Business Analytics Education and Business Research Methods: A Framework for Validating Qualitative Results Using Sequential Mixed Methods

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Abstract: This paper contributes to advancing qualitative and mixed-methods research in business by offering a comprehensive framework that rigorously validates qualitative findings through an explanatory sequential mixed-methods approach. Qualitative research broadly investigates and exposes facts from an epistemological perspective. However, challenges related to the generalisation and validity of the qualitative results require further inquiry, specifically in computer science and business technology research, such as business data analytics. Thus, this article aims to guide researchers in sequentially validating qualitative research methods using Grounded Theory Methodology GTM, bias reduction, and Structural equation modelling (SEM). The study suggests three sequential stages of mixed-methods research design — the research methods employed (GTM) to extract qualitative categories. Data was collected from postgraduate students using semi-structured interviews that were analysed using a rigorous (GTM) coding technique. Accordingly, results underwent a process of bias reduction as an initial phase of validation of qualitative results, and finally, results were validated using quantitative SEM analysis. The proposed framework meticulously demonstrates how an ordered set of stages in a research design can validate qualitative results while steering a study in conceptualising Business Analytics (BA) as an academic field. The research makes significant contributions to the practical and theoretical implications of qualitative results, mixed methods research design, and validation processes in business computing education research fields, thereby enhancing the understanding and application of these methods in real-world scenarios.

Keywords: Business research, Business analytics, Education, Mixed methods, Grounded theory, Coding, Structural equation modelling

1. Introduction

This study aims to establish a validated, replicable framework for enhancing the trustworthiness of qualitative research findings in Business Analytics education. It offers practical guidance for curriculum designers and contributes to methodological rigor in qualitative research. This work builds on Al-Eisawi's (2022) earlier study, which introduced a detailed and scrutinised framework tailored for novice researchers using Grounded Theory Methodology (GTM). Expanding on that foundation, the current study presents a functioning validation framework that ensures the accuracy, credibility, and reliability of qualitative findings (Creswell & Miller, 2000). Validation in qualitative research is inherently complex, with confirmability being a core concern (Lub, 2015). Trustworthiness can be challenged at various stages—data collection, coding, and bias reduction (Inayat et al., 2024). To address these challenges, the study integrates mixed methods, combining qualitative and quantitative approaches to improve result precision (Finlay, 2002).

1.1 Research Problem, Question, and Objectives

Despite the increasing use of qualitative methods in Business Analytics education, there remains a lack of structured, replicable frameworks for validating the conceptual insights these methods produce. This study outlines a clear framework for using a mixed-methods approach that combines qualitative grounded theory methodology (GTM) with quantitative partial least squares structural equation modelling (PLS-SEM). This approach helps validate the categories identified through the qualitative GTM coding process. The practical example provided serves as a solid base for applying GTM analysis as the main qualitative research method in Business Analytics (BA). The design aims to illustrate the interaction between qualitative and quantitative methods, which will be explained in the subsequent sections of the paper. As a result, the study addresses the following research question:

RQ1: "How can a sequential mixed methods approach validate qualitative findings in the conceptualization of Business Analytics Education ?

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To address the research question, this study sets out the following objectives:

- To apply Grounded Theory Methodology (GTM) in analysing qualitative data collected from postgraduate students, identifying key categories relevant to Business Analytics education.
- To implement a systematic bias reduction process to enhance the trustworthiness of the qualitative findings prior to quantitative validation.
- To validate the identified qualitative categories using Partial Least Squares Structural Equation Modelling (PLS-SEM), thereby confirming their empirical relevance and structural coherence.
- To develop a comprehensive sequential mixed-methods validation framework that can be replicated in business research contexts, particularly in business computing and analytics.
- To contribute to the conceptual development of Business Analytics (BA) as an academic discipline by demonstrating how qualitative findings can be rigorously validated through a mixed-methods approach.

This study intends to bridge qualitative research and quantitative validation through a structured and replicable design. This approach ensures that insights from qualitative methods are conceptually rich and statistically sound. By integrating Grounded Theory Methodology (GTM) and Partial Least Squares Structural Equation Modelling (PLS-SEM), researchers can enhance the credibility of their findings in business and technology. Additionally, applying this framework in Business Analytics education supports curriculum development and promotes evidence-based training for future analysts.

The remainder of this paper is organised as follows. Section 2 presents a literature review that addresses validation in qualitative research, mixed-methods design, and business analytics education. Section 3 outlines the proposed research design framework, while Section 4 details the methodology, including data collection and analysis procedures. Sections 5 and 6 provide the analysis and results of both the qualitative and quantitative stages. Finally, Section 7 offers conclusions, implications, and directions for future research.

2. Literature Review

To ensure a rigorous foundation for the study, a thematic literature review strategy was employed. This approach enabled a focused exploration of the core areas underpinning the research question and facilitated the mapping of theoretical constructs to methodological choices. The review process concentrated on three interrelated themes: (1) validation in qualitative research, (2) exploratory sequential mixed methods, and (3) conceptual challenges in Business Analytics (BA) education. These themes were selected for their direct relevance to the study's central aim—validating qualitative findings through a sequential mixed-methods framework applied to BA learning.

This section breaks down the research question by providing an overview of the core concepts and relationships. In doing so, it critically demonstrates a significant research gap concerning the lack of structured, context-specific frameworks for validating qualitative insights in business analytics education. The literature reviewed reinforces the need for the proposed framework and supports its conceptual and methodological underpinnings

2.1 Validation in Qualitative Business Research Methods

In qualitative studies, validity differs significantly from that in quantitative studies. Unlike quantitative studies, qualitative research lacks specific measures to ensure validity (Patton et al., 1999). The differences between quantitative, qualitative, and mixed research are primarily due to paradigmatic and ontological variations and the subjective nature of qualitative research (Inayat et al., 2024). These differences also extend to the research purposes, which are influenced by the field's context and the available literature. In quantitative research, validity is widely recognised and accepted, but the same level of recognition and acceptance is not seen in qualitative studies (Drapeau, 2004). Numerous researchers have avoided using the word "validity," as suggested by Smith (1983), to address the gap between quantitative and qualitative research in terms of epistemological and ontological assumptions. Therefore, they argue that validity and reliability should be disregarded in qualitative studies. Several scholars, including Foucault (1972) and Kirk and Miller (1986)), The critical importance of truthfulness in empirical qualitative studies has been strongly emphasised (Inayat et al., 2024).

