations to ensure robust and reliable structural equation modelling.

4.2. Indicators of how well the model fits the data

Statistical methods evaluate model strength and data relationships. Multiple Regression Analysis (MRA) examines linear predictions between variables. Covariance-Based Structural Equation Modelling (CB-SEM) validates theoretical models using latent constructs and large datasets. Factor Analysis (FA) identifies underlying structures, aiding in measurement refinement. Partial Least Squares SEM (PLS-SEM) is optimal for predictive research involving small samples or non-normal data, using variance-based estimations. PLS-SEM model reliability is assessed via Cronbach's alpha and Composite Reliability (CR), with values >0.70 indicating acceptable internal consistency. CR is preferred for accounting for varying factor loadings. Validity requires convergent validity (factor loadings >0.70, AVE >0.50) and discriminant validity, assessed using the Fornell-Larcker criterion or Heterotrait-Monotrait (HTMT) ratio (HTMT <0.85). Model fit indicators include the coefficient of determination (R^2), where values >0.50 denote strong explanatory power. Predictive relevance (Q^2), obtained through blindfolding, and bootstrapping procedures further validate model significance and reliability. In qualitative research, NVivo supports organization, analysis, and visualization of data. Despite its learning curve, its user-friendly interface and integration with tools like SPSS, R, and Excel make it valuable for mixed-methods research. NVivo's advanced features word clouds, cluster analysis, and matrix coding enhance interpretation, positioning it as a leading QDA tool.

4.3. Limitations and Further Research

Despite its advantages, PLS-SEM has limitations. It is less effective in testing well-established theories compared to CB-SEM, which provides better model fit indices. PLS-SEM also lacks a universal goodness-of-fit measure, making result interpretation more complex. Additionally, small sample sizes, while permissible, can reduce statistical power and lead to less reliable estimates. Future research should explore hybrid approaches combining PLS-SEM with other statistical methods to enhance robustness. Expanding its application to emerging fields such as artificial intelligence, sustainability studies, and behavioural economics can provide deeper insights. Similarly, NVivo's limitations include a steep learning curve and high software costs, which may restrict accessibility. Future research should explore automation in qualitative analysis, integrating AI-driven coding and sentiment analysis to improve data processing efficiency. Comparative studies between NVivo and emerging qualitative data analysis tools can also help refine best practices in qualitative research.

5. Conclusion

This study compares PLS-SEM and NVivo in educational mixed-methods research. Instead of unique ideas, the author provides a realistic framework for researchers especially early career researchers to choose tools that match their research goals, data architectures, and institutional limitations. This work extends technical description to methodological awareness for applied educational research by merging practical use cases with a decision assistance matrix. The results suggest social science instructors and researchers use quantitative and qualitative techniques strategically and thoughtfully. This study concludes that successful research technique requires technical rigour and fitness for purpose choosing instruments that match an educational research project's aims, scope, and environment. Quantitative research success depends on selecting the appropriate statistical methods. This comparative analysis of MRA, CB-SEM, FA, and PLS-SEM highlights their strengths and limitations, guiding researchers in making informed choices. PLS-SEM proves particularly useful for handling non-normal data distributions, small sample sizes, and intricate variable interactions, making it applicable across diverse fields such as healthcare, engineering, business, and social sciences. Its ability to explore latent variables through reflective and formative assessments provides deeper insights into causal relationships. The predictive power of PLS-SEM makes it invaluable for studying market trends, organizational behaviour, consumer satisfaction, and technology adoption. As research methodologies evolve, PLS-SEM continues to advance, offering robust analytical techniques that enhance hypothesis testing and conceptual validation. NVivo, as a qualitative research tool, demonstrates significant advantages in organizing and managing diverse data sources. This study evaluates NVivo's efficiency in coding, analysing, and visualizing qualitative data, enhancing research reliability and accuracy. NVivo's advanced query functions facilitate deeper analysis, revealing meaningful patterns and relationships within qualitative datasets. Its support for collaborative research ensures consistency in multi-user projects, strengthening the overall validity of findings. Comparative analysis with other QDA tools confirms NVivo's advantages in functionality, user support, and integration capabilities. While challenges exist, such as software cost and an initial learning curve, the benefits of using NVivo particularly in ensuring methodological rigor and data-driven insights outweigh these limitations. Researchers who invest time in mastering NVivo will likely achieve superior qualitative research outcomes, leading to more comprehensive and well-substantiated findings.

Declarations

Author Contributions. Mahadi Hasan Miraz conceptualized and designed the study, conducted the qualitative data analysis using NVivo, and wrote the first draft of the manuscript. Rohana Sham managed the quantitative data analysis, including statistical testing and benchmarking, and contributed to the manuscript revision. Sanmugam Annamalah was responsible for literature review, usability testing, and final proofreading. All authors reviewed and approved the final manuscript.

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