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Data Analytics Strategies for Management Accountants in Small and Medium Enterprises

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Walden University
2024

Abstract

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MS, Strayer University, 2018

BS, George Mason University, 2015

Doctoral Study Submitted in Partial Fulfillment

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Abstract

Data analytics has increasingly become vital in maintaining competitive advantage in the contemporary business environment. Small and medium enterprises (SMEs) have been among the top beneficiaries of data-driven decision-making processes; however, management accountant leaders often do not effectively use data analytics strategies for decision-making purposes to maintain a competitive advantage. Grounded in the diffusion of innovation theory and the technology acceptance model, the purpose of this qualitative pragmatic inquiry study was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. The participants were 12 SME management accountants and business leaders with data analytics experience. Data were collected through a review of publicly available documents and semistructured interviews. Thematic analysis resulted in the identification of five key themes: data analytics strategies, data analytics processes, types of data analytics, challenges, and approaches to overcoming these challenges. A key recommendation that emerged from the study is for SME managers to implement data analytics programs, training, and development. The implications for positive social change include the potential for management accountant leaders to improve their financial transparency, which is crucial in boosting investor confidence, stimulating capital investment, fostering local tax base growth, and promoting job creation.

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Dedication

This doctoral study is dedicated to God Almighty for providing me with His wisdom, strength, guidance, patience, mercy, protection, and blessings upon my life and academic achievements. I am so thankful for the courage He bestowed upon me and uplifted my spirit during challenging times, enabling me to go through this journey successfully. This self-accomplishment would not have been possible without His unwavering support.

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I want to express my heartfelt gratitude to my husband and children for their endless support throughout my academic journey of becoming a Doctor of Business Administration in Accounting. Your listening ears when I was practicing my defense presentation meant a lot. To my husband, I appreciate you taking on household duties and bringing me meals at the library, allowing me to focus on my studies. I couldn't have done this without you. To my parents, I am so thankful to you all for instilling in us the passion for education. You both dedicated so much to ensure we received the best schooling possible, often sacrificing your own needs. To my siblings and family, your encouragement and support have meant the world to me. This has been a long journey, and I'm overjoyed to celebrate this successful end with you all.

Secondly, I would like to thank all the participants who took part in the interview process. I appreciate all the time and effort you all dedicated to this study, and I want to extend my sincere gratitude for your priceless contribution to my research on data analytics strategies among SME management accountants in Virginia. Your insights and skills have added significant depth to my understanding and your perspectives certainly improved the quality of my research findings.

Lastly, I would like to thank the Walden University DBA department and the instructors for their guidance throughout my doctoral journey. A special thanks to Dr. Roger Mayer, my committee chair, Dr. James Glenn, my second committee, and the research reviewer team for their great support, guidance, and encouragement through the final stage of completing my study. Without this support system, I would not have accomplished this study successfully.

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Section 1: Foundation of the Study

Data analytics has gained momentum in contemporary society due to its immense contribution to increasing organizations' competitive advantage and driving innovation. Data analytics entails discovering valuable insights from transformed and interpreted massive data volumes when uncovering meaningful insights, patterns, and trends used in making faster and better decisions (Bhattarai et al., 2019; Houtmeyers et al., 2021). Organizations deploy data analytics when integrating data resources in decision-making processes (Rehman et al., 2019; Tavera Romero et al., 2021). The increased incorporation of data analytics in various organizations, especially in decision-making, has made management easier. Bergmann et al. (2020) and Cozzoli et al. (2022) argued that big data and artificial intelligence have contributed to data analytics' significant role in decision-making, leading to a durable competitive advantage and a relative competitive advantage.

Management within organizations gain valuable insights and decision-making skills, which are vital in making informed decisions. According to Côrte-Real et al. (2020), Wang and Wang (2020), and Willetts et al. (2022), organizations use data analytics to identify patterns, trends, and insights that can help in reducing costs, optimizing operations, and creating more effective strategies that can unravel the hidden insights and information required for the decision-making process.

Background of the Problem

Data analytics and small and medium enterprise (SME) performance are integral to the successful engagement of business. The general business problem that prompted me to search the literature was that management accountant leaders often do not effectively use data analytics strategies for decision-making purposes to maintain a competitive advantage.

Despite the clear benefits, barriers persist, including (a) lack of understanding and skills, (b) data quality and availability, (c) technological infrastructure, (d) cultural resistance, and (e) data privacy and security concerns (Hariri et al., 2019). Given the complexity involved in data analytics combined with a rapidly changing technology environment, the dynamic evolution leaves many organizations lacking the necessary skills and understanding to properly utilize it (Wang & Wang, 2020). Data need to be accurate, reliable, and relevant for the analysis to be meaningful. Implementing data analytics strategies can require substantial updates to an organization's technological infrastructure (Côrte-Real et al., 2020). Lack of knowledge can make it difficult to fully leverage data analytics and hinder adoption.

Many organizations have a long history of decision-making based on intuition or tradition, and there can be resistance to changing these practices (Tavera Romero et al., 2021). Cultural resistance can slow the adoption of data analytics. With the use of data analytics comes the responsibility to protect that data (Bergmann et al., 2020). Some organizations may be wary of adopting data analytics due to the potential risks associated with data breaches (Batko & Slezak, 2022). To overcome these barriers, organizations can invest in education and training, improve their data collection and management processes, update their technological infrastructure, and implement policies and procedures to protect data (Jones et al., 2021). With the right strategies and resources, organizations can effectively use data analytics to improve decision-making and maintain a competitive advantage. With this background, the focus shifts to the problem and purpose of this study.

Problem and Purpose

The general business problem was that management accountant leaders often do not effectively use data analytics strategies for decision-making processes to maintain a competitive advantage. The specific business problem was that some SME management accountant leaders in Virginia lacked strategies to use data analytics for decision-making purposes to maintain a competitive advantage. The purpose of this qualitative pragmatic inquiry study was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage.

Population and Sampling

The target population was SME managers in Virginia who have successful experience using data analytics for decision-making purposes. I used purposeful sampling to target 12 management accountants from multiple SME organizations in Virginia. Purposeful sampling utilizes the immediate proximity of qualified participants by accepting their will and availability within the research timelines (Ames et al., 2019). Data collection was through interviews and the collection of publicly available organizational documents for review. Using multiple data sources ensured that I had adequate information for triangulation (see Mtisi, 2022).

Nature of the Study

The qualitative pragmatic inquiry approach was well suited for this study. The approach allowed me to explore strategies, identify key concepts, and organize data rather than examining relationships between variables as in a quantitative method (see Saldaña, 2014; Yin, 2018). The lack of resources, time, and the need for numerical data made me not use the mixed method approach (see Venkatesh et al., 2016). Mixed methods research integrates quantitative and qualitative research techniques into a single study. Researchers use mixed-method studies to gather and analyze quantitative and qualitative data simultaneously or sequentially (Dawadi et al., 2021). The mixed method approach allows for triangulation of findings and can provide a more complete perspective on complex phenomena. Researchers use a mixed method approach when the goal is to combine statistical data with qualitative insights or when different aspects of a research question require different data types. The chosen qualitative method was appropriate for my study because it helped me explore data analytics strategies management accountant leaders use for decision-making purposes to maintain a competitive advantage. Qualitative studies were used when the goal was to generate rich, context-specific insights and explore discrepancies that quantitative methods may overlook.

The chosen qualitative pragmatic inquiry design allowed for an in-depth exploration of a problem within a real-world context. The design included interviews and the collection of publicly available organizational documents for review. A pragmatic inquiry approach involves comprehensively examining multiple methodological principles, including actionable knowledge, experiential process, and the interconnectedness between acting, experience, and knowing. Kelly and Cordeiro (2020) claimed that the pragmatic inquiry approach's methodological principles were crucial in strengthening the research process stage involving data collection, analysis, dissemination, and conclusion. Pragmatic inquiry was particularly useful when the research aims to interrogate the research data's value and meaning by exploring its practical implications. The pragmatic inquiry design was appropriate for my studies as it interrogated the meaning and value of research data on data analytics strategies for decision-making purposes to maintain a competitive advantage. Other designs, including phenomenological or ethnographic designs, are crucial for exploring lived experiences and examining specific cultures (Ataro, 2020; Vanni & Crosby, 2023; Yin, 2018). I did not deploy phenomenological or ethnographic research designs because they were not suitable for my study, considering I was not exploring participants' lived experiences or a particular culture.

Research Question

What data analytics strategies do SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage?

Interview Questions

1. What data analytics strategies do you use in your organization for decision-making purposes to maintain a competitive advantage?
2. What type of data analytics software/tools does your organization use for your cost analysis, and what other tools and data sources are lacking to improve

data?

3. What data analytics process does your organization follow? (i.e. IMPACT cycle -- identify the question, master the data, perform test plan, address and refine the result, communicate insights, track outcomes).
4. What types of data analytics are being used, and when do you use them? (descriptive, diagnostic, predictive, and prescriptive analytics).
5. What are some other data analytics strategies being used? How do you describe the use of these strategies, and what are the reasons for selecting these strategies?
6. What are some of the challenges faced during the implementation of data analytics strategies? How did you overcome these challenges? And how do you measure success?
7. What are the biggest challenges you have faced gaining access to relevant quality data, and how did you and your team effectively resolve them?
8. What other comments do you have in regard to management accountants' use of data analytics for reporting and management support?

Conceptual Framework

The conceptual frameworks that ground this study included the diffusion of innovation theory (DIT) and the technology acceptance model (TAM). DIT, developed by Rogers in 1962, is a framework that explains how information becomes valuable over time and spreads through a specific population or integrated social system (Rogers, 1962). The theory suggests that the adoption of a new idea or item follows a distinct process of the following five stages: knowledge, persuasion, decision-making, implementation, and confirmation.

Researchers use TAM to explain how users decide whether to adopt and use a new technology (Davis, 1985; Rogers, 1962). TAM illustrates that user acceptance of a technology is determined by two key factors: perceived usefulness and ease of use. Researchers use the theory to demonstrate that perceived usefulness is the degree to which a user believes that using a technology will enhance their job performance, while perceived ease of use is the degree to which a user believes that using a technology is free of effort. TAM applies to varied industries, such as healthcare, education, and business, and it is one of the most influential models of user acceptance. The theory was essential because it provides an understanding of how users respond to new technologies and can be used to inform the design of new technologies while improving user acceptance.

The logical connection between the framework and my study was that I explored data analytics strategies in SMEs, and DIT and TAM were valuable frameworks for understanding how organizations adopt and use technology. The theories were relevant to the research topic as they deal with implementing innovation in organizations for better decision-making and overall performance.

Operational Definitions

Big data: Big data refers to vast volumes of structured and unstructured data generated, collected, and processed at a high velocity from various sources (Bergmann et al., 2020; Bose et al., 2023).

Competitive advantage: This refers to the competitive advantage gained by SMEs through effective data analytics strategies that enable them to achieve cost efficiencies, reduce expenses, and deliver products or services at lower costs than competitors (Bose et al., 2023).

Data analytics: Refers to the process of examining, cleaning, transforming, and interpreting large volumes of data to uncover meaningful insights, patterns, and trends using various statistical, mathematical, and computational techniques to analyze data and extract valuable information that can aid in decision-making, problem-solving, and strategic planning (Bhattarai et al., 2019).

Data analytics strategies: For this study, data analytics strategies refer to the specific methodologies, tools, and techniques used by SME management accountant leaders to analyze and interpret data for decision-making related to cost management and maintaining a competitive advantage in the market (Bhattarai et al., 2019).

Decision-making purposes: Decision-making purposes encompass the various areas of business decision-making in which data analytics strategies were employed, such as cost analysis, pricing decisions, budgeting, resource allocation, and identifying cost-saving opportunities (Bhattarai et al., 2019).

Management accounting: Also known as managerial accounting, it is a specialized branch of accounting that focuses on providing financial and nonfinancial information to help internal management make informed decisions, plan and control the organization's operations, and achieve organizational goals efficiently (Andreassen, 2020).

Small and medium-sized enterprises (SMEs): Refers to businesses that fall within a specific size range based on various criteria such as the number of employees, annual turnover, or total assets (Akpan et al., 2021).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are pieces of information that the researcher considers true, even without concrete evidence (Theofanidis & Fountouki, 2019). In this study, various assumptions were made. The initial assumption was that the method to be used in this study would be both valid and reliable to capture management accountant leaders' descriptions of data analytics strategies they use for decision-making purposes to maintain a competitive advantage for SMEs in Virginia. The second assumption pertaining to the sample was whether it adequately represented all management accountant leaders in Virginia and whether all participants thoroughly understood the internal audit methodology and data analytics strategies used. Lastly, the third assumption was that participants were to clearly comprehend and respond truthfully to the questions.

Limitations

Limitations refer to factors or conditions that may restrict the research findings' scope, accuracy, or generalizability (Theofanidis & Fountouki, 2019). In this context, a limitation involves the potential for researcher bias during the analysis of interview responses, influenced by the researcher's knowledge and experience with the subject matter (Yin, 2018). I acknowledge the lack of complete control over the selection of individuals interviewed as participants volunteer to take part. Consequently, the participants may not be experts in the research topic, which could impact the validity of their comments, as they might not fully reflect industry best practices. Another limitation was the rapid change in technology in the business world today, which can impact the value of the study results over time.

Delimitations

Delimitations are the intentional boundaries or parameters set by researchers to narrow the focus of the study (Theofanidis & Fountouki, 2019). Delimitations in this research could involve specifying the geographic scope to only include SME management accountant leaders in Virginia, excluding other regions. Additionally, the study might focus specifically on data analytics strategies related to competitive advantage while excluding other decision-making factors. Another delimitation was limiting the study to SME management accountant leaders in Virginia, excluding leaders from other regions or different business sectors. Concentrating on data analytics strategies related to maintaining a competitive advantage, excluding other decision-making purposes or strategies, was another delimitation factor for this study. Focusing on specific data analytics tools, techniques, or approaches used by SME management accountant leaders rather than exploring all aspects of data analytics also demits this study. Delimitations help researchers define their study's scope and relevance and clarify what was within and outside the study's boundaries.