McKinnon (1988) highlighted the unintended biases and impacts that can arise from a researcher's influence. He also pointed out the challenges in obtaining reliable data and the limitations of human observation, all of which raise concerns about the quality of research findings in the quest for objectivity (Abib & Hoppen, 2019). Maxwell (1992) categorised validity into five types: descriptive, interpretive, theoretical, generalization, and

valuation validity (Abib & Hoppen, 2019). These categories are illustrated in Figure 1 below , along with a brief explanation of Maxwell's types of validity.

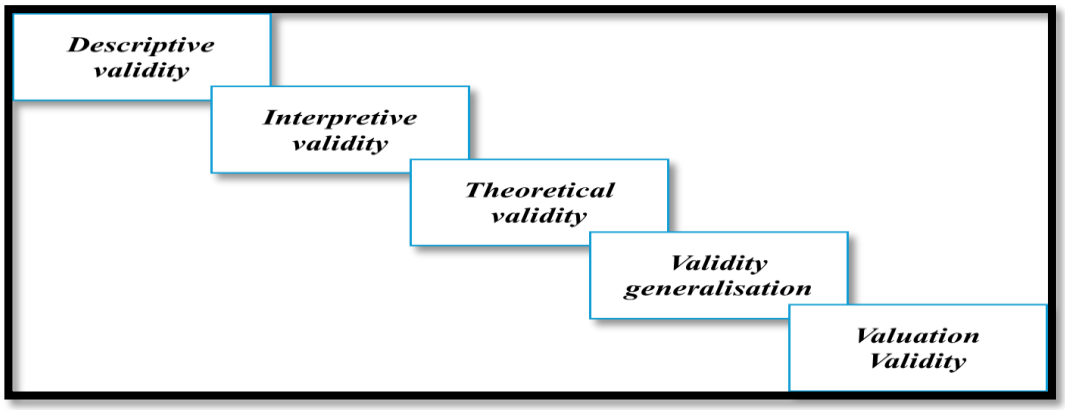

Figure 1: Maxwell's (1992) Qualitative validity is divided into five types

Below is a brief description of each validity type :

- Descriptive validity refers to displaying information that disregards the explanation process and only concentrates on facts heard and seen (Abib & Hoppen, 2019).
- Interpretive validity refers to the researcher's explanation of events, objects, and actions, incorporating deliberate processes and obscure intentions (Edmonds & Kennedy,2017).
- Theoretical Validity: refers to the theoretical elaboration formulated through research analysis and its alignment with the data. This involves assessing the accuracy of the concepts and qualitative categories extracted, thus recognising their interactions and relationships (Drapeau, 2004).
- Validity Generalisation: This validation extends the explanation to other specific situations, populations, times, and places. It usually occurs through the development of theories that can encompass larger and different situations (Abib & Hoppen, 2019).
- Valuation validity refers to the critical analysis essential for learning and developing a deeper understanding. It permits a thorough review of qualitative research results.

Overall, these five validity types are interdependent and collectively ensure that qualitative findings are not only empirically grounded but also theoretically sound, contextually meaningful, and ethically robust. Applying all five types is especially pertinent in mixed methods research, where qualitative insights inform quantitative validation, as in the present study.The current research employs Grounded Theory Methodology (GTM), with a primary focus on validity assessment. Grounded theory diverges from the metrics used in quantitative research by prioritising trustworthiness, credibility, and rigour. According to Strauss and Corbin (1990), in GTM, validity ensures that the theory developed is firmly based on data and logic and recommends additional observations. They propose using standards such as fit, interpretation, scope, and control to assess the validity of GTM results.

2.2 Exploratory Sequential Mixed Methods

This paper introduces an interpretative, exploratory, and sequential mixed-methods approach, a versatile instrument for validating qualitative results. Edmonds and Kennedy 2017 defined the exploratory sequential technique as a progressive approach employed whenever qualitative data can enrich quantitative results. It explores a concept before validating it, allowing for greater adaptability in extracting innovative ideas. One of the distinct advantages of using an exploratory sequential approach is the enhanced validity it provides, as noted by Heesen, Behnke & Zurn (2022) and Flick (2018) highlighted that the semi-structured interview-based qualitative methodological technique is particularly effective in addressing unresolved issues and developing ideas based on discoveries. Such interviews generate extensive data that facilitates the exploration of complex concepts, making them an ideal method for understanding the intricacies and depth of various issues (Drapeau, 2004). As illustrated in Figure 2 below, this process enables researchers to initiate context-rich exploration and progress toward robust empirical testing. The qualitative phase uncovers concepts and relationships grounded in participant narratives. In contrast, the subsequent quantitative phase—using tools such as Partial Least Squares Structural Equation Modelling (PLS-SEM)—validates these constructs and enhances the credibility of the findings.

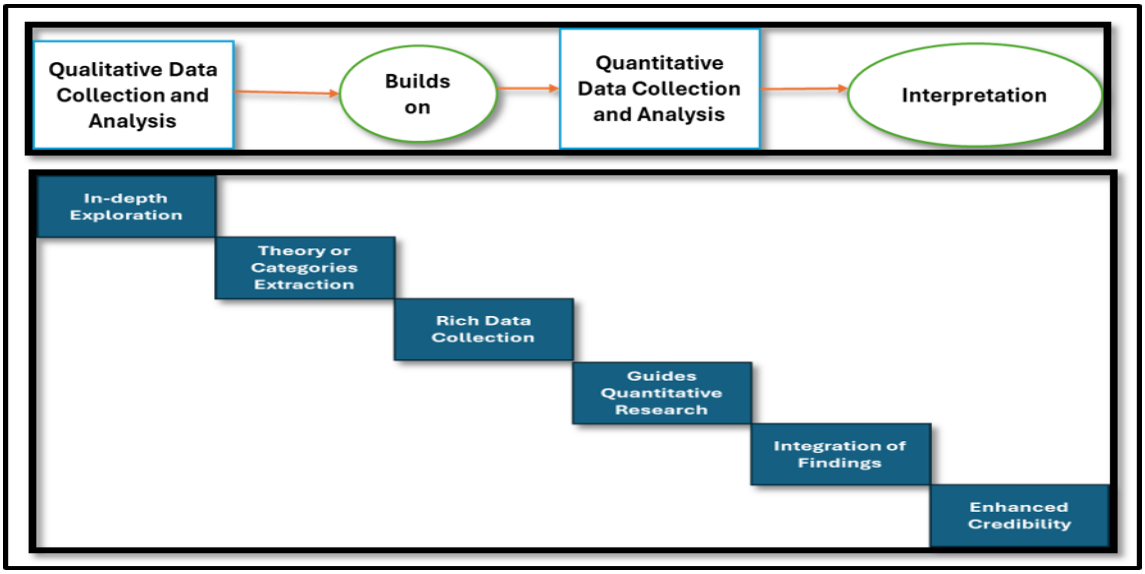

Figure 2: Steps in exploratory sequential mixed methods (Creswell, 2019)

This rich data is subsequently used to strengthen the research hypothesis Smith, 2020). When discussing the quantitative methodological approach, Bajpai (2011) emphasises the benefits of primary data sources, particularly noting that such data is often directly relevant to the research objectives as it is collected individually. Applying both quantitative and qualitative approaches within a single research study provides a more significant opportunity to gain deeper insights into the subject while achieving a higher degree of validity and accuracy compared to using a single approach (Creswell & Plano Clark, 2017; Tashakkori & Teddlie, 2010). Figure 2 above illustrates steps in exploratory sequential mixed methods influenced by (Creswell 2009).

2.3 Conceptual Challenges in Business Analytics (BA) Education

Challenges in computer science and business technology, specifically in business analytics, involve the academic discipline of using statistical and quantitative analysis, data science, explanatory and predictive models, and fact-based management to drive decisions and actions (Barefah, 2024). It includes operational research, information systems, and machine learning. It can be described as descriptive, predictive, prescriptive processing, and modelling heterogeneous data, prompting researchers to address the generalisation and validity of qualitative results (Anderson and Nesterova, 2024).

However, the challenge lies in the overlapping nature of BA with other academic disciplines, which may lead to elevated student attrition rates due to not understanding the core concepts relating to business analytics (Anderson & Nesterova, 2024). It is challenging, particularly for students requiring a previous understanding of the prerequisites mentioned in their early academic degrees (Barefah,2024). Studies and systematic literature reviews on BA validated the intersection mentioned above.Given these challenges (Wilder & Ozgur, 2015), the current study employs the exploratory sequential mixed-methods framework to identify and validate key qualitative categories that support conceptualising BA for educational purposes. These categories were derived from qualitative data and tested using PLS-SEM, demonstrating the framework's practical application in improving BA curriculum design and learner support.

2.4 Addressing the Gap in Existing Literature

While qualitative research has moved away from traditional notions of validity used in quantitative studies (Patton et al., 1999; Drapeau, 2004), there is still no widely accepted framework for assessing validity in qualitative business research. Scholars argue that conventional metrics are misaligned with the interpretive nature of qualitative inquiry (Smith, 1983; Inayat et al., 2024). Although models like Maxwell's (1992) offer useful classifications, their practical application remains unclear (Abib & Hoppen, 2019). Moreover, limited research explores how validity is addressed within specific approaches, such as Grounded Theory (Strauss & Corbin, 1990), especially in the context of business analytics education. This highlights a need for clearer, context-driven validation frameworks in qualitative business research.

3. Proposed Design Framework

The proposed research design mirrored the study's underlying goal. Building a structure encapsulating the qualitative and quantitative approaches presented in sequential exploratory stages is implied, as shown in Figure 3 below. Both approaches followed methodical phases, including the initiation point, which started with research questions and hypotheses, the analysis process, and the expected results from both strategies. The research design is illustrated in Figure 3 below. The quantitative work reported in this paper builds on the qualitative categories extracted to define business analytics and analyse them using partial least squares structural equation modelling (PLS-SEM) It is vital to mention that using GTM as a core approach was unnecessary for theme creation, as the themes were pre-defined in the Mitra, Kumar & Sharma (2021) model or for extracting theories. The main goal was to extract categories and link them into themes.

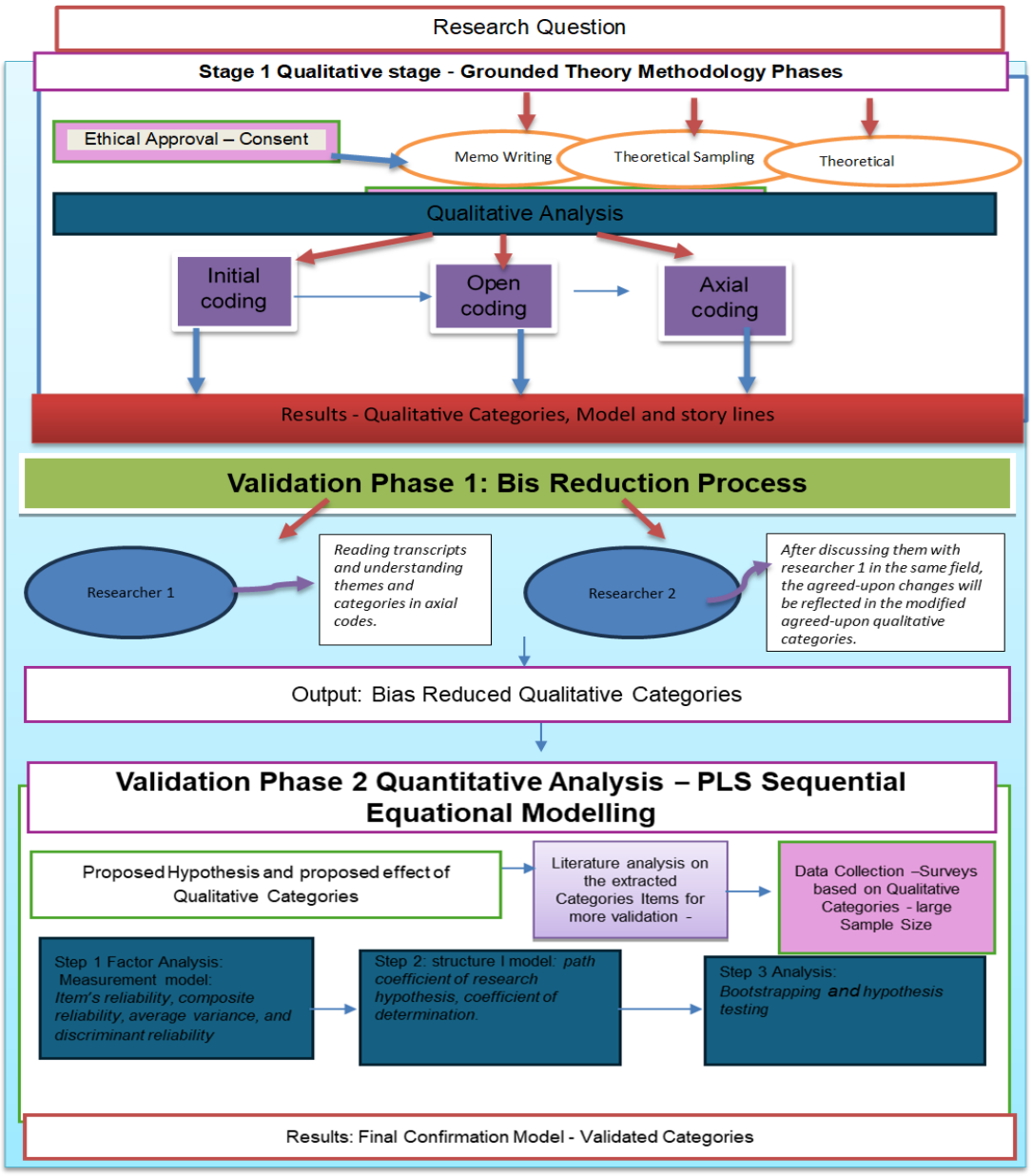

Figure 3: Proposed Validation Model using Mixed Methods

4. Methodology

As mentioned, the methodology highlighted the implementation of the proposed validation model, as illustrated in Figure 3, which incorporates mixed methods. The qualitative data was collected through semi-structured

interviews with 20 MSc-level BA students. The data was then analysed using Grounded Theory Methodology (GTM) coding techniques. The extracted grounded measures were used to identify primary constructs that were then treated as potential BA categories and shaped into a grounded relational conceptual model (Al-Eisawi, 2022). These measures were also quantitatively validated and evaluated using the qualitative analysis results to determine their effects on student academic success (Ibarra-Sáiz, Rodríguez-Gómez & Boud, 2021). Furthermore, quantitative surveys were conducted on "300" students from various higher education institutions teaching BA in their master's program. The collected data underwent analysis using Partial Least Squares – Structural Equation Modelling (PLS-SEM).

5. Analysis

5.1 Stage 1: Qualitative Data Sample and GTM Analysis

This study selected GTM as the initial research strategy based on Locke's (2001) endorsement of its suitability for investigating structural conduct and the facilitation of theme linkage to categories that support the creation of the business analytics categories. Accordingly, the following research question guided the initiation and direction of qualitative data analysis:

RQ2: "What are the categories of each core proficiency in BA that improve student academic success in business analytics novice learners?"

Semi-structured interviews were chosen as the core data collection channel for "20" participants. The interviews enclosed open questions, given that the research follows GTM. Interview questions probed how each student could explain the existence of potential scopes treated as previous professionals in enhancing or limiting their advancement in studying BA as a postgraduate and how they exploited such realisation. In each interview, a set of (12) questions were asked of each student participating in the study. The data of students participating in a sample study for qualitative analysis. All of them are pursuing a postgraduate degree in Business Analytics. The students have diverse academic backgrounds, including Computer Science, Accounting, Business Administration, Linguistics, Law, Pharmacy, and Civil Engineering. Their professional experience varies significantly, ranging from no experience to up to eight years, and spans various industries such as banking, consulting, marketing, risk management, system analysis, and pharmaceuticals.

The current research was influenced by a model proposed by Mitra, Kumar & Sharma (2021) which offered an interpretation of BA as a major. These models decomposed BA into four indicators or dimensions, as shown in Figure 4 below.

It is vital to mention that using GTM as a core approach was not necessary for theme creation, as the themes were pre-defined in the Mitra, Kumar & Sharma (2021) model or for extracting theories. The main goal was to extract categories and link them into themes.

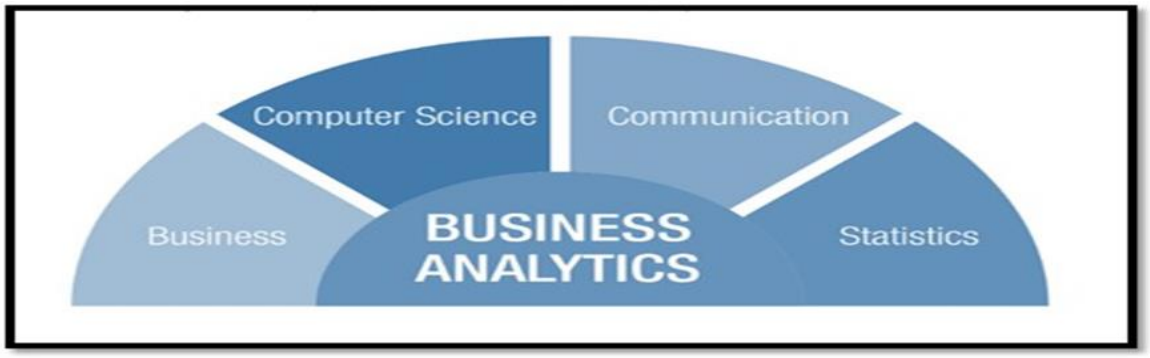

Figure 4: BA decomposed themes influenced by (Mitra, Kumar & Sharma, 2021)

This research treated the above indicators as core dimensions /themes in the grounded theory. The model in Figure 4 displays the four dimensions of BA: business and management, computer science and information systems, communication as skills, and statistics. These themes were qualitatively analysed using grounded theory methodology to extract categories representing proficiencies in the BA major, which was later validated quantitatively using structural equation modelling in stage three of the proposed model. The process of coding in GTM involves condensing the data while maintaining its essence and meaning (Charmaz, 2014). Open, axial and selective coding were used to analyse student interview transcripts (Gibbs, 2018). Open coding entailed

reducing the data by assigning a phrase to represent a specific aspect (Charmaz, 2014). Axial coding was then used to categorise and assign themes to the data (Bryant, 2002).

The study collected a large amount of data through semi-structured interviews with students, aiming to create a concise data abstraction (Bryant, 2011). To condense the size of the transcripts, specific phrases were assigned to represent the data, and then the data was labelled accordingly. The process involved identifying data collection sites and organising the categories thematically using the axial coding process. The design model presented in Figure 3 includes a unique GTM approach: memo writing and theoretical saturation. Memo writing is a process in which the researcher takes notes throughout the research. Memos may contain written observations of events, categories, and relationships collected and analysed initially (Gibbs, 2018). An example of memo writing while collecting data is shown below in Figure 5 below.

Interview Question	Student Answer	Memo	Memo /Date – Time
Do you think there are specific technical issues that can improve your performance in business analytics?	*In my case and as having specialised experience from the company I worked for before joining the MSc program, I felt that some proficiencies supported my success in the major, such as my ability to work with data and build **databases** using Oracle easily, accordingly, build analytical models, and derive valuable insights.*	*****relate this to Computer science and information systems Node in NVivo. Suggested codes in the interview - ** **Check for other related nodes ****	*August 2023 – PSUT -Main campus – 14:30 PM*

Figure 5: Memo Writing /open coding analysis example from the study

The open coding process resulted in (16) final categories after filtering and classification out of 57, as shown by the extracted categories and themes in Figure 6 below. In addition, Table 1 below illustrates that codes were extracted from several lines and direct quotes from the lines of the students' semi-structured interviews and transcripts (Packer-Muti, 2016). For instance, the category name 'familiarity with statistical tools 'was selected over initial codes. The essence was reducing the data collected via the semi-structured interviews to capture valuable information and qualitative categories (Heath & Cowley, 2004). Finally, categories that might relate to what BA referenced for interviewed students were selected.

Table 1: Axial codes and open codes resulting from GTM

Axial Coding /Theme /Business Analytics Dimension Category (C) Abstract Definition/ Description	Open coding / /Category (C)	Abstract Definition/ Description	Sample from interviewed students' transcripts
Statistics	(C1)Familiarity with general statistics concepts	Statistics is the mathematical study of data collection, analysis, interpretation, presentation, and organisation (Wang, Han & Yang, 2015)	"*In one of the prerequisites, I faced some challenges in regression and inferential statistics.* " "*We had to take hands-on for understanding*
	(C2) Familiarity with Statistical Data Analysis	Statistical data analysis involves collecting, cleaning, exploring, and interpreting data using statistical methods.(Yin & Fernandez, 2020)	
	(C3) Familiarity with Statistical Tools and Languages	Yin and Fernandez (2020) highlighted standard tools and programming languages used for statistical analysis, data manipulation, and visualization.	

Axial Coding /Theme /Business Analytics Dimension Category (C) Abstract Definition/ Description	Open coding / /Category (C)	Abstract Definition/ Description	Sample from interviewed students' transcripts
	(C4) Good knowledge of Mathematics	A strong grasp of mathematics is essential for careers in quantitative fields as it provides a problem-solving framework.	*statistical concepts that should be visualized for a deeper understanding. "*
Communication Skills	(C5) Data storytelling knowledge	Data storytelling involves using narrative techniques to effectively communicate insights taken from data analysis to a wider audience.	"*During my professional at a bank I had to create reporting for data scenarios and present them for strategic levels which helped me in my modules* "
	(C6) Solid written communication	Having strong written communication skills is essential for achieving success in academic, professional, and personal situations. It is crucial to express your thoughts, ideas, and opinions effectively in writing to ensure that your message is understood by your audience.	
	(C7) Business communication skills	Effective communication is crucial for business success. It involves conveying information, ideas, and messages to achieve specific goals.	
	(C8) Social Intelligence Skills (interpersonal communication).	Developing social intelligence involves self-reflection, practice, and an authentic desire to connect with and understand others.	
Business	(C9) Knowledge of Management Principles	Organizational management principles provide a framework for decision-making, leadership, and efficient business operations.	
	(C10)Knowledge in Strategic Planning	Organizations need to define their direction and allocate resources through strategic planning.	"*My BSc level back in 2020 was E-marketing I feel it didn't me help as a background for Business Analytics* "
	(C11) Knowledge in Digital Marketing	Digital marketing is a form of advertising that includes a range of online strategies and channels. The main objective of digital marketing is to promote products, services, or brands through various online platforms.	
	(C12) Knowledge in Project Management	Project management involves planning, organising, securing, and managing resources to achieve specific goals within a defined timeframe.	*" I remember using my BSc PowerPoint slides for one of my MSc modules in Business analytics , I think it was from project management modules and how to create Gantt and pert charts* "