Significance of the Study

The particular challenge in the business lies in the inadequate utilization of data analytics strategies by management accountant leaders for decision-making purposes to maintain a competitive advantage. This qualitative pragmatic inquiry study aimed to investigate the data analytics strategies employed by SME management accountant leaders in Virginia for decision-making purposes to sustain a competitive advantage.

Contribution to Business Practice

The outcomes of this qualitative pragmatic inquiry study could offer valuable insights for business practice by providing effective data analytics strategies that help in improving competitive advantage by reducing costs and enhancing fraud detection efficiency. Auditors play a critical role in assuring stakeholders that controls were effective and that financial reporting was accurate (Wang & Wang, 2020; Willetts et al., 2022). The integration of business intelligence, big data, and data analytics presents challenges (Church et al., 2022). Real-time analytic information was essential for managers to identify activities that may impact resources, such as cost, revenue, and risk (Côrte-Real et al., 2020). Early detection of inconsistencies improves audit efficiency and decreases review costs, directly impacting operational expenses (Hallikainen et al., 2020). Lower operational costs contribute to increased profitability for SME businesses.

Implications for Social Change

The findings from this qualitative study may have positive implications for social change as business leaders can employ these strategies to bolster confidence in financial statements. Higher-quality audits at lower costs lead to improved trust in financial reporting backed by data analytics. Increased confidence in financial statements can result in greater leverage, which, in turn, opens up new business opportunities and enhances employment prospects. Additionally, great confidence in financial statements may attract more investors to the company, stimulating increased capital spending, job creation, and local tax base growth. Overall, these positive social changes can have a broader impact on the business community and society at large.

A Review of the Professional and Academic Literature

The rapidly changing and dynamic contemporary landscape has prompted the development of multiple technologies and increased availability, thus making data analytics paramount in organizations' decision-making processes. A literature review on the role of data analytics in organizations promotes increased competitive advantage and helps in understanding data analytics’ nuances. Reviewing existing literature comprehensively allowed me as a researcher to examine emerging methodologies and practices that can help in making informed decisions. The review was also crucial in identifying existing gaps in the current knowledge regarding data analytics and its influence on an organization’s decision-making processes. The gaps provide guidance concerning future innovations and directions when integrating data analytics into an organization’s decision-making processes. In addition, the review was helpful in understanding data analytics’ ethical considerations and challenges in organizational dynamics. The literature review section includes various models like DIT, TAM, and alternate theories; data analysis for management accountants; SMEs in the U.S. economy;

challenges SMEs face requiring data analytics for competitive advantage; challenges associated with implementing data analytics in SMEs; and data analytics strategies.

Data Analytics

Data analytics plays a crucial role in various organizational systems. Management is among the organizational systems in which data analytics has been beneficial. Data usage and advanced data analytics in control systems is an important development in management accounting (Franke & Hiebl, 2022; Moll & Yigitbasioglu, 2019). Although the advanced analytics perceived impacts on management accounting are unclear, big data and advanced analytics are revolutionary practices whose influence on an organization’s performance and management are apparent (Akpan et al., 2021; Bhattarai et al., 2019; Church et al., 2022; Hariri et al., 2019). Ferraris et al. (2019) reiterated that this development could transform management accounting by ending static accounting. The emergence of data analytics has revolutionized various organizational systems, especially management, where it has taken over the decision-making role. Hence, it was apparent that an organization’s competitive advantage and innovation would increase significantly through data analytics. Rapid technological changes create significant turbulence in data analytics and how organizations implement their activities.

Technology and Data Analytics

While some researchers have labeled data analytics as a disruptive technology, some have associated the technology with improved accounting management. Bag et al. (2020) noted that though disruptive, using big data and analytical tools for automation improved some accounting processes. As a disruptive technology, the adoption of data analytics could result in poor decision-making as people in management could make rushed decisions without detailed consultation (Daniel, 2019). Further wrong decision-making based on data analytics could jeopardize management accounts and increase the risks faced by the firm. Agreeing with Daniel (2019), Jones et al. (2021) reported that no evidence had been presented regarding predictive analytics' impacts on companies' efficiency, business insights, and accuracy. Chan et al. (2019) compared advanced data analytics to the arrival of information systems such as enterprise resource planning (ERP). Based on the above, it is unclear how data analytics could improve a firm's accounting and finance functions.

Business Forecasting and Data Analytics

Numerous studies have explored the potential impacts of data analytics in business forecasting. Scholars have argued that besides data analytics’ role in management, it is also crucial in business forecasting and other accounting practices and functions, although researchers should consider conducting extensive research on the issue to determine the influence of data analytics on organizations (Dubey et al., 2019; Hamilton & Sodeman, 2020; Mikalef et al., 2019; Schnegg & Möller, 2022). The existing research does not provide adequate information on the impacts of data analytics on management accounting practices and functions hence researchers still need to investigate the impacts. Moller et al. (2020) also established that the management of firms has yet to prioritize the digitization of accounting and financial actions, citing the limited instances where data analytics has been applied successfully. For many companies, adopting and implementing data analytics is an ongoing process (Tabesh et al., 2019). Organizations face challenges in determining the extent of influence data analytics has on their systems. Given the gap in research regarding data analytics, this study sought to address this gap by focusing on the application of data analytics in accounting functions.

Given the complexity associated with data analytics and the rapidly evolving technological landscape, many organizations have encountered difficulties in integrating data analytics into their systems. Hariri et al. (2019) argued that a lack of necessary expertise and comprehension has made it difficult for organizations to effectively harness data analytics potential. This knowledge gap can impede the full utilization of data analytics and hinder its adoption. The specific business problem was that management accountant leaders often do not effectively use data analytics strategies for decision-making purposes to maintain a competitive advantage. The purpose of this qualitative multiple case study was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage.

To research literature regarding this topic, I read peer-reviewed and nonpeer-reviewed journal articles, publications of government agencies, and academic books. The keywords and databases searched included *big data, data analytics, accounting data analytics, cost management, certified management accountants, chief management accountants, SMEs,* and *accounting strategies/techniques*. Databases included ABI/Inform, Science Direct, ProQuest, Scopus, Emerald, and Google Scholar.

My literature review includes a review of literature related to (a) DIT and TAM (b) alternative theories, (c) introduction to data analytics, (d) types of data analytics, (e) a step-by-step guide to data analytics processes, (f) the importance of data analytics for management accountants, (g) the importance of SMEs to the U.S. economy, (h) challenges SMEs face requiring data analytics for competitive advantage, (i) challenges of implementing data analytics in SMEs, and (j) data analytics strategies.

DIT

The DIT was a theoretical framework that can be relevant when exploring data analytics strategies used by SME management accountant leaders in Virginia for decision-making purposes to maintain a competitive advantage. The DIT proposed by Rogers (1962) focused on how new ideas, technologies, or innovations spread and were adopted within a social system. In the context of data analytics strategies for decision-making, DIT can help understand how these innovative approaches were adopted and integrated into the practices of SME management accountant leaders. DIT provides key performance indicators (KPIs) to measure the rate of adoption and the factors influencing that serve as barriers and facilitators (Takahashi et al., 2024). The theory categorizes adopters into different segments based on their willingness to embrace innovations, ranging from early adopters to laggards (Rogers, 1962). Understanding which factors facilitate or hinder the adoption of data analytics strategies can provide insights into the successful implementation of such practices to maintain a competitive advantage.

Four Main Elements in the DIT

Adoption. While an idea, project, or practice might have been invented a while ago, if an individual perceives it as new, it is an innovation. According to García-Avilés (2020), DIT considers innovation as a practice, project, or idea that is new and has been adopted recently. To qualify as an innovation, the idea, project, or practice must fulfill all three steps of the innovation-decision process: knowledge, persuasion, and decision. A detailed discussion of the innovation-decision process will be discussed later in this section. In technology clusters, there are concerns that there was a significant lack of literature on diffusion (Rogers, 2002). Rogers (2002) defined a technology cluster as a concentration of technological elements that, despite being different from each other, their functions were closely related.

Adoption of innovation was hindered by uncertainty. The perceived consequences of innovation may result in the observed uncertainties. Rogers (2002) stated that the changes that occur in a social system or to an individual because of rejecting or accepting an innovation define consequences. The uncertainties associated with an innovation might be reduced by ensuring everyone was informed of the consequences, including the drawbacks and benefits of adopting an innovation. The consequences of adopting an innovation can be desirable or undesirable (functional or dysfunctional). The consequences can also be anticipated versus unanticipated (recognized and intended or not) and direct versus indirect (immediate result or result of the immediate result).

Communication Channels. Communication channels are the second element of diffusion. Communication is creating and sharing information between people to achieve a shared understanding (Takahashi et al., 2024). Reaching a mutual understanding through communication occurs through various communication channels between sources. An institution or an individual where the message originates is known as the source, and a channel was the means through which a message or information gets to the receiver from the source (Rogers, 2002). Diffusion incorporates a communication channel, a receiver, the source or other adoption units, and an innovation (Takahashi et al., 2024). The two communication channels used in diffusion are interpersonal communication and mass media. Examples of interpersonal channels include communication between two or more people. The communication channels in mass media are newspapers, radio, and television.

In addition to including all the mentioned elements, the interpersonal relationships between communicating individuals make it a highly social process (Takahashi et al., 2024). Given the strength of interpersonal relationships, people can create or change their attitudes using interpersonal communication channels. Moreover, interpersonal communication channels may be characterized by homophily. As a characteristic of communication, homophily is how closely communicating parties share socioeconomic status, education, and beliefs. The DIT framework was based on the precepts of heterophily, where two or more people in a communication channel have different characteristics. The nature of the DIT among participants contributes to some of the observed challenges.

The communication channels can also be international and local, which aids communication between external sources and people within the social system. All mass media channels are worldwide, while interpersonal communication channels can be worldwide or local. Because of their unique characteristics, mass media and cosmopolitan channels are common at the knowledge stage of the innovation-decision process. Rogers (2002) noted that the persuasion stage of the innovation-decision process is better suited to interpersonal and local communication channels.

Time. Behavioral researchers ignore the aspect of time. The time dimension in diffusion research illustrates its significance in understanding the innovation-decision process (Takahashi et al., 2024). Rogers (2002) explained that the dimension of time is included in the innovation-decision process and the rate of adoptions and adopter categorization.

Social System. The last element of the diffusion process is the social system. A social system refers to a set of units with shared characteristics that collaborate to achieve a common objective (Rogers, 2002). Social structures influence the DIT because the process happens in the social system. A structure is how the units in the system are arranged. Rogers (2002) asserted that the social system's nature influences an individual's innovative capabilities. Individual innovativeness is the main criterion for categorizing adopters.

Innovation Decision Process

The innovation-decision process refers to seeking and processing information to reduce the uncertainties associated with the pros and cons of adopting an innovation (Rogers, 2002). The innovation-decision process involves five steps: knowledge, persuasion, decision, implementation, and confirmation. The steps follow each other back-to-back in a timely ordered fashion, starting with knowledge as the first stage.

Knowledge. As the first stage of the innovation-decision process, the knowledge stage is where people obtain crucial information and develop an understanding of the existing innovation. The individuals use this stage to respond to the “What?” “How?” and “Why?” questions about innovation and why it should be adopted (Rogers, 2002). The what, how, and why questions form the basis of the three types of knowledge explored in the innovation-decision process: awareness-knowledge, how-to-knowledge, and principles of knowledge.

How-to-knowledge is the second type of knowledge in the first stage and is associated with information on how an innovation can be adopted and used appropriately. Rogers (2002) explained that faculties experience significant challenges using an innovation if they lack the technical knowledge of that particular technology. Takahashi et al. (2024) reiterated that innovation may be underused and its objectives may be underachieved as additional help will be needed to ensure the technology was accurately used in training students. How-to-knowledge is critical in the innovation-decision process as the levels inform the chances of an innovation adopting technical knowledge and experiences with the technology. The how-to-knowledge is crucial when seeking to adopt and use innovations that seem complex.

The principles-knowledge is the third type of knowledge and compounds the innovation's principles of how and why. Seemann (2003) asserted that while an innovation may be adopted without the principles of knowledge, its misuse may result in it being dropped. The faculty's lack of vision explaining why and how the innovation will be adopted and integrated into the student's academic curriculum is a significant barrier to using technology in teaching. Seemann noted that the successful adoption of technology in the classroom is aided by knowledge of why and experience knowledge regarding a particular technology. Arguably, individuals might be theoretically knowledgeable about the innovation but fail to adopt the innovation. Rogers (2002) explained that knowledge is not enough to adopt an innovation as the choice is influenced by the users' attitude, which may either strongly advocate for or against the innovation.

Persuasion. The persuasion stage is the second stage of the innovation-decision process and occurs when there was a negative and positive attitude towards an innovation. Rogers (2002) asserted that a positive or negative attitude toward innovation is not enough to influence a rejection or adoption of innovation directly or indirectly. A person's attitude is informed as they learn and experience innovation and informs the need for persuasion. In this stage, the individual is centered on understanding the innovation and how they feel about it (Takahashi et al., 2024). The individual involvement at the persuasion stage is more intimate and sensitive.

The opinions and beliefs that people have about a particular innovation and the influence of peers and colleagues inform their uncertainties about a particular innovation. An individual will likely adopt an innovation if their close peers positively evaluate it. Positive subjective evaluations reduce the uncertainties about an innovation aiding its adoption. Sherry (1997) explained that while information about a particular innovation is readily available from scientific evaluations and experts, information from trusted colleagues and friends will determine whether a teacher will use a particular technology in the classroom. The persuasion stage allows individuals to continuously look for information about the innovation before making any innovation decisions in the next step.

Decision. The decision stage is the third stage of the innovation-decision process, when an individual either chooses to accept or reject an innovation. Rogers (2002) noted that at this stage, people may fully accept and integrate innovation into their daily activities or reject it in totality and not include it. An innovation is likely to be adopted if it is in the trial phase, as people will tend to experience the innovation before deciding whether to adopt or reject the innovation. Adopting an innovation may be enhanced by allowing individuals a vicarious trial. Despite the vicarious trials, the innovation may still be rejected. The innovation may phase active or passive rejection. Rogers explained active rejection as when an individual tries an innovation but rejects it at the end of the trial phase.