Axial Coding /Theme /Business Analytics Dimension Category (C) Abstract Definition/ Description	Open coding / /Category (C)	Abstract Definition/ Description	Sample from interviewed students' transcripts
Computer Science and Information Systems	(C13) Knowledge of various Programming languages	Programming languages play a critical role in software development. With so many options out there, it can be tough to know which one is the best fit for your project.	" *I'm currently registered in Coursera Udemy to improve my programming literacy required for the business analytics program.* "
	(C14)Basic Knowledge of Database	A database is a structured collection of data that can be easily retrieved by a computer program. DBMS is software that helps create, organise, and manipulate databases.	" *I'm challenged with new database topics repeated in lots of modules in Business Analytics.* "
	(C15)Coding familiarity	Coding familiarity is the level of experience and comfort with programming languages.	" *I do not have any database, nor programming experience; my background was civil engineering.* "
	(C16) Knowledge in Software engineering and systems	Software engineering and systems are two communicated fields that play critical roles in developing, continuing, and optimising software applications and the causing infrastructure.	

The table classifies themes and dimensions in business analytics, detailing core categories such as statistics, communication skills, business, and computer science/information systems. Each category is labelled (e.g., C1, C2) and includes an abstract definition or description and quotes from student interviews to illustrate their experiences (Heath & Cowley, 2004). For instance, familiarity with general statistics concepts involves understanding data collection and analysis, while statistical data analysis focuses on methods of interpreting data. Communication skills cover areas like data storytelling and business communication.

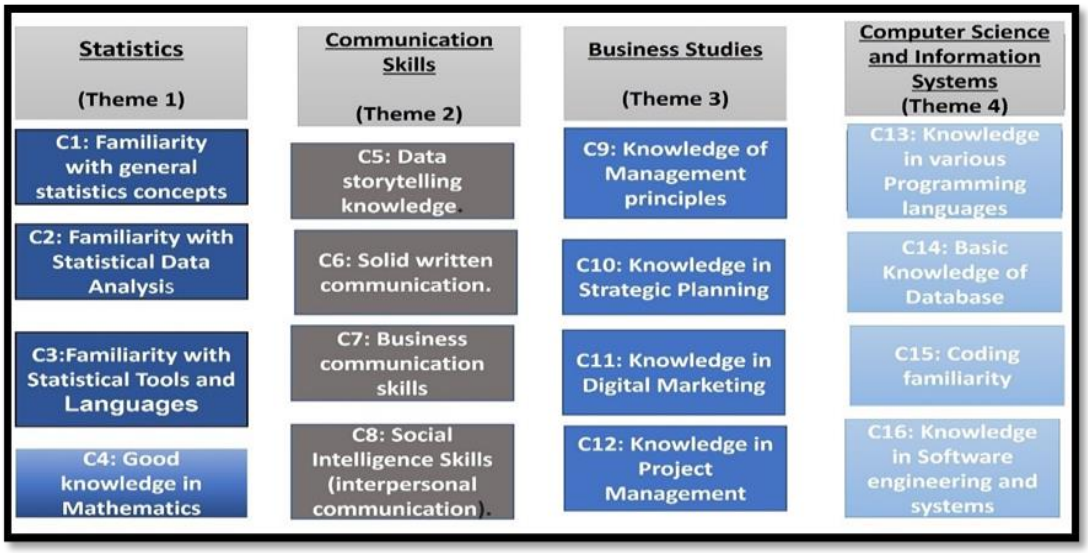

Figure 6: Final qualitative BA extracted categories

Business principles include management and strategic planning knowledge. Computer science skills emphasise familiarity with programming languages and databases. This structured approach highlights the diverse competencies required in business analytics due to the qualitative analysis in GTM.

5.2 Stage 2: Bias Reduction for Qualitative Results

As presented in the proposed model in Figure 3 above , which illustrates the validation process as a mixed methods approach, stage two of the framework implemented the bias reduction phase. A key challenge in the validation process within qualitative research is evaluating the quality of the extracted categories initially, as suggested by Mays and Pope (2000), drawing from a researcher's philosophical angle. In this research, developing a valid theory or set of theories was not the primary goal of the study. Therefore, it was imperative to assess the quality of the required categories as key components used later in extracting the BA conceptualisation categories. An approach suggested by Mays and Pope (2000) in qualitative research enriches coded results by reducing bias that may be present in single-researcher analysis explained in figure 7 below.

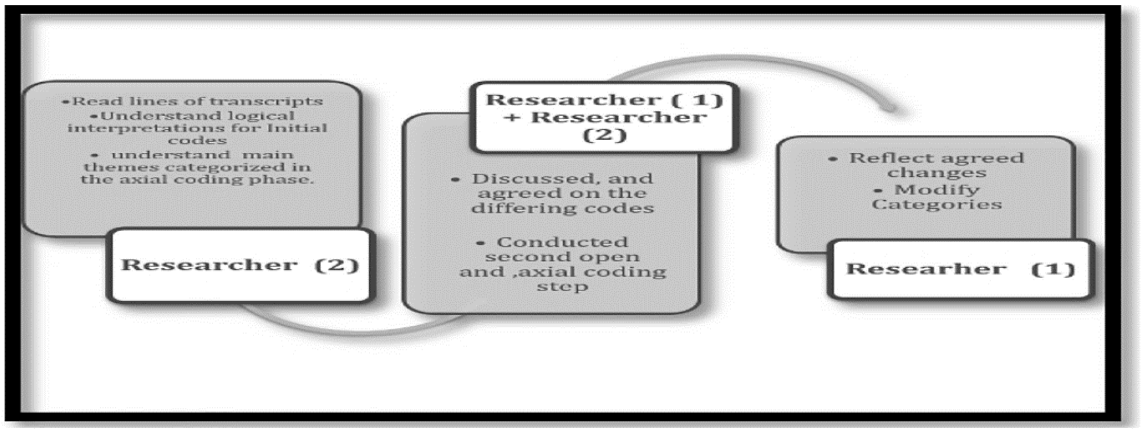

Figure 7: Bias reduction in stage 2 validation GTM categories influenced by (Al-Eisawi,2022)

The coding process began with Researcher 2 analyzing transcript lines to derive initial codes and identify key themes. Both researchers then collaborated to compare interpretations, resolve discrepancies, and conduct a second round of open and axial coding. Finally, Researcher 1 refined the coding structure by reflecting on agreed changes and modifying categories accordingly.

5.3 Stage 3: Validation Using Quantitative Methods

Stage 3 of the validation process aims to empirically assess and evaluate the ground constructs that are required as proficiencies within the BA to be validated as solid qualitative results. As illustrated in the proposed phases of validation, the quantitative part, guided by the proposed framework, the hypothesis proposed that student performance in the BA degree can be influenced by a significant academic series of previous knowledge (York, Gibson and Rankin, 2015); therefore, the capability to output as a sequence of refined knowledge results in improved academic performance and progress. This proposition aims to assess empirically and further interpret the extracted categories to develop four hypotheses (Creswell,2019), which address the potential positive relationship between previous knowledge dimensions associated with a business analytics major and academic success in the business analytics field. The following hypotheses are proposed:

> ***H1****. A positive relationship exists between proficiencies in statistics and academic success in a business analytics major.*
>
> ***H2****: "There is a positive relationship between "proficiencies in communication skills and academic success in business analytics major.*
>
> ***H3****. There is a positive relationship between Business and Management proficiencies and academic success in a business analytics major.*
>
> ***H4.*** *A positive relationship exists between computer science and information systems proficiencies and academic success in a business analytics major.*

The quantitative data for this study were collected through online surveys employing Likert-scale inquiries with students. Quantitative data was first analysed to establish a non-biased response by comparing early responses received with responses received after reminders later. The constructs were defined again as extra validation in

the qualitative phases review subsections indicated in Tables in 2 and 3 below based on the theoretical model presented above.

Table 2: BA qualitatively extracted measures linked to the source

Construct	Indicators	Item	Source/ results from qualitative open coding categories and literature review
Statistics	SK1	Familiarity with general statistics concepts	(Davenport & Harris, 2017)
	SK2	Familiarity with Statistical Data Analysis	(Mitra, Kumar & Sharma, 2021)
	SK3	Familiarity with Statistical Tools and Languages	(Kmetz. & Davis., 2014)
	SK4	Good knowledge in Mathematics	(Wilder & Ozgur, 2015)
Communication skills	CS1	Data storytelling knowledge.	(Mitra, Kumar & Sharma, 2021)
	CS2	Solid written communication Skills	(Wang & Byrd, 2017)
	CS3	Business communication skills	(Wang & Byrd, 2017)
	CS4	Social Intelligence Skills (interpersonal communication).	((Zaring, Gifford & McKelvey, 2011)
Business And Management	BM1	Knowledge in Management principles	(Yin & Fernandez, 2020)
	BM2	Knowledge in Strategy and Planning	(Wang, Han & Yang, 2015)
	BM3	Knowledge in Digital Marketing	(Wang, Han & Yang, 2015)
	BM4	Knowledge in Project Management	(Wang, Han & Yang, 2015)
Computer Science and Information Systems	CSIS1	Knowledge in various Programming languages	(Wilder & Ozgur, 2015)
	CSIS2	Basic Knowledge of Database	(Davenport & Harris, 2017)
	CSIS3	Coding familiarity	(Wilder & Ozgur, 2015)

Table 3: Academic success literature constructs

Construct	Indicators	Items	Source
Academic Success	AS1	Knowledge of BA proficiencies affected my success as a whole GPA	(York, Gibson and Rankin, 2015; Bunce & Hutchinson, 1993)

Construct	Indicators	Items	Source
	AS2	Career Success	(York, Gibson and Rankin, 2015)
	AS3	Acquisition of skills and competencies	(York, Gibson and Rankin, 2015)
	AS4	Attainment of Learning Objectives	(York, Gibson and Rankin, 2015)
	AS5	Persistence	(York, Gibson and Rankin, 2015)
	AS6	Acquisition of skills and proficiencies	(York, Gibson and Rankin, 2015)

After that, data were analysed using PLS-SEM to confirm the validity of the measures and constructs (Harris & Yan, 2018). Moreover, to assess the proposed research hypotheses. Separate universities were engaged in the study, ensuring they offered BA majors in their postgraduate business schools. The decision to engage different universities and students is influenced by the fact that in technology-based majors such as business analytics, big data, and artificial intelligence, many students rely heavily on their previous academic or professional experience that might have been acquired after receiving their first degrees, including various levels of technical understanding. A total of (300) responses were received using online surveys. Moreover, a screening question was enclosed within the sent survey to verify that the students are registered or have already graduated with a postgraduate business analytics degree within the interviewed organisations (Harris & Yan, 2018). The survey included more than three universities for quantitative validation.

6. Results

Quantitative data was uploaded and analysed using Smart PLS for factor analysis to assess constructs and indicator reliability and validity, and for path analysis to test relationships and hypotheses, results in Table 4 in the . The PLS-SEM method is known for its ability to analyse data with small sample sizes. In PLS, a measurement item is called an indicator (Hair, Ringle and Sarstedt, 2013) , and the constructs are called latent variables (Hair et al., 2017). This indicates that the indicators are sufficient and relevant for measuring the latent variable (Hair, Ringle and Sarstedt, 2013). In reflective indicators, the connection path is always from the construct to the indicator (Heath& Cowley, 2004). The measurement model of this study is shown in Figure 8 below.

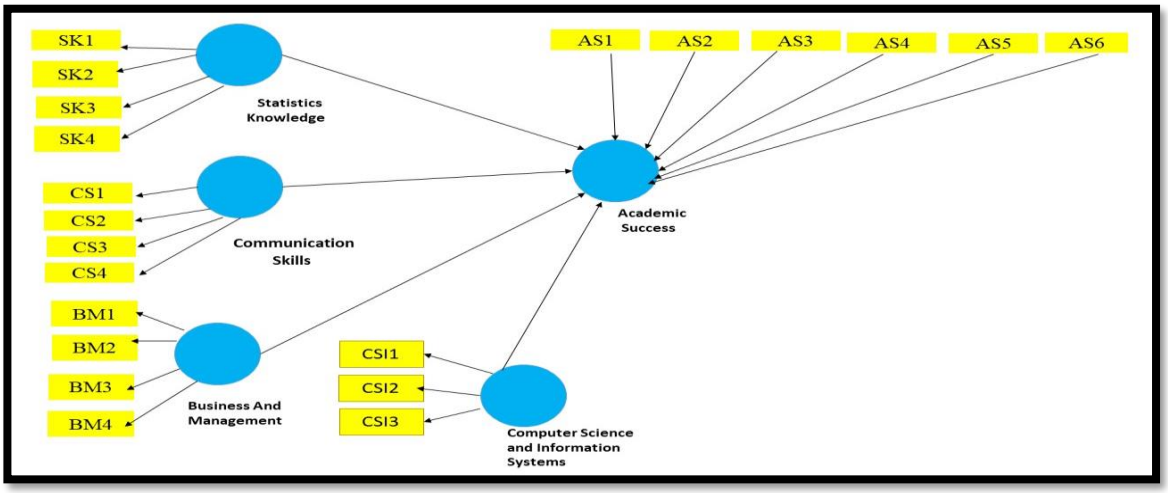

Figure 8: The measurement final model using SamrPls3.0

The analysis reveals a significant impact of computer science, database, and business management indicators on the academic success of BA students transitioning to master's studies. Moreover, the model confirmed that when students academically reach a level of success upon their proficiencies, this can lead to a validation of the qualitative categories extracted earlier, as well as what the hypothesis testing also reveals. In conducting the bootstrap test for PLS-SEM, we examined the significance of path coefficients and evaluated the properties of

the structural model. We used t-statistics to determine the importance of the path coefficients, following the rule proposed by (Hair, Ringle and Sarstedt, 2013) . According to their rule, a t-statistic greater than 1.96 was considered significant for path coefficients at the 95% confidence level (Harris & Yan, 2018). To assess the hypotheses in the research model, the regression weights where examined as shown in Table 4 in below.

Table 4: Hypothesis testing, path coefficient, T values, and P values

Hypothesis	Effect	Coefficient	T-Statistics	Supported /Not 'Supported
H1	Statistics -< BA	0.759	5.1436	Supported
H2	Communication skills -<BA	0.5659	4.0721	Supported
H3	Business and Management -<BA	0.8188	6.4963	Supported
H4	Computer science and information systems -<BA	0.8959	7.8876	Supported

We measured the path coefficients between each pair of constructs to conclude the strength of the relationships in the model. As shown in Table 4 in the above , all hypotheses were supported, and the relationships among the constructs were discovered to be significant. The confirmed model, illustrated in figure 8, confirms the relationships and effects between the constructs and can add validation to the extracted categories as they were applied to the pragmatic effect. The results show that all proposed hypotheses are statistically significant at $p < 0.001$. Computer Science and Information Systems had the strongest effect on Business Analytics ($\beta = 0.896$, $t = 7.89$), followed by Business and Management ($\beta = 0.819$, $t = 6.50$), Statistics ($\beta = 0.759$, $t = 5.14$), and Communication Skills ($\beta = 0.566$, $t = 4.07$). These highly significant results confirm the importance of technical and managerial skills in shaping Business Analytics competence.

7. Conclusion

This research adds to mixed methods by establishing an empirical framework that rigorously validates qualitative results. The study enhances the credibility of mixed-method approaches by providing robust empirical provisions using a systematic three-stage framework. It underlines practical implications, affirming its essential role in addressing complex, real-world issues related to business technology and modern disciplines. By combining Grounded Theory Methodology (GTM) with structural equation modelling, the research presents a comprehensive framework that can be used to explore further and validate the multifaceted nature of BA qualitative categories for novice students in this field.

The findings of this study successfully fulfilled all five research objectives. Grounded Theory Methodology (GTM) was effectively applied to analyse qualitative data from postgraduate students, resulting in the extraction of 16 core categories related to Business Analytics education. A systematic bias reduction phase was then implemented to enhance the credibility of these findings. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), the identified categories were empirically validated, with all hypothesized paths showing highly significant results ($p < 0.001$). These outcomes confirm the structural coherence of the constructs and support the development of a replicable mixed-methods validation framework. Ultimately, the study contributes to the conceptual advancement of Business Analytics as an academic discipline by demonstrating a robust and methodical approach for validating qualitative insights through a mixed sequential exploratory design, thereby enhancing academic discussions on Business Analytics.

As an implication, the study provides a foundation for future research to investigate how these interdisciplinary competencies interact and contribute to academic and professional success in BA. The study's insights, derived from qualitative interviews and quantitative validation, suggest that targeted interventions in these areas can be enhanced. A possible limitation of this study is the extent to which its findings can be generalised across different educational settings or student groups. Given its focus on business methods related to novice students in business analytics, the framework might need adjustments to be effectively applied to learners with varying backgrounds, skill levels, or in other technology-focused disciplines. This could also limit the broader applicability of the results to other institutions or professional environments.

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