On the other hand, passive rejection was when an individual does not consider or even consider adopting an innovation. Rogers (2002) asserted that in passive rejection, the individual is aware of the innovation but does not even attempt to try using the innovation as in active rejection. Although the two forms of rejection exist, their empirical evidence in existing diffusion research is minimal. The stage knowledge-persuasion-decision may be knowledge-decision persuasion, especially in collectivistic cultures. The order, knowledge-decision-persuasion, transforms individual decisions into a collective decision regarding adopting a particular innovation (Takahashi et al., 2024). After deciding to adopt the innovation, the process moves to the implementation stage.

Implementation. The implementation stage follows the decision stage of the innovation-decision process. After deciding to adopt the innovation, individuals must address the uncertainties associated with innovation diffusion (García-Avilés, 2020). Despite having decided to adopt an innovation, uncertainties can still influence the implementation of innovation. To address issues with innovation uncertainty, an individual will need technical assistance from change agents. Rogers (2002) noted that the unique quality of an innovation gradually disappears even as a separate new idea emerges.

The implementation stage is also characterized by reinvention of innovation. Rogers (2002) defined reinvention as a process whereby users of an innovation modify or change it during the implementation phase after adoption. Invention and innovation are interpreted differently in the implementation stage. Innovation is the process of adopting and using a new idea. At the same time, invention is creating or discovering a new idea, project, or practice (Rogers, 2002). An innovation's rapid adoption and institutionalization are achieved via repeated product reinvention. For example, computers are innovations with many applications and opportunities that can be exploited for reinvention.

Confirmation. The last stage of the innovation-decision process is the confirmation stage. At the confirmation stage, individuals seek support for their decision to adopt and implement innovation. Rogers (2002) noted that an individual may reverse the decision to adopt and implement an innovation if there are conflicting reports. Although this is the case, individuals will seek information that backs their decision to adopt a given innovation. Thus, in the confirmation stage, an individual's attitude is crucial. At this stage, the researcher may either reject or continue using technology based on their attitude and support for the innovation from other people.

An individual may discontinue the use of an innovation for one of the following two reasons: the first rejection is replacement discontinuance, where an individual replaces an innovation with an innovation, they deem to be better for the intended role. The second type of discontinuance is disenchantment discontinuance, where an innovation is rejected because of unsatisfactory performance. Disenchantment discontinuance may also be because the needs of the individual will not be met using the innovation. An individual may reject an innovation if its relative advantage is not achieved. Thus far, an innovation's adoption and use rates are influenced by whether the innovation meets the individual's needs and provides its relative advantage.

TAM

The TAM, developed by Davis (1985), focuses on explaining users' acceptance and usage of technology. The TAM identifies two key factors that influence technology adoption: perceived usefulness and perceived ease of use (Davis, 1985). In the context of data analytics strategies for decision-making, TAM can help determine the extent to which SME management accountant leaders perceive data analytics as useful and easy to use for their cost-advantage objectives.

The TAM was a three-stage process to assess whether an individual will adopt or reject a technology. In TAM, the cognitive responses of an individual (perceived usefulness and perceived ease of use) are triggered by external factors that inform their affective responses or attitude and intention towards using a particular technology (Davis, 1989, 1993). Users' behavioral intentions predict user behavior, perceived usefulness, and perceived ease of use. Davis (1989) asserted that perceived usefulness and ease of use assume that positive behavioral outcomes require less labor. Attitude toward behavior can be used in place of behavioral intention to evaluate the potential consequences of a behavior (Ajzen, 2011; Davis, 1993).

A behavior is likely to occur if the affective response is higher. Perceived usefulness can impact the actual use of a technology directly. Perceived usefulness is an essential variable in predicting user behavior. Davis (1993) asserted that despite perceived ease of use not affecting user behavior directly, it influences the impacts of perceived usefulness. With the TAM, it is assumed that an application will be considered for use by the user if it was easy to use. Davis asserted that application should be based on the user's significance and ease. Thus, an application will be adopted based on its ease of use and significance to the user.

There is a consensus that the development of the TAM and its use as a technology measure make significant theoretical and practical contributions to the field. In one application, TAM was used to test the usability of was given the lack of validated subjective measures, as well as evaluate what motivated users to adopt and use different technologies (Ajzen, 2011). The cognitive and affective factors that mediate and characterize technology acceptance have been well understood using constructs that strongly correlate with user behavior (Davis, 1989). Users are driven by distinct factors during technology adoption, and they could be affective or cognitive factors as long as they foster technology acceptance. The choice of the factors varies from one user to another.

By applying TAM, researchers can assess the perceived benefits of data analytics in aiding decision-making for cost optimization. TAM can also help identify any barriers or challenges that management accountant leaders may encounter when using data analytics tools and techniques. Understanding these factors can guide efforts to improve the adoption and usage of data analytics strategies among SME management accountant leaders. Overall, both DIT and TAM provide valuable theoretical lenses for exploring how data analytics strategies were embraced and utilized by SME management accountant leaders in Virginia. By leveraging these frameworks, researchers can gain insights into the factors that influence adoption and acceptance, ultimately aiding in the effective implementation of data analytics to maintain a competitive advantage in the competitive business landscape.

Alternative Theories

Resource-Based View

The resource-based view (RBV) is a theoretical framework used by researchers to emphasize the importance of an organization's unique resources and capabilities in gaining and sustaining competitive advantage. When investigating data analytics strategies for management accountants in SMEs, the RBV provides valuable insights into how the organization's data analytics capabilities can contribute to achieving and maintaining a competitive advantage.

How organizations achieve sustainable competitive advantage can be explained using resource-based theory. Researchers use RBV to describe and understand how organizations have analyzed and used available resources. Barney (1986) concurred with Hamel and Prahalad’s (1996) focus on the attributes of a firm that were hard to imitate and provide a competitive advantage and improved performance. Competitors were less likely to imitate resources that were not easy to purchase or transfer. To learn or use these resources, organizations were more likely to change their culture or environment besides extending their learning curve to master using them. Conner (1991) asserted that unique capabilities and inputs informed the differences in performance between competing firms. Organizations choose different inputs and capabilities that determine their performances.

Origin of RBV. The specific reasons why firms may either succeed or fail in the marketplace were well explained by RBV (Dickson, 1996). On firm success, Barney (1986) asserted that resources that were hard to imitate, not easy to substitute, and valuable helped firms achieve a superior competitive advantage. Researchers studying RBV reported that organizations could be categorized as either a collection of humans, physical, or organizational resources (Barney, 1986; D’Oria et al., 2021). An organization’s sustainable competitive advantage for improved performance is derived from valuable organizational resources that are hard to imitate and substitute (Barney, 1986). To be regarded as providing a competitive advantage and enhancing sustainable performance, a resource must meet the VRIN criteria:

1. Valuable (V): Resources are considered valuable if the firm recognizes their strategic value. The value of resources is measured by reduced market competition and increased market opportunities. Organizations will be less likely to harbor resources without strategic value to their performance.
2. Rare (R): Among existing competitors, resources used by a firm must be challenging to find. The resources used by a firm to achieve a competitive advantage must be unique and rare. Many businesses in the market lack a competitive advantage because the resources in their possession are not unique and cannot be executed to outperform competitors in the market.
3. Imperfect imitability (I): This criterion means a resource used by a firm can be copied and imitated by competitors. Imperfect imitability can be mitigated using resources that were difficult to acquire and a complex and unclear relationship between competitive advantage and capability. Firms can achieve and sustain competitive advantage if they acquire resources that were difficult to imitate.
4. Nonsubstitutability (N): The nonsubstitutability criterion is when a firm's resources have no alternative or substitute. Nonsubstitutable resources ensure sustained competitive advantage as substitutes cannot generate the same quality performance as the original resource.

The RBV emphasizes that valuable resources help the firm reduce operational costs and achieve high sales, high margins, and increased financial value at reduced costs (Barney, 1986). Valuable resources allow organizations to design and implement strategies to improve their operational effectiveness and efficiency (Barney, 1986). In addition to stressing the significance of valuable resources, RBV enhances managers' understanding of the value of assets in improving firm performance and the importance of competence as a crucial organizational asset. Firm managers also use RBV to improve organizational success through organizational competencies, culture, and past experiences (Hamel & Prahalad, 1996). The firm managers nurture particular cultures and competencies which they believe would contribute to the organization’s success.

The RBV defines resources as information, characteristics, assets, knowledge, and organizational processes that organizations control and use to implement their strategies and achieve market sustainability (Barney, 1986). Technological abilities, brand names, and efficient procedures were some examples of resources owned by a firm (Spanos & Lioukas, 2001). In addition to the mentioned definition, other researchers have categorized resources as tangible or intangible (Hall, 1993; Itami & Roehl, 1991). Researchers have grouped resources based on the value they have on a firm and whether the resources enable firms to achieve objectives (D’Oria et al., 2021; Wade & Hulland, 2004). The organizations choose which resources to prioritize when working to achieve their ultimate goals.

The value of a firm's resources can be expressed in two ways. The first way is whether the resources reduce the firm's operational costs (low-cost resources). The second way is whether the resource increases the value of a firm, also known as differentiated resources. Based on whether the resources are low-cost or differentiated, firms can use valuable resources to improve efficiency and effectiveness, reduce operational costs, and improve customer satisfaction (Barney, 1986; Thomas & Bogner, 1994). Based on the preceding discussion, a resource will only be considered valuable if it improves the performance of an organization relative to that of competitors. A sustainable competitive advantage is achieved if a resource meets all of the mentioned conditions and improves the organization's efficiency and effectiveness, reduces operational costs, and improves customer satisfaction. A resource is not valuable if it will not help the organization achieve a sustainable competitive advantage.

The value and distribution of resources, according to RBV theory, are based on availability. Market competition is equivalent if the resource is readily available to all competitors. If the resources are rarely available and only heterogeneously distributed, the resource becomes a source of competitive advantage. As a result, firms with heterogeneous resources enjoy resource-based advantages and maintain a sustainable competitive advantage over firms that experience resource-based disadvantages (Laser, 2021). The heterogeneity of the available resources demonstrates the different capabilities of firms. Orishede (2021) explained that compared to firms with superior resources, firms with marginal resources can only record marginal performance, while the former were expected to record improved value in assets and finances. The differences experienced in the distribution of resources between firms may be due to decisions made by the organization's management, the time when the organization joins the competitive market, different products and learning systems, and knowledge variability (Helfat & Maritan, 2023). The organizations examine the market before deciding on how they would distribute the resources to ensure they maintain their competitive advantage in the market. Each organization allocates resources in its different sectors depending with their performances to ensure they remain at the top.

In addition to improving firm performance regarding customer satisfaction efficiency and resource heterogeneity, resources provide firms with varied competitive advantages. The degree of competitive advantage a firm gain through its resources was best described by the inimitability and mobility of the said resources. Dagnino et al. (2021) reported that highly mobile resources were sources of temporary competitive advantage to firms. The researchers explained that with mobile resources, any firm could acquire the resource and gain a competitive advantage for the time the resource was in its possession. As the resources move, the chance of a firm losing its competitive advantage was high. Resources may also result in a superior competitive advantage. Laser (2021) asserted that in firms with strategic assets and resource-based assets that enjoyed heterogeneity of existing resources, their competitive advantage was enhanced and sustainable.

The RBV pioneers encourage researchers to identify the specific data analytics capabilities that set SMEs apart from their competitors. Investigating the types of data analytics tools, techniques, and skills that management accountants possess in SMEs can help uncover unique resources that contribute to competitive advantage (Church et al., 2022). The RBV suggests that a sustainable competitive advantage can be achieved when an organization's resources and capabilities were valuable, rare, difficult to imitate, and nonsubstitutable (VRIN; Cuthbertson & Furseth, 2022). Maintaining a competitive advantage depends on the value and uniqueness of the selected resources. Organizations focus on choosing unique and valuable resources that supersede those chosen by other organizations to gain a competitive advantage.

Six Sigma

Six Sigma was another alternative theory that was used for this study. Six Sigma is a set of tools and methodologies used to advance business processes by reducing errors and defects, reducing variation, and increasing efficiency and quality. The goal of Six Sigma is to achieve a level of quality that is nearly perfect, with only 3.4 defects per million opportunities. Six Sigma is a statistically driven model used in businesses to enhance quality by determining the source and number of errors in a process and methodically eradicating them (Niñerola et al., 2020). Bill Smith, an engineer at Motorola, introduced Six Sigma in 1984 to minimize inconsistencies in Motorola's electronic production processes which led to faults in products. From that point, the tactics, instruments, and organizational values that formulate Six Sigma have evolved to include Lean principles and Total Quality Management across a multitude of sectors to bolster operational performance. Over time, the term "defect" was expanded to encompass any shortcoming in business operations that hinders a firm from fulfilling its customer requirements.

The phrase Six Sigma is a statistical term defined as a result that is six standard deviations from the mean result (Niñerola et al., 2020). In the 1920s, Walter

Shewhart, a pioneer in statistical process control, suggested that a deviation of three sigma from the average in lean manufacturing signifies an excessive defect rate, necessitating process refinement (Niñerola et al., 2020). Before Six Sigma, a three-sigma standard was the norm until Bill Smith suggested a deeper data analysis approach, setting Six Sigma as the threshold for process adjustment. Aiming for zero defects was virtually unattainable, a notion termed infinity sigma. Hence, Six Sigma protocols permit only 3.4 defects per million opportunities chances for a fault, whereas Three Sigma permits 66,807 defects for the same number of opportunities (Niñerola et al., 2020). With appropriate data sets, firms adopting Six Sigma techniques employ statistical methods to establish a foundational sigma. The foundational sigma depicts the proximity or disparity from the six-sigma goal and acts as a benchmark for gauging future advancements.

Data Analysis for Management Accountants

Introduction to Data Analytics

Data analytics is a complex set of processes that requires in-depth understanding. Data analytics involves the process of examining, interpreting, and transforming large sets of data to uncover valuable insights, patterns, trends, correlations, and meaningful information (Nguyen et al., 2022). Data analytics involves using various techniques, tools, and algorithms to analyze data, gain a deeper understanding of it, and make data-driven decisions (Sarker, 2021). Data analytics are applied across different domains and industries to solve complex problems, optimize processes, and improve overall performance (Baig et al., 2019). According to Côrte-Real et al. (2020), data analytics plays a crucial role in converting raw data into actionable knowledge, empowering organizations to make informed choices and drive strategic initiatives. In my view, data analytics facilitates the conversion of raw data into actionable events that can aid organizational businesses. Data analytics has several components.

Data collection, data preprocessing and cleaning, data exploration and visualization, data analysis, insight generation, and decision-making and action are the basic components of data analytics. The first one is data collection, which refers to the process of gathering relevant data from multiple sources, which can be structured data (organized in databases or spreadsheets) or unstructured data (text, images, audio, video, etc.; Villanueva & Chen, 2019). The next component is data cleaning and preprocessing, whereby raw data may contain errors, missing values, and inconsistencies. Data cleaning involves removing or correcting these issues to ensure data accuracy and reliability (Ridzuan & Zainon, 2019). Preprocessing involves transforming and standardizing the data to make it suitable for analysis (Baig et al., 2019). The third component is data exploration and visualization, where analysts explore the data using visualizations and statistical techniques to understand its characteristics, distributions, and relationships. Data visualization helps present complex information more understandably and insightfully (Villanueva & Chen, 2019). The fourth component is data analysis, whereby data analysis techniques, such as descriptive statistics, inferential statistics, machine learning, and artificial intelligence, are applied to extract valuable insights from the data (Côrte-Real et al., 2020). This analysis can range from simple summary statistics to sophisticated predictive and prescriptive models.

The fifth component is insight generation whereby the data analysis phase generates insights and patterns, helping answer specific questions or solve particular problems (Villanueva & Chen, 2019). These insights may reveal opportunities, identify inefficiencies, or provide guidance for decision-making. The last component of the phase is the decision-making and action (Côrte-Real et al., 2020). This is where organizations can make more informed and data-driven decisions based on the insights gained from data analytics. These decisions can range from strategic planning to operational improvements, marketing strategies, risk assessments, and more (Ridzuan & Zainon, 2019). Overall, data analytics is widely used in various fields, including business, finance, marketing, healthcare, manufacturing, logistics, and more (Baig et al., 2019). Data analytics empowers organizations to gain a competitive edge, optimize operations, improve customer experiences, and drive innovation.

Types of Data Analytics

The common types of data analytics include descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Descriptive analytics is the first stage of looking at historical data to gain insights into prior performance. Ge (2018) focused on effectively condensing and presenting material; for instance, creating reports and dashboards to display KPIs or trends in sales, production, or consumer behavior may be part of descriptive analytics. Diagnostic analytics sifts through data more deeply to determine the reasons behind previous results or trends. The process of diagnostic analytics aids in addressing the "why" issues raised by the patterns that have been noticed (Hung et al., 2020). For instance, diagnostic analytics can entail performing a root cause analysis to determine why sales of a specific product decreased. Predictive analytics forecasts future patterns or outcomes using statistical algorithms and historical data. The method entails creating prediction models that can be applied to decision-making. Predictive analytics can be used, for example, to forecast future sales trends or customer turnover (Rehman et al., 2019). Prescriptive analytics goes beyond forecasting to suggest particular actions that should be performed to optimize results. Managers and researchers use the method of prescriptive analytis to make recommendations for tactics or actions to take to get the intended effects.

Data Analytics Processes

Business Case Evaluation. Analyzing the business case is the first stage in every data analytics endeavor. This first stange entails identifying a business opportunity or issue that data analytics can solve. Data analysts and business stakeholders must work together throughout this step to identify the goals and determine the potential value of data-driven insights. During this phase, organizations consider variables including return on investment (ROI), resource allocation, and strategic alignment with corporate objectives (Bharadiya, 2023). This step results from a clear problem statement that serves as the framework for the entire data analytics project.

Data Identification. The process of finding and cataloging pertinent data sources that can be used to meet the business case was known as data identification. This step necessitates a deep comprehension of the firm's data ecosystem, which includes both internal and external data sources. Data may come from external providers, databases, spreadsheets, logs, or APIs (Hung et al., 2020). Effective data identification ensures that the required data was available for analysis and helps with acquisition decisions.

Data Acquisition and Filtering. Data acquisition is gathering or extracting data from these sources after they have been identified. Data collection may come from databases, APIs, web scraping, or other sources. Data are processed to choose only the pertinent bits in the essential phase of filtering; filtering could eliminate duplicate records, outliers, and inconsistent data (Hung et al., 2020). A clean dataset must be created in order to conduct further investigation.

Data Extraction. Data extraction focuses on converting unstructured data into a format that can be analyzed. This frequently entails data transformation activities, including data normalization, data format conversion, and parsing. To construct a single dataset, data extraction may also involve joining or merging data from many sources (Houtmeyers et al., 2021). This step results in a tidy, structured dataset that was ready for analysis.

Data Validation and Cleansing. For data to be accurate and reliable, cleansing and validating the data was essential. Data are meticulously checked for mistakes, missing numbers, and inconsistencies throughout this process. Data quality checks are conducted to find and fix problems (Houtmeyers et al., 2021). Imputing missing numbers, fixing data mistakes, and ensuring data integrity are all examples of cleaning processes. Working with high-quality data is the goal to prevent skewed or incorrect analytical outcomes.

Data Aggregation and Representation. To make data appropriate for analysis, they must be summarized and compressed. Reports, dashboards, and in-depth analysis are often produced using aggregated data. Selecting the best formats for data visualization, such as tables, charts, graphs, or interactive dashboards, is referred to as data representation (Houtmeyers et al., 2021). Effective data aggregation and representation make a deeper comprehension of data patterns and trends possible.

Data Analysis. The fundamental step in every data analytics process is data analysis. Data analysis is the process of examining and interpreting data to extract meaningful insights, identify patterns, and inform decision-making. Data analysts investigate relationships, conduct hypothesis testing, and develop predictive models to address several business queries (Houtmeyers et al., 2021). The analysis's findings offer useful information that influences choices.

Data Visualization. Data visualization is a crucial step for making complex information easier for analysis. According to Bharadiya (2023), presenting data in a visual style to make complex information easier to grasp and analyze is known as data visualization. Bar graphs, line graphs, scatter plots, heat maps, and other visualizations are all possible. Effective data visualization improves storytelling and communication, allowing stakeholders to understand insights and make decisions based on the research quickly.

Utilization of Analysis Results. The last phase is utilizing the conclusions drawn from data analysis to guide decisions and motivate company activities. This step could entail developing action plans, carrying them out, and monitoring the effects of choices.

Closing the loop in the data analytics process through analysis results ensures that data-driven insights convert into real-world business benefits (Bharadiya, 2023). The company's management integrates data-driven insights into its systems to achieve its ultimate goals.

The Importance of Data Analytics for Management Accountants

Data analytics in accounting can be used in the context of budgeting in terms of digitizing and increasing the efficiency of the budgeting process (Bergmann et al., 2020). Studying the adoption and use of data analytics in budgeting, Bergmann et al. (2020) reported that data analytics helped digitize the budgeting process, increasing efficiency and convenience and reducing budgeting time. With data analytics, Bergmann et al. stated that the budgeting process was the first to be digitized, given its significance and criticality in the company processes. Automation of the budgeting process was also informed by the small number of employees tasked with the company's budgeting processes (Villanueva & Chen, 2019). Bergmann et al. focused on the digitization aspects of data analytics, including infrastructure for which more research was needed. The ideas discussed below are the importance of data analytics in management accounting.

Track Financial Performance. Some previous researchers have reported the impacts of data analytics on management accounting as being unclear. Recent studies have demonstrated that management accountants can use data analytics to track the company's financial performance and identify areas that need improvement (Schnegg & Möller, 2022). Tracking the company's financial performance and identifying improvement areas is crucial to enhancing efficiency and profitability. Studying the benefits of big data analytics in healthcare organizations, Batko and Slezak (2022) found that data analytics enabled healthcare organizations to identify patterns in their spending. An accurate depiction of how the company utilizes its funds is made possible by the availability of detailed data on what is procured, when, and at what cost. Similar to Batko and Slezak, Cozzoli et al. (2022) noted that in supply chain management, big data analytics is used to track supplier performance, expenditure costs, and income from sales. Thus, as a tool for tracking financial performance, the information obtained from big data analytics helps companies determine whether they are making financial gains.

Using data analytics, management accountants can make an accurate risk analysis of the company's performance and profitability based on real-time financial performance data. Different from Batko and Slezak (2022), Moro Visconti and Morea (2019) established that in healthcare financing, big data analytics is crucial in making important financial predictions but also shortens the steps engaged in the supply chain, fosters collaboration, and enhances flexibility, which improves the financial performance of the healthcare facility. In a different study, Bergmann et al. (2020) corroborated the results reported by Moro Visconti and Morea in that tracking the company's financial performance over time provides accountants with information on company expenditures and investments, which proves crucial during budgeting. Moreover, big data analytics tools automate the accounting process to overcome the challenges of sifting through large volumes of data and provide accountants with refined data on company financials for deliberations and decision-making (Bergmann et al., 2020). Using big data analytics to analyze financial accounting data, including cash flow and balance sheet statements, helps the company predict its total revenues, including net profits and losses (Chakri et al., 2023). From the analysis, big data has proven to be useful in predicting an organization's total revenues. Data analytics, especially big data, makes the prediction and analysis of an organization's financial position easy.

Improved Decision Making. Big data analytics has improved management accountants' access to huge volumes of data for their analysis. Access to huge volumes of data provided business accountants with information and insights enhancing their decision-making capabilities. Quality decision-making has been associated with improved customer relationships and customer service (Bergmann et al., 2020). Research conducted by Hung et al. (2020) on the relationship between big data analytics and banking revealed that using big data analytics to analyze B2B data improved supply chain performance and business efficiency and how the banks interacted with their customers and managed risks. Using the information in big data helped banks make decisions that promptly address customer challenges, improving customer service (Bergmann et al., 2020). Consistent results were reported by Hallikainen et al. (2020) after analyzing data retrieved from 417 B2B firms in the United States. The results indicated that big data analytics helped businesses access information on customer preferences and used the information to maintain the preferences, increasing sales (Côrte-Real et al., 2020; Hallikainen et al., 2020). Using data analytics to analyze customer and business data, management accountants can promptly address customer concerns, fostering positive customer-business relationships and increasing sales.

Businesses have used big data analytics to analyze huge volumes of data and thus make well-informed decisions. The information obtained via data analytics has been used by businesses to make crucial decisions on better adapting to the changing market environment. Exploring the benefits of big data analytics, Cozzoli et al. (2022) asserted that the predictive capabilities of big data analytics helped management accountants make important operational and organizational decisions that helped strategically position the healthcare organization in the market. Similarly, Bose et al. (2023) noted that although considered a disruptive technology, skilled accountants have used big data and big data analytics to make important strategic decisions that have improved the company's productivity and competitiveness. Using the massive amounts of data provided by big data, companies have used big data analytics to forecast business performance and the market for better preparation (Ragazou et al., 2023). Across the reviewed literature, researchers have demonstrated that analyzing huge volumes of data regarding customer relationships and the market environment strategically positioned businesses for improved profits and competitiveness.

Management accountants have used big data analytics to make important market and financial decisions that have improved the performance of their respective companies and firms. While reviewing the literature on big data analytics and financial performance, it was established that the ability to track the company's expenditure and predict total revenues helped the company in making important decisions on how to cut losses by only investing in profitable ventures (Akter et al., 2022; Chakri et al., 2023). Linking big data analytics to the operational sustainability of businesses, Raut et al. (2019) reported that businesses used big data analytics to mine information that informed their business performance and operation management. In a review of current literature, Wiener et al. (2020) explained that big data analytics helped businesses use the available information to make important decisions that would inform their performance and improve their competitiveness. Despite enhancing the decision-making ability of management accountants, a lack of big data skills and infrastructure has hindered the effective use of data analytics in decision-making, consequently improving business performance and efficiency.

Big Data Analytics and Reduced Risks. In the preceding sections, researchers have demonstrated that management accountants have used big data analytics to improve performance and decision-making (Bergmann et al., 2020; Chakri et al., 2023; Wiener et al., 2020). Improved financial performance was achieved by minimizing the risks the company or firm faces. As such, management accountants can use data analytics to identify risks and how to mitigate such risks. Moll and Yigitbasioglu (2019) found that internet-related technologies such as blockchain, artificial intelligence, and data analytics enhance management accountants' capabilities to sift through volumes of data identifying risks that may affect company performance. With the ability to anticipate and identify the risks likely to be encountered, the management can develop strategies to reduce such risks and thus protect the company from loss. Contrary to Moll and Yigitbasioglu, Fanelli et al. (2022), in a review of the literature, contended that while data analytics influenced decision-making, the huge volumes of data may result in some risks being overlooked, and the consequences may be grave for the business as it may not only incur losses but also lose its competitive advantage.

Businesses that have applied data analytics in their accounting practices have reported improved vigilance and prompt identification of financial risks. For instance, Sheng et al. (2020) explained that using predictive and prescriptive data analytics proved crucial to predicting the market's future and what risks to expect from COVID-19. Franke and Hiebl (2022) contended that businesses with employees skilled in data analytics used the technology to identify risks and make sound decisions on mitigating such risks. However, Franke and Hiebl concurred with Moll and Yigitbasioglu (2019) that data analytics was a new technology that disrupted accounting practices. A limited number of data analytic specialists and limited evidence of its application identification and reduction of risks faced by accountants creates a gap in research that this study sought to address (see Bose et al., 2023). Overall, using data analytics for market forecasts and decision-making has helped businesses and companies avoid mistakes that might be costly, minimize losses, keep their customers, and maintain their reputation.

Increased Efficiency. Data analytics has improved the efficiency of management accountants and other business employees through automation and digitization of tasks. Automation of tasks and practices enhanced the efficiency of the budgeting process and reduced the time taken to formulate and implement the budget (Bergmann et al., 2020). Besides budgeting, Hung et al. (2020) noted that in the banking sector and B2B firms, data analytics has automated supply chain relationships and transactions, sustaining profitability, meeting customer needs, and generating value for business. Similar findings were reported by Hallikainen et al. (2020), who explained that data analytics automated the collection and analysis of customer data. Using customer data ensured that the businesses were better placed to offer quality and efficient customer service, boosting sales. The studies reviewed thus far have established that automation of services through big data analytics improves the efficiency of businesses.

Automating tasks through data analytics frees time for management accountants to focus on other important strategic initiatives to improve business performance and competitiveness. After studying the impact of big data analytics on company performance, Oncioiu et al. (2019) established that the technology helped companies assess their strategies and tasks that could be automated to enhance their professional capabilities in marketing and decision-making roles. Supporting Oncioiu's et al. findings, Andreassen (2020) explored digital technology and role-changing in accountants. The results indicated that digital technologies such as data analytics and artificial intelligence expanded the tasks and assignments handled by management accountants, increasing their productivity. However, there were concerns about digital technology rendering management accountants obsolete by narrowing their roles (Akter et al., 2022; Andreassen, 2020). Nielsen (2022) established that using technology such as data analytics in management accounting increased the participation of management accountants in business activities, promoting homogenization sustainability in accounting through automation of tasks. Thus far, data analytics through automation of tasks allows management accountants to engage in other company activities such as decision-making.

The Importance of SMEs to the U.S. Economy

In the U.S. economy, SMEs play a significant role in generating employment and driving economic activity. Traditionally, a firm is considered small-to-medium sized based on the number of people it employs, with a common threshold being fewer than 500 employees in the United States. For instance, a recent report co-produced by Facebook and the Small Business Roundtable surveyed approximately 86,000 SME owners who used this 500-employee cut-off (Facebook, 2021). This criterion was also employed in U.S. Census Bureau statistics reporting.

According to the Statistics of US Businesses (United States Census Bureau, 2023), of the 5.97 million firms in the United States, an overwhelming 99.7% had fewer than 500 employees. These smaller firms collectively accounted for around $133.19 billion, which was over 35% of the total annual sales, receipts, or value of shipments, amounting to approximately $373.7 billion (United States Census Bureau, 2023). Moreover, SMEs have significantly impacted employment, providing jobs to over 60.56 million people in 2020, representing more than 47% of the total employment in the United States (United States Census Bureau, 2023). Additionally, SMEs contributed about 40% of the annual payroll in the United States (United States Census Bureau, 2023). Given the importance of SMEs in the U.S. economy, it was crucial to examine the nature and development of analytics capabilities within these businesses. To do so, it is important to begin by understanding relevant definitions related to data analytics (DA) and its general application by businesses.

SMEs collectively contribute significantly to the nation's Gross Domestic Product (GDP) because they have a substantial combined effect on economic production, which supports steady economic growth. According to Bryson et al. (2002), SMEs constitute a significant portion of the business landscape, with smaller turnovers than large corporations. SMEs' combined economic activity generates a significant aggregate output over a metropolitan area. In support of the findings, Baker and Judge (2020) argued that during the COVID-19 pandemic, the federal government decided to save SMEs from shutting down because of their immense contribution to the growth of regional economies. Slattery and Zidar (2020) made a similar point, highlighting that the federal government adopted the provision of incentives to small businesses to allow for business growth and, ultimately, economic growth. As per the findings of the reviewed studies, it was evident that SMEs contribute immensely to economic growth through cumulative turnovers.

SMEs' involvement in international commerce increases the nation's export earnings and aids in sustaining a positive trade balance and economic growth. As per the findings of Kyung and Whitney (2020), export earnings by local governments declined during the COVID-19 pandemic because of SME closure. The outcomes emphasize the importance of SMEs in economic growth through international export trades. Alluding to the previous findings, Bartik et al. (2020) argued that through the introduction of novel goods, services, and business models, the promotion of competition, and the stimulation of innovation, privately funded SMEs run by entrepreneurs propel economic growth through the export of novel goods. Similarly, exporting generates foreign exchange earnings, stabilizing currency value and strengthening the country's global market position as a critical leader in economic growth (Shahbaz et al., 2019). Thus far, the reviewed studies have shown that SMEs involved in the export business were major contributors to the country's economic growth through foreign exchange earnings.

Millions of people are employed by SMEs, which also helps to lower unemployment rates. Indeed, SMEs employ millions in various sectors, enabling quick market response and creating employment opportunities to meet local and regional needs, thus fostering economic growth (Fairlie, 2020). Otto et al. (2020) established that people can work for themselves by owning and running small enterprises in various industries. Ownership offers independence and reduces unemployment rates in the country, thus leading to sustainable economic growth. On the same note, Azoulay et al. (2022) established that SMEs can play a crucial role in offering employment opportunities to immigrants, which can positively curb unemployment and contribute to economic growth in the country. Evidence in the reviewed studies indicates that SMEs generate employment opportunities, lower unemployment rates, and contribute to the economy's growth.

SMEs support the growth and welfare of their communities by hiring locals, which encourages local and national economic development. SMEs generate local employment by handling tasks like production, sales, customer service, and administration, contributing to job creation, reducing community unemployment rates, and fostering economic growth (Miller-Adams et al., 2019). Similar findings were reported by Gherghina et al. (2020), indicating that SMEs offer a variety of job opportunities for people with different skill sets, including entry-level and specialized roles, helping to create a diverse local workforce, reduce unemployment, and foster economic growth. Shoeib et al. (2021) revealed that SMEs in rural areas of the country source employment from local communities, thus increasing employment rates, developing skills, and enhancing economic growth. The reviewed studies have revealed that SMEs provide job opportunities across various sectors, including manufacturing, services, retail, and technology, helping to lower unemployment rates and increase economic growth.

SMEs provide significant job opportunities because they offer employment opportunities to diverse individuals, leading to lower unemployment rates and economic stability in the United States. Empirical evidence across the extant literature indicates that SMEs span different industries, including technology, agriculture, manufacturing, and professional services; this provides diverse job opportunities across various sectors to ensure the availability of jobs (Chege & Wang, 2020). In a quantitative study, Naradda Gamage et al. (2020) investigated the impact of SMEs on the economy. They found that SMEs were embedded within local communities across various sectors, providing job opportunities and thus ensuring employment stability for the enhanced U.S. economy. Similar findings to Naradda Gamage et al. were also reported in a qualitative study conducted by Hossain et al. (2022) to examine SMEs and economic growth in the United States. Hossain et al. reported that SMEs were critical to the U.S. economy. They support employment availability and stability across diverse U.S. communities, developing local and regional economies. The synthesized findings indicate that SMEs play a crucial role in ensuring the availability of jobs to the US economy across diverse industries.

During downturns and periods of economic uncertainty, SMEs tend to remain afloat and more resilient than larger companies. This ability to sustain economic hardships helps the United States maintain job stability during challenging economic moments. Recent empirical evidence has indicated that SMEs promote inclusivity by offering employment opportunities to diverse people, including minorities, women, veterans, and persons with disabilities, inclusivity that fosters diversity in the labor force (Prasanna et al., 2019). Belitski et al. (2022) conducted a quantitative study to investigate SMEs and economic growth during COVID-19 in the United States and found that SMEs were significant job creators for the U.S. population especially in rural areas across different sectors including manufacturing and technology. Consistent findings of Belitski et al. were reported in a qualitative study conducted by Meyer and Meyer (2020) to explore the impact of SMEs on the U.S. economy and established that entrepreneurs with innovative ideas often found startups, and these businesses need more employees to meet their demand for growth, contributing to job creation. In the synthesis above, it can be confirmed that SMEs were key job creators in the U.S. economy.

Small and medium-sized businesses generate significant amounts of tax revenue for the local, state, and federal governments of the United States. Some studies have demonstrated that SMEs are part of the revenue-generating resources to the federal, local, and state governments of the United States by submitting income taxes as well as corporate taxes to the tax collectors (Liu et al., 2022). In a quantitative study, Slattery and

Zidar (2020) examined SMEs and tax revenue resources for the U.S. government. The findings indicated that SMEs report their business income tax returns to the government, which helps the local, state, and federal governments with economic development activities such as infrastructure development and funding education (Slattery & Zidar, 2020)). On the same note, Saez and Zucman (2022) investigated SMEs' contribution to the U.S. economy. They demonstrated that SMEs across diverse industries, including manufacturing, technology, and agriculture, were obliged to pay taxes to the government through sales, property, and PAYE taxes. These taxes help the government run its economic growth functions (Saez & Zucman, 2022). Combined, the findings synthesized demonstrate that SMEs play an essential role in developing the U.S. economy through tax revenue generation.

Challenges SMEs Face Requiring Data Analytics for Competitive Advantage

Limited Resources

Purchasing data analytics tools and software can be financially difficult for SMEs with restricted budgets because of the hefty prices associated with licensed software, cloud-based solutions, or employing data analytics specialists. Several studies have shown that SMEs with limited budgets struggle to acquire data analytics. For example, Akpan et al. (2022) reported that most SMEs operating in the informal sector encounter comparable obstacles, such as limited cash flow to fund the acquisition of advanced technologies and innovations such as data analytics required to enhance business operations and restructure processes. Similarly, other researchers have indicated that the economic repercussions of the COVID-19 pandemic further led to resource deterioration for SMEs, making them unable to purchase data analytics technology (Liguori & Pittz, 2020). In addition, the high demand for skilled data analysts and their ability to command higher salaries presents challenges for SMEs in attracting and retaining talented professionals (Willetts et al., 2022). As per the findings of the reviewed studies, it was evident that SMEs find it difficult to acquire data analytics because of the high cost of acquisition and maintenance required.

Data analytics application often demands strong hardware, IT infrastructure, and enough data storage capabilities, which may be beyond the resources of SMEs to invest in the necessary technologies. Existing literature has suggested that SMEs continue to perform their key accounting activities using Excel spreadsheets and lag in adopting data analytics technologies because of the cost of necessary infrastructure required to adopt data analytics (Church et al., 2022). In a previous study, Tabesh et al. (2019) highlighted the barriers to implementing big data strategies, including limited resources and capital to purchase the required infrastructure and hire data analysts to operate and maintain data analytics infrastructure. Likewise, Jaeger and Upadhyay (2020) emphasized that high startup costs in purchasing data analytics infrastructure hindered SMEs with limited financial capabilities from implementing data analytics. Overall, the reviewed studies have highlighted that SMEs were impeded from incorporating data analytics into their operations because of the high cost of purchasing and maintaining the technology and limited resources.

Data Quality and Availability Challenges

Data acquired by SMEs may contain mistakes, inconsistencies, or missing information, making it unsuitable for detailed analysis. Researchers have established that the data's correctness, completeness, and dependability substantially impact the effectiveness of data analytics, with SMEs frequently having difficulties in assuring high-quality data for analytics (Luck et al., 2021). In agreement with Luck et al. (2021), Côrte-Real et al. (2020) posited that a strong level of data quality was crucial in generating substantial value in business processes through the utilization of big data analytics with many SMEs failing to guarantee quality data for analysis thus hindering full adoption of data analytics.

Because of SMEs' limited resources, lack of data governance, or reliance on manual data input procedures, SMEs may have trouble acquiring and gathering the high-quality and pertinent data needed for data analytics, thus hindering the successful implementation of data analytics. Combining the evidence from the reviewed studies, SME low data quality hinders the successful implementation of data analytics.

SMEs often face financial constraints when gathering external data or accessing relevant datasets, which hinders their ability to enhance their data and consolidate a comprehensive dataset for analysis. Previous research has indicated that data analytics relies on vast amounts of data to provide insights and trends, but difficulties in obtaining or low data quality can result in inaccurate and unreliable analyses, discouraging SMEs from embracing data analytics (Nguyen et al., 2022). Similarly, Akpan et al. (2021) found that during the COVID-19 pandemic, businesses had to adopt new technologies to support their operations, with SMEs encountering challenges in obtaining readily available, high-quality data for analysis. Other researchers have emphasized that timely access to data was crucial for well-informed decision-making, yet SMEs face obstacles because of limited real-time data capture, restricting their ability to adapt quickly to changing business technologies, including the adoption of data analytics (Qin & Chiang, 2019). The evidence reviewed so far indicates that the lack of data availability and quality presents a significant challenge in SMEs' adoption of data analytics in business.

Lack of Expertise Challenges

Data analytics requires specialized knowledge and experience in statistics, programming, and data processing; it was common for SMEs to lack staff with the necessary abilities to evaluate and understand data. Through a qualitative study, Lloyd and Payne (2019) indicated that SMEs frequently lack the means to engage specialized data analysts for their data analytics needs because of limited financial and human resources, distinguishing them from bigger organizations and discouraging them from adopting data analytics. In a similar study, Amankwah-Amoah et al. (2021) found that during the COVID-19 pandemic, the adoption of emerging technologies, such as data analytics by SMEs was hindered by a lack of expertise and complexity, thus a need for a period of adjustment, especially for those with no prior experience in data science. In addition, Dey et al. (2022) highlighted the challenges SMEs face in adopting data analytics, among them being the shortage of skilled employees with the necessary expertise to manipulate and maintain data analytic technology. Combining the findings from the reviewed studies, it was evident that a lack of expertise in the maintenance and operation of data analytic technologies has hindered SMEs from purchasing the infrastructure.

SMEs may face challenges in effectively utilizing data analytics tools and hiring data scientists because of the competitive market for data analytics talent, leading to a reliance on external consultants and incurring additional costs for data-related tasks. The time-consuming and costly process of retraining accountants in data analytics can further discourage SMEs from adopting the technology despite acknowledging its potential advantages, mainly because of financial and resource limitations (Moll & Yigitbasioglu, 2019). Inadequate expertise in recruiting, training, and retaining employees proficient in data analytics also contributes to the reluctance of SMEs to adopt big data analytics in their operations (Daniel, 2019). Emphasizing the previous findings, the reliance on external consultants for data-related activities further highlights SMEs' shortage of internal data analytics knowledge, resulting in additional costs and potential delays in acquiring crucial insights (Dubey et al., 2019). The findings underscore the challenges SMEs face in adopting data analytics because of the lack of expertise, leading to increased training costs and talent outsourcing.

Integration of Data Systems Challenges

Integrating data systems can be an intensive investment in time and money for SMEs, as they may encounter difficulties acquiring costly data integration solutions or hiring expert IT personnel to manage the process. Research conducted by Gill et al. (2022) highlighted the challenges SMEs face because of disparities in data from various software applications and variations in data formats and architectures across systems, making it challenging to utilize data analytics effectively. Hariri et al. (2019) also found that SMEs using outdated systems incompatible with modern analytics tools and lacking adequate IT infrastructure to handle large volumes of data from diverse sources may experience complications in data integration, hindering their adoption of data analytics. Jones et al. (2021) further supported the findings, revealing that SMEs were often burdened with day-to-day responsibilities, leading to a scarcity of time for data integration and analytics, alongside the complexity of handling sensitive customer information from multiple sources. The reviewed studies demonstrate that integrating data from different systems poses significant challenges for SMEs, potentially compromising data quality and privacy.

SMEs commonly use various software and systems to manage various areas of their operations, with the integration of disparate technologies to create a coherent data environment for analytics being complicated and time-consuming. Indeed, when datasets come from diverse sources or have distinct formats, inconsistent data, and coding discrepancies might emerge, leading to misleading or erroneous analytics findings and discouraging SMEs from using data analytics (Wang & Wang, 2020). Similarly, the major challenges in transforming heterogeneous large datasets into actionable outcomes in SMEs include computational complexity, data security, and operational integration of big data, which complicates the desire of SMEs to adopt data analytics (Bhattarai et al., 2019). Sharma et al. (2022) also reiterated that data synchronization creates considerable challenges for SMEs, requiring enormous resources and high-speed connectivity, which may delay data analytics implementation. Together, the reviewed studies have shown that integrating data systems was a complex procedure in data analytics, thus discouraging SMEs from adopting the technology.

Challenges of Implementing Data Analytics in SMEs

Data Quality and Integration Challenges

Quality assurance and data integrity are among the major challenges facing the implementation of data analytics in SMEs. Côrte-Real et al. (2020) demonstrated that organizations face various data analytics implementation barriers, including incompatibility, inaccurate data entry, duplication, and silos. In a quantitative study, Choi and Luo (2019) conceptualized data quality and blockchain adoption and found that low-quality data hinders the integration of processes into blockchain systems in organizations due to incompatibility and inaccurate data entry. Similarly, Raut et al. (2019) analyzed linking big data analytics and operation practices for business management in organizations; the findings suggested that integrating data from different sources raised security and privacy concerns as well as a lack of standardization in data formats or units across different systems, making it hard to implement data analytics in organizations. Combined, it can be suggested that maintaining data quality and integrity and protecting sensitive information could be key challenges in implementing data analytics in organizations.

Other researchers have reported significant differences associated with data analytics integration in organizations. For instance, some scholars have indicated inconsistent data formats, outdated information, and complex Extract Transform Load (ETL) processes were a challenge (Butt, 2020; Seenivasan, 2023). Typically, organizations have disparate systems and departments that collect and store independent data, creating data silos and making it difficult to integrate data analytics (Himanen et al., 2019). A quantitative study conducted by Baig et al. (2019) to investigate big data implementation in data analytics demonstrated that data requires real-time integration, and ensuring timely data updates and maintaining data consistency was a barrier to data analytics adoption because an increase in data volume needs real-time integration. While some researchers highlighted data incompatibility and complex ETL processes as challenges to data analytics implementation (Tabesh et al., 2019), other studies posited that integrating data from different sources raised concerns about the security and privacy compliance of data (Ferraris et al., 2019). Despite the disagreements in findings, it can be concluded that data quality and integration requirements are key challenges to implementing data analytics in organizations.

Lack of Skilled Workforce

Finding and retaining talent with data analytics skills has been a challenge in implementing data analytics in organizations. Past research has indicated that a lack of talent and skilled staff is a key challenge faced by organizations when implementing data analytics, a challenge that is multifaceted and impacts several aspects of data analytic adoption (Butt, 2020). Notably, Kumar et al. (2020) conducted a quantitative study to explore the barriers to data analytics adoption in a circular economy using the ISM-ANP system and reported that data analytics needs skilled personnel with knowledge and expertise in data science, domain knowledge, and programming and statistics; thus, lack of knowledge and inadequate skilled workforce hindered the implementation of data analytics in organizations (Kumar et al., 2020). Consequently, Ghadge et al. (2020) confirmed that without competent employees in organizations with skills in data analytics, organizations could struggle to gain important insights from their data, resulting in opportunities and uninformed decision-making. Together, the results discussed demonstrate that the lack of skilled employees with technological knowledge in data analytics has greatly challenged organizations.

Cost and Resources

Data analytics adoption requires significant technology, tools, training, and infrastructure investments. Current empirical evidence indicates that the successful adoption of data analytics needs significant investments in diverse areas, and limited allocation of critical resources can hamper the progress and limit the expected potential benefits of data analytics in organizations (Akpan et al., 2022; Dubey et al., 2019). In a quantitative study, Vermunt et al. (2019) analyzed 43 case studies of circular business models (CBM) based on interviews with 31 firm technical managers to examine barriers to implementing data analytics. Agreeing with Akpan et al. (2022), Vermunt et al. found that data analytics requires huge infrastructure and specialized technology tools to process, store, and analyze large volumes of data, and investing in such resources can be quite costly, especially for small firms. However, other empirical research has suggested that hiring data analytics specialists and other specialized professionals can be expensive, considering the skills and large salaries required to attract a talented and skilled workforce (Mikalef et al., 2019). Although there are various barriers to data analytics implementation, the cost of resources is a significant challenge to organizations.

The high cost and resources needed to ensure data security and compliance make it difficult for organizations to implement data analytics. As empirical research has suggested, making sure there is data security and privacy compliance requires organizations to invest heavily in cybersecurity measures, encryption technologies as well and data auditing processes to safeguard sensitive data, which requires more costs in resources (Müller, 2019). Further, other studies, such as Tseng et al. (2021), focused on sustainable industrial and operation engineering trends and challenges toward Industry 4.0 data analysis adoption in organizations. Confirming Müller's (2019) results, the lack of investment in data security and compliance may lead to noncompliance with data protection laws, resulting in legal actions and damage to reputation; such investments require high cost of resources such as skilled workforce, technical tools, and technology knowledge among staff (Tseng et al., 2021). In contrast to Tseng et al.'s findings, Wamba et al. (2020) found no significant relationship between cost and resources and the adoption of data analytics. Thus far, the results discussed indicate a need for huge investment in resources for data analytics implementation.

Resistance to Change

Organizations encounter resistance to change as a challenge to implementing data analytics. Current literature has recognized that implementing data analytics involves the introduction of new work processes, methodologies, and technologies, which can disrupt the existing working procedures, and this can be met with resistance among staff and other stakeholders within the organization because of fear of unknown (Mikalef et al., 2021; Rialti et al., 2019). Chan et al. (2019) introduced building information modeling and revealed that the uptake of BIM in construction projects was met with resistance because of a lack of understanding and training among staff, while Cichosz et al. (2020)

analyzed digital transformation in logistics and found that the main obstacle to digital data transformation was lack of resources and resistance to change among employees who feared their job security. Contrary to Chan et al. and Cichosz et al., Kamal et al. (2020) associated lack of leadership support and disruption to routine with resistance to change as a key challenge to the implementation of data analytics. The findings suggest that employees' resistance to change is a challenge to implementation of data analytics.

Stakeholders within the organizations are likely to resist implementing data analytic technology because of fear of their job security. Resistance to change has elicited considerable disagreement over its effect on data analytics implementation. Kretschmer and Khashabi (2020) considered resistance to change a challenge for organizations who want to implement data analytics, revealing that an organizational culture that does not encourage learning and innovation among its staff makes employees less willing to accept the new technology and processes adopted by the organization. A similar disagreement about resistance to change can be observed in Fischer et al. (2020), who reported a lack of leadership support and a threat to job security in fear that migration to data analytics might replace their roles in the organization, and Brock and Von Wangenheim (2019), who maintained that data analytics was likely to challenge existing power structures in the organization because those who relied on traditional methods may feel outdated and fear for the unknown. While there is disagreement in findings, it can be suggested that resistance to change hinders organizations in implementing data analytics.

Data Security and Privacy Concerns

With the increasing use of data analytics, organizations face challenges in ensuring data security and protecting clients' data privacy. Keshta and Odeh (2021) suggested that ensuring data security and privacy was crucial to maintaining trust with client regulation compliance and safeguarding the reputation of the organizations. Some have argued that successful data breaches and cyber-attacks can contribute to financial losses, legal liabilities, and damage to the reputation of the organization; such data breaches can also lead to the theft of sensitive information and intellectual property, which was a challenge in implementing data analytics in organizations (Hamilton & Sodeman, 2020).

On the other hand, it has been urged that organizations face challenges in ensuring that only authorized personnel can access specified data sets to prevent unauthorized sharing of an organization's data (Tawalbeh et al., 2020). The argument is only valid for smaller organizations with limited resources and not large organizations with adequate technical resources to implement data analytics (Jin et al., 2019). The findings discussed suggest that data security and privacy compliance provide a challenge to organizations whose intent was to implement data analytics.

Data analytics helps SMEs to understand customer preferences, market trends, and competitor activities, allowing for informed business decisions and market competitiveness. Indeed, SMEs may use data analytics to get insights into preferences, buying behaviors, and trends by analyzing customer data such as purchase history, browsing tendencies, and demographics (Sheth, 2021). Similarly, data analytics assist

SMEs in discovering and evaluating market trends, enabling them to analyze customer opinions, forecast market movements better, and proactively adjust their strategy to remain competitive (Iacobucci et al., 2019). Agreeing with Sheth (2021) and Iacobucci et al. (2019), Campbell et al. (2020) established that SMEs can use data analytics to track competitor activity, pricing tactics, marketing initiatives, product launches, and consumer feedback. The activity aids in the identification of strengths and shortcomings, allowing for distinction, improvement, and competitive advantages (Campbell et al., 2020). As per the findings of the reviewed studies, it is evident that the challenge of market understanding by SMES can be solved by adopting data analytics in studying market trends and customer preferences for competitive advantage.

Data analytics provides SMEs with helpful information about client preferences, market trends, and competition activity, which allows business leaders to adapt goods, create successful marketing tactics, and increase operational efficiency, giving them a competitive advantage. Data analytics may help SMEs segment their customer base and develop tailored marketing strategies by improving customer engagement and loyalty, giving them a competitive advantage over business rivals (Moscovici et al., 2022). Along the same lines, using data analytics for consumer behavior analysis, SMEs may improve marketing tactics, optimize product offers, and increase customer satisfaction, giving them a competitive advantage (Farida & Setiawan, 2022). Related findings were established by Parnell and Crandall (2021), who argued that SMEs may leverage big data analytics to identify threats, opportunities, and crisis trends in the market, thus gaining a competitive advantage over their peers in being ready for crises. Thus far, the reviewed studies have shown that SMEs can position themselves as competitive players by understanding customers, market trends, and competitors and maximizing growth opportunities using data analytics.

The overall resilience of an SME may be improved by using data analytics to help detect possible hazards, assess their effect, and develop measures to reduce them. Through a qualitative study, Araz et al. (2020) found that SMEs may detect risks by using data analytics to examine historical financial data and identify risks and vulnerabilities that might affect their operation. Agreeing with Araz et al., Iakovou and White (2020) found that SMEs may leverage data analytics capabilities to identify potential business risks and manage them for competitive advantage over their peers. Gherghina et al. (2020) alluded to the previous findings by establishing that SMEs were adopting data analytics to identify potential risks during crises and how to manage them to remain operational and competitive effectively. Evidence in existing literature shows that many SMEs face risk management challenges but have adopted data analytics to manage the risks and effectively remain competitive in the market.

Data analytics enables SMEs to quantify risks' impact and estimate financial and operational consequences, thus effectively managing them to gain a competitive advantage. Studying the importance of data analytics to SMEs, research reported that by modeling risk scenarios and their effects, SMEs may analyze scenarios using statistical models, thus estimating outcomes and evaluating risks' financial and operational ramifications (Attaran & Woods, 2019). Halabi et al. (2022) established that small-scale construction companies adopted data analytics to assess and manage employee fall risks.

Similar results were revealed by Boyson et al. (2022), who found that SMEs can use data analytics to prioritize risks by combining severity and likelihood estimates to rank potential consequences and focus on addressing significant risks with the greatest impact, allowing them to remain competitive. Putting together the evidence reviewed, it is evident that data analytics helps SMEs analyze and manage risks in a timely manner, thus allowing them to maintain a competitive advantage in the market.

The continuous maintenance and improvement of the data analytics systems may require intensive resource utilization, and SMEs may not be able to allocate the required resources over time. Empirical evidence from past literature has indicated that data analytics tools require specialized skills for their maintenance, including skills in data engineering and database administration; SMEs may struggle to attract and retain staff with such essential knowledge in data analytics for their system upkeep (Haddara et al., 2022). Other researchers, such as Song et al. (2021), investigated data analytics and SMEs using a quantitative study design and found that SMEs may have limited tools and processes required to maintain high data quality for a long because data analytics needs high-level data quality with accuracy and consistency. Zide and Jokonya (2022) refuted Haddara et al.'s (2022) findings by conducting a quantitative study to determine the challenges faced by SMEs during data analytics implementation. Zide and Jokonya that although SMEs may face challenges in expertise, outsourcing skilled personnel may promote the seamless implementation of data analytics. This can be confirmed that SMEs face system maintenance and upkeep challenges in adopting data analytics.

Technological evolution makes it difficult for SMEs to maintain their systems because data analytics keeps evolving with new tools and algorithms. Researchers have demonstrated that adequate maintenance of data analytics systems is essential for SMEs to derive value from data analytics investment by ensuring systems remain relevant, accurate, and secure (Hasnan et al., 2022). Wang and Wang (2020) explored data analytics in SMEs in a quantitative study, demonstrating that data analytics systems require data retention and compliance through managing policies to ensure compliance with regulations on data protection. Lack of compliance with the data protection policies may be costly to the SMEs regarding legal liabilities (Wang & Wang, 2020). Similarly, Welte et al. (2020) agreed with Wang and Wang's findings by analyzing data analytics in SMEs in a quantitative study, stating that data analytics system requires backup and disaster recovery to protect the whole data analytics system from unexpected situations. This needs regular system testing and updates, which may be challenging for SMEs (Welte et al., 2020). The findings indicate that SMEs have limited data analytics system maintenance and upkeep resources.

Selecting the right vendor for the right data analytics tools can be overwhelming for SMEs with inadequate knowledge of the data analytics landscape. Studies have revealed that choosing the right vendor was critical for SMEs when adopting data analytics because the wrong vendor choice contributes to inefficiencies and missed opportunities (Musaad et al., 2020). In a systematic literature review, Tong et al. (2022) determined sustainable supplier selection for SMEs, demonstrating that the data analytics market was complex and needs the right service provider with the tools compatible with the SME's values and processes. Some SMEs lack the needed knowledge and skills to identify those vendors with the right tools. On the other hand, some researchers, such as Borštnar and Pucihar (2021), stated that SMEs may choose the right vendors. However, those service providers were expensive, making it difficult for the SMEs to afford their services. Agreeing with Borštnar and Pucihar, Chien et al. (2021) also revealed that most SMEs may not possess adequate technical expertise to identify the right vendors for their data analytics implementation and provide ongoing system maintenance and support. The synthesized findings demonstrate that SMEs' lack of expertise in data analytics may contribute to their selection of the wrong vendors for service provision.

Data Analytics Strategies

Data analytics can be a valuable tool for SME management accountant leaders within various organizational systems. The SME management can deploy data analytics with the aim of maintaining a competitive advantage and making more informed decisions (Wang & Wang, 2020). The first strategy is cost tracking and analysis, which includes implementing robust cost-tracking mechanisms to monitor expenses across different departments and processes (Baig et al., 2019; Nguyen et al., 2022). The use of data analytics helps to analyze historical spending patterns, identify cost drivers, and detect any abnormal fluctuations in costs (Akter et al., 2022). This information will enable management accountants to make data-driven decisions on cost-reduction strategies (Moll & Yigitbasioglu, 2019). The second strategy is activity-based costing (ABC), which is vital in allocating indirect costs to specific activities or products (Quesado & Silva, 2021). ABC helps managers define and measure the actual cost of products or services, allowing management accountants to identify high-cost activities and explore opportunities for process optimization and cost reduction.

Budget variance analysis is the third data analytics strategy. The strategy uses data analytics to compare actual financial results against budgeted figures to identify significant variances and investigate the underlying reasons for deviations (Rialti et al., 2019). Budget variance analysis will help management accountants take corrective actions promptly to control costs effectively (Bergmann et al., 2020). The fourth strategy is supplier performance analysis. The technique involves analyzing supplier data to evaluate their performance in terms of cost, quality, and delivery (Akter et al., 2022; Chakri et al., 2023). Identify top-performing suppliers who offer competitive pricing and negotiate better terms with them to maintain competitive advantages (Raut et al., 2019; Rialti et al., 2019). Costs determine a company's position, and it is important to identify suppliers with reasonable pricing to maintain competitive advantages.

The fifth strategy is inventory management. The strategy uses data analytics to optimize inventory levels and reduce carrying costs (Ferraris et al., 2019). This helps analyze historical sales data to forecast demand accurately, preventing overstocking or stockouts. Efficient inventory management helps minimize storage costs and potential wastage. The sixth strategy is cost-benefit analysis (Qin & Chiang, 2019). This strategy uses data analytics to perform cost-benefit analyses for various projects and investments. The cost-benefit analysis approach enables management accountants to prioritize initiatives that offer the most significant competitive advantages and returns on investment (Sharma et al., 2022). The eighth strategy is activity efficiency analysis. The strategy requires one to actively identify inefficiencies in business processes such as allocated resources through data analytics (Liguori & Pittz, 2020; Moll & Yigitbasioglu, 2019). To determine if some bottlenecks or redundancies can be eliminated to reduce costs, analyze the time and resources allocated to different activities.

The ninth strategy is pricing optimization. This strategy uses data analytics to analyze customer buying behavior, price elasticity, and competitor pricing to optimize product or service pricing (Dash et al., 2019). Strategic pricing decisions can help SMEs maintain a competitive advantage while remaining competitive in the market. Another strategy is fraud detection and prevention (Akpan et al., 2021). The strategy involves implementing data analytics tools to detect potential fraud or misuse of resources (Silva et al., 2021). It is important to regularly monitor financial transactions for anomalies or irregular patterns, ensuring that the organization's resources are not misappropriated (Gill et al., 2022). Lean Six Sigma is another data analytics strategy that integrates lean principles and Six Sigma methodologies into the decision-making process.

Data analytics can be used to identify areas for process improvement, waste reduction, and cost-saving opportunities (Dash et al., 2019). The last data analytics is continuous monitoring, which seeks to establish a continuous monitoring system that regularly tracks key cost metrics and provides real-time insights to management accountant leaders. Timely access to data ensures proactive decision-making to maintain competitive advantages (Dubey et al., 2019). By embracing these data analytics strategies, management accountant leaders in SMEs can optimize costs, streamline operations, and position their organizations competitively with a sustained competitive advantage in the market.

The synthesis of research gaps indicates that there was a lack of studies focusing on data analytics strategies utilized by SME management accountant leaders for decision-making to maintain a competitive advantage (see Hariri et al., 2019). Despite the increasing recognition of data analytics' importance in business decision-making, the specific application and impact of data analytics strategies in SMEs, particularly in the domain of competitive advantage maintenance, remain understudied (Jones et al., 2021). Existing literature on data analytics in SMEs often emphasizes its general benefits, such as improved efficiency, better decision-making, and enhanced competitiveness (Côrte-Real et al., 2020; Wamba et al., 2020). However, there was a dearth of research that delves into the specific data analytics strategies employed by management accountant leaders in SMEs to achieve competitive advantage and how these strategies align with the organization's financial objectives.

The research gaps also point out the need to explore the factors that hinder or facilitate the adoption of data analytics in SMEs, particularly in the context of cost management (Akpan et al., 2021; Liguori & Pittz, 2020). Understanding the barriers and challenges faced by SMEs in implementing data analytics can provide valuable insights to address these issues and encourage wider adoption of data-driven decision-making practices (Wang & Wang, 2020). Furthermore, there is a lack of empirical evidence on the business value gained by SMEs through the application of data analytics in cost management (Wang & Wang, 2020; Willetts et al., 2022). Data analytics is a complex phenomenon whose implementation requires considerable measures. Organization leaders intending to integrate data analytics in SMEs should ensure it identifies all the factors likely to hinder the process.

Comparative studies between SMEs that have effectively leveraged data analytics to maintain competitive advantage and those that have not can offer valuable insights into the potential benefits and outcomes of such strategies (Church et al., 2022; Kumar et al., 2020). There was a need for research to also focus on identifying the core capabilities required for SMEs to implement data analytics for competitive advantage maintenance successfully (Church et al., 2022; Willetts et al., 2022). This involves understanding the necessary skills, resources, and organizational culture needed to support data-driven decision-making and cost-optimization initiatives.

In conclusion, the existing research gaps highlight the significant knowledge deficit concerning data analytics strategies used by SME management accountant leaders for maintaining competitive advantage (Church et al., 2022; Wang & Wang, 2020; Willetts et al., 2022). Addressing these gaps through empirical studies and comparative analysis can provide valuable guidance to SMEs seeking to harness the potential of data analytics in cost management and inform decision-makers about the most effective strategies to achieve sustainable competitive advantages in their organizations.

Transition

Companies' adoption and use of data analytics were anchored on their ability to implement data analytics tools successfully. Companies that have attempted to adopt and implement data analytics tools for management accounting have reported several challenges despite the perceived increase in success rates (Vitale et al., 2020). Some challenges included but were not limited to a lack of data analytics and big data specialists, difficulties sorting and analyzing the huge amount of data associated with big data, and increased risks of collecting poor data (Bergmann et al., 2020). To better understand the factors that might encourage or discourage the adoption of data analytics, researchers must explore the factors that influence the success and failure of information systems as they mirror each other. Despite the apparent importance of data analytics for maintaining a competitive advantage, there seems to be a gap in the existing research, particularly in the context of SME management accountant leaders in Virginia. This gap presents an opportunity for researchers to conduct studies specific to this region and demographic. By investigating the data analytics strategies employed by SME management accountant leaders, researchers can uncover valuable insights into how these leaders use data to optimize costs and gain a competitive edge. Section 2 presents the project.

Section 2: The Project

Data analytics is the process of examining, interpreting, and transforming large sets of data to uncover valuable insights, patterns, trends, correlations, and meaningful information (Nguyen et al., 2022). Data analytics refers to the integration of an organization's data resources into all aspects of decision-making processes, which play an increasingly critical role in decision-making and are fundamentals for durable competitive advantage (Bergmann et al., 2020). Decision makers use data analytics to identify real-time patterns, trends, and insights to reduce costs, optimize operations, and compete more effectively. In Section 2, I described my role as a researcher in this pragmatic inquiry study, described the rationale for that choice of methodology and research design, and described the data collection and analysis procedures for conducting the study. The chapter aims to describe the research in a manner that enables future researchers to duplicate the study precisely.

Purpose Statement

The general business problem was that management accountant leaders often do not effectively use data analytics strategies for decision-making processes to maintain a competitive advantage. The specific business problem was that some SME management accountant leaders in Virginia lacked strategies to use data analytics for decision-making purposes to maintain a competitive advantage. The purpose of this qualitative pragmatic inquiry was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage.

Role of the Researcher

Qualitative pragmatic inquiries provide profound insights into complex processes, and the researcher is crucial. When doing a qualitative pragmatic inquiry, the researcher is the one who gathers data, so they have control over the study's path and direction. Using the points of view put forward by Kaushik and Walsh (2019) and Ramanadhan et al. (2021), the role of the researcher section delves into detail about how the researcher was involved in gathering and interpreting data. The accuracy and dependability of the study's results were enhanced by carefully using questioning techniques, following ethical guidelines, and taking proactive steps to lower bias. Kaushik and Walsh stressed the importance of using three sources of information when doing qualitative pragmatic inquiry research in the business world. They stressed how important it was to use a variety of data sources to improve the validity and dependability of the study.

As the researcher, I continuously self-reflected on my biases, beliefs, and potential influence on the research process and outcomes. I maintained a reflexive or spontaneous journal or diary to capture thoughts, reactions, and evolving insights throughout the study. My journal entries helped me think about and deal with their biases (Bukamal, 2022). Rashid et al. (2019) explained the member-checking process as asking participants for feedback on the study results to ensure that the interpretations align with the participants' thoughts. I established a rapport with participants, creating a comfortable environment for them to share their experiences, feelings, and perspectives. Most participants were unwilling to share their ideas and thoughts in unfriendly environments, making it difficult to gather correct information (Iniguez-Gallardo et al., 2021). As the researcher, I ensured that the environment was friendly for the participants to engage in the interview and also express their feelings freely.

According to Walden University's guidelines, researchers must adhere to prescribed ethical standards during the research process. For this study, I adhered to the protocols of *The Belmont Report* (U.S. Department of Health and Human Services, 1979) in agreement with ethical standards and protection of human research participants (Califf & Sugarman, 2015). The Belmont Report outlines fundamental ethical principles and guidelines for research involving human subjects. The Belmont Report principles, including respect for persons, beneficence, and justice, were adhered to at all times during this study. Beneficence gives respect to research participants by incorporating consent as a requirement of the study. Justice allows ethical conduct in fair practice and handling of research outcomes. Persons were provided with autonomy and treated as autonomous with guaranteed protection. An ethical conduct was paramount, and all efforts of harm to the persons were neutralized. Gioia (2021) reinforced the importance of upholding participants’ confidentiality and seeking consent. I was responsible for ensuring the ethical treatment of participants, including obtaining informed consent, ensuring confidentiality, and respecting participants' rights and well-being.

I shared my experience with the participants to maintain transparency and reduce bias. I have been an accountant for 8 years and have worked in public, private, nonprofit, and for-profit organizations. In some organizations, data analytics has been a struggle, but there are always strategies to ensure that data analytics is successful. Although some of the management accountants lacked data analytics strategies for decision-making, they showed interest in data analytics and were always ready to learn its significance. Management accountants are working to understand the value and use of data analytics software. A deeper understanding of these problems that management accountants like me face will be relevant to this study. To reduce bias, I checked other sources to ascertain that the information I gathered was valid and did not favor a particular group. Also, I ensured that the participants reviewed the information I collected to ascertain that my interpretation of the data aligned with their beliefs to prevent bias.

An interview protocol (see Appendix A) was used alongside the interview questions (see Appendix B). Yin (2018) discussed the importance of an interview protocol as an important tool and guide for researchers. An interview protocol helped me stay consistent amongst all participants, build rapport with the participants, follow the interview questions, and stay focused. The researchers' unique perspectives, when coupled with reflexivity, can bring depth and richness to the study, which is characteristic of qualitative research (Tomaszewski et al., 2020). In summary, I was deeply embedded in the process of qualitative methods and not merely an observer but also an active participant, interpreter, and narrator.

Participants

The participants for this study were SME management accountant leaders and managers in Virginia. The participants were chosen on the aspect of having used data analytics in the decision-making process for more than a year. Statistics have shown that there are 766,826 SMEs in Virginia, or 99.5% of all businesses, employing 1.6 million individuals or 47.1% of all employees in the state (Peak Business Valuation, 2023).

Researchers must examine the ethical considerations associated with participant recruiting, drawing upon the works of Malmqvist et al. (2019). The focus was on choosing participants with relevant knowledge and experience about the investigated topic. LinkedIn was used to look up companies and individuals with the necessary knowledge and experience to participate in the study. Through LinkedIn messaging and emails, I contacted potential participants. Accounting officers of SMEs were the primary target participants of the study with at least a year of experience in data analytics and management. Participants had to be accountants with management and data analytics knowledge.

Walden's guidelines were primary to the selection of participants. An Invitation letter (see Appendix C) describing the study was sent upon participant selection. I investigated utilizing invitation letters to establish initial communication with prospective participants. These letters provided comprehensive details regarding the study and addressed potential concerns about time commitments and the assurance of anonymity. If potential participants accepted the invitation, a consent form was sent. The form informed the participant of their rights, participation requirements, the purpose of the study, and a voluntary request for participation before the study begins. I examined the thorough procedure for gaining approval from the Institutional Review Board (IRB) before commencing the study, assuring meticulous adherence to ethical criteria.

Developing a trustworthy relationship between the researcher and participants was crucial for a successful study (see Yin, 2018). I communicated with participants through emails and phone calls during this process. The participants were assured of their privacy and confidentiality in the study. To be transparent, I disclosed information about myself, relationships, and interest in the study and ensured that there was no bias in the selection of participants. Participants were informed that after completion of the study, their information would be stored in a safe, password-protected lock box for 5 years, after which the files would be deleted and destroyed permanently per Walden’s Guidelines. Protecting participants' information and identity alongside self-disclosure by researchers is foundational in building a working relationship with the participants.

Research Method and Design

Research Method

The qualitative research method was used for this study. The purpose of this qualitative pragmatic research was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. Qualitative research was an investigative approach employed across various academic fields. A qualitative approach enables the researcher to gain deep insights (Savin-Baden & Major, 2023) into the perceptions and experiences of SME management accountant leaders in Virginia instrumental in developing data analytics strategies to maintain cost. The pragmatic inquiry was based on inquiry having the capability of making a practical difference through reasonable solutions. This method ignites vision and values aimed at driving sustainable performance through solving problems and improving the present conditions. Allemang et al. (2022) claimed that qualitative pragmatic inquiry strengthens the research’s outcomes and process. Given its ability to offer a thorough examination of specific situations (Patton, 2002), the qualitative methodology was deemed the best fit for this research.

The quantitative method involves using inferential statistics to examine relationships between variables, group differences, and hypothesis testing, so this will not be the best choice for addressing my business problem (Bougie & Sekaran, 2019). The lack of resources, time, and the need for numerical data made me not use the mixed method approach (Venkatesh et al., 2016). The chosen qualitative method was appropriate for my study because it will help me explore data analytics strategies management accountant leaders use for decision-making purposes to maintain a competitive advantage. Woods et al. (2022) suggested that qualitative researchers focus on rapport-building, which was aimed at ensuring that the data collected were valid and the research participants were safe. Researchers in this domain employ inductive reasoning when making specific observations concerning particular occurrences before making conclusions. They then gather data to evaluate whether the statistical findings validate particular occurrences when making broader generalizations. Typically, theories inform the formulation of research questions, which were framed hypothetically, guiding data collection that was measurable, structured, and consistent.

Qualitative research emphasizes understanding through immersion and observation in specific settings. Speziale et al. (2011) argued that participant observation could provide insights into how individuals' behaviors might vary across different days, times, or shifts, offering a richer context. Qualitative researchers delve into complex, comprehensive investigations in natural environments, drawing from various methodological traditions. This approach seeks to address social or humanistic concerns by painting a vivid picture, analyzing textual data, and capturing detailed participant perspectives (Srivastava & Thomson, 2009). Leung (2015) emphasized that qualitative studies offer as much value as quantitative ones, especially in domains like the psycho-social dimensions of health services, policy formation, and health management. While quantitative, qualitative, and mixed methods were contemplated for this investigation, a purely quantitative approach wouldn't capture the in-depth narratives that a qualitative method could (Speziale et al., 2011). Mixed methods, as described by Leedy et al. (2019), amalgamate aspects of both qualitative and quantitative research.

Research Design

The pragmatic inquiry design was used for this study. Several research designs were considered preceding the choice of pragmatic inquiry research with semi-structured interviews utilizing related communication. A descriptive case study was focused and detailed, carefully examining inquiries about a phenomenon through mining for abstract interpretations of data and theory development (Tobin, 2010). Descriptive research studies the patterns and connections concerning theoretical constructs to advance theory development (Tobin, 2010). Timmons and Cairns (2010) wrote that the use of pragmatic inquiry in research creates knowledge and comprehension and can set a standard for good teaching practices through the development and implementation of policy and gaining experience through exposure to a particular phenomenon.

The qualitative method and pragmatic inquiry design were particularly well suited for my studies because they allow me to explore strategies, identify key concepts, and organize data rather than examine relationships between variables as in a quantitative method (Saldaña, 2014; Yin, 2018). The pragmatic inquiry design allows for an in-depth exploration of a problem within a real-world context. The design involves interviews and a review of publicly available data. A pragmatic inquiry design was appropriate for my study as it allowed for the examination of a variety of different businesses, their current processes, and how they use data analytics strategies for decision-making purposes to maintain a competitive advantage. Other designs, like phenomenological or ethnographic designs, were not suitable for my study because I was not exploring participants' lived experiences or a particular culture.

Data saturation is “the point in data collection when all important issues or insights were exhausted from data, which signifies that the conceptual categories that comprise the theory were ‘saturated’ so that the emerging theory was comprehensive and well-grounded in data” (Hennink & Kaiser, 2022, p. 1). According to Saunder et al. (2018), the researcher does not have a set sample size or can determine the exact sample size to get at data saturation. Data saturation can be reached when the information received from new participants yields no new insights when compared to previously collected data (Yin, 2018). In this study, I ensured that data saturation was accomplished. Data were collected continuously from participants until saturation was reached. Once data saturation had been reached, I stopped collecting data, and data were compiled to present findings and data storage.

Population and Sampling

A purposeful sample of twelve SME chief financial officers (head accountants and management accountants), involving individuals who have used data analytics in the decision-making process for over a year, were recruited via email in Virginia using Virginia's SMB databases and LinkedIn as public records. The exact final sample size was determined when data saturation was accomplished. Determining an appropriate sample size in a qualitative descriptive design was a function of the moment data saturation occurs rather than statistical power or representativeness, as was the case in quantitative research (Savin-Baden & Major, 2023). Data saturation was the point at which another interview was unlikely to add significant new themes, and the researcher had thoroughly explored and understood the phenomenon of interest. Researchers often conduct ongoing data analysis as they collect data and continue data collection until saturation was reached. The sample size will vary depending on the complexity of the research topic.

The purposeful sampling method was used for this study. According to Berndt (2020), a qualitative study has different types of sampling techniques. The three discussed are purposeful sampling, snowball sampling, and self-selection sampling. Self-selection techniques involve the researcher setting criteria for the study, and participants choose to participate freely. This kind of sampling method is time-saving, and participants who willingly participate are likely to be truthful in their responses and committed (Berndt, 2020).

The snowball sampling method is a sampling technique where future participants are recruited by existing participants from people they know. Snowball sampling is valuable when participants are difficult to identify (Berndt, 2020). The last and not the least method is the purposeful sampling technique. The technique relies on the researcher's judgment, and it is when the researcher recruits participants based on their knowledge and expertise of the research topic. This includes expert sampling, typical case sampling, and variation sampling (Berndt, 2020). For this research, the purposeful sampling method was used as it helped me select qualified participants for the study to share their knowledge and expertise on data analytics strategies for management accountants. Purposeful sampling can be useful in qualitative research with many stages and goals. An advantage of using purposeful sampling is that a researcher with limited resources is able to identify the most knowledgeable participants willing to share their experiences about the specific phenomenon of interest (Ames et al., 2019).

Ethical Research

The purpose of this qualitative pragmatic inquiry was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. The *Belmont Report* principles, including respect for persons, beneficence, and justice, were adhered to at all times during this study. The Belmont Report was a foundational document in the domain of ethics related to research involving human subjects. Published in 1979 by the National Commission for the Protection of Human Subjects of Biomedical and Behavioural Research in the United

States, the report outlines fundamental ethical principles and guidelines for research involving human subjects.

Qualitative research involves understanding how individuals interpret their lived experiences. Researchers use qualitative research when they seek to understand the lenses through which people perceive their encounters with the world (Merriam & Tisdell, 2015). Using a qualitative methodology was deemed suitable to address the research inquiries and to articulate the head accountants' perceptions concerning their experiences creating competitive advantage through cost control. There are various specific methodologies within qualitative research, and one such approach is the qualitative case study method. Before conducting any research, I pursued approval from Walden University IRB before reaching out to participants. The IRB was the final administrative body to approve or deny research. After I got my approval notification from the IRB (approval number 07-01-24-1162777), I contacted participants based on the selected criteria. All participants were given a consent form, which describes the research topic, the participant's rights, benefits, and risks that were included in participating in the study. The participants were informed that they could withdraw at any time during the process. Incentives like gift cards were offered to any participants who chose to participate in the study.

Protection of interview and internal financial data was paramount and consistent with Walden University's IRB ethical research standards. Researchers must maintain the identity of participants and the confidentiality of their data, as emphasized by *The Belmont Report*. I stored study data securely in a password-locked file on local storage with access to only me and Walden University staff. I safeguarded participants' information in encrypted files and designated a unique code (instead of using the participant's name) for each participant while storing it in an individual folder. The phone interviews were audio-recorded and will be retained for 5 years. All study data are stored securely in a hard drive for 5 years in a password-protected storage area in my home.

Data Collection Instruments

I was the data collection instrument for this study. Data collection instruments refer to the tools used to gather information or data to solve a problem, such as paper questionnaires or computer-enabled interviews. Data sources include interviews, organizational documents, secondary archived records, case studies, artifacts, checklists, internet surveys, questionnaires, direct observation, or physical interviews (Taherdoost, 2021). The primary technique that gives more accurate and relevant data is using interviews because it allows the researcher to employ data collection tools, including psychological and emotional intelligence and psychometrical knowledge, to ascertain the accuracy and reliability of the information (Yin, 2018). Secondary data sources are equally important because they give verified data that are accounted for and tested. Secondary data, in some cases, can be used as a stratum or control data used to compare it with the primary source data (interview; Mazhar et al., 2021).

In this multiple case study, semi-structured interviews were used. I asked open-ended interview questions (see Appendix B) to participants. Secondly, data were collected from publicly available documents for review. I used an interview protocol (see

Appendix A) to direct and guide the process. The interview protocol helped to maintain structure and consistency with all the participants throughout data collection.

In qualitative research, member checks mean the researcher gives back the data collected to the respondents for cross-checking and validation that the information the researcher captured is genuinely what the respondent gave (Motulsky, 2021). Member checks are a simple error-proof method of validating that the information provided is authentic, accurate, and trusted. Member checks are essential because the respondent's degree of trust in providing information has much to do with the degree of trust attributed to that information.

Validating qualitative data was difficult because I was the data collector and a data analyst, giving a possibility for bias (see Sahakyan, 2023). In this case, member checking minimizes bias because giving back data to the respondents assists in checking for accuracy and correctness. As the researcher, I followed the member-checking process for all my participants to increase reliability and validity. I first gave the participants the data I collected and allowed them to review the information and confirm whether the data aligned with the information they gave previously or their experiences to maintain validity. Also, a phone call or email was done to discuss any discrepancies between their responses (transcripts) and my interpretations. The data triangulation technique was used for this study in order to triangulate publicly available organizational documents and interviews. According to Bans-Akutey and Tiimub (2021), triangulation entails a description of a researcher’s deployment of multiple study approaches when extracting specific information and analyzing the findings critically to establish credibility and validity.

Data Collection Technique

Data collection was through semi-structured interviews and document reviews. Using multiple data sources ensured that I had adequate information for triangulation (see Arias Valencia, 2022). Data collection entails the process of gathering and analyzing valid, credible, trusted, accurate, and reliable data from various sources to solve research problems, trends, or statistical probabilities, among others; the evaluation of possible outcomes was the data collection (see Sree & Bhanu, 2020). I used open-ended questions and reviewed publicly available organizational documents.

The secondary sources controlled the research to make the outcome more credible and accurate. Interviews give more valid and reliable data than questionnaires or observations. In this study, the data collection techniques that were used to collect data were Zoom video conference, phone calls, or on-site. After receiving IRB approval, consent was sent to eligible participants for permission to participate in the study. Once consents were accepted, follow-up phone calls and emails were done to schedule interviews. In this research, a pilot study or pre-interview was not conducted. Semi-structured interviews and member checking were used. I followed the interview protocol found in Appendix A, guiding this process and delivering consistency amongst all participants. During the semi-structured interviews, I used an app called Trint and an audio recorder to record the interview. The app also transcribed the recordings. Through the process of member checking, a summary of my interpretation of the interview was sent to participants for validity and accuracy. Participants made additional comments if needed.

The advantages of the data collection technique included my ability to obtain firsthand, original, and unique data directly from the source and using structured interviews targeting a large population. Recorded interviews allow manipulation of the respondent, are easy to carry out, give more credible results, and provide a better response than a questionnaire (Jain, 2021). The recorded interviews provided in-depth and insightful information and were flexible to carry out. Lastly, the technique allows the interviewer to detect responses, spontaneity, and biased responses, provides nonverbal clues to the respondent, and allows the interviewer to modify questions to capture the required information better. On the contrary, the technique has disadvantages in that it is resource extensive and expensive to carry out compared to questionnaires. The use of secondary sources has the advantage that it is time-efficient and cheaper and easier to obtain data, saving time and cost required to conduct an interview; it allows more time for analysis. Furthermore, the researcher can access data from databases that would not be possible to collect; data can be captured from credible sources, which are more reliable than the primary sources collected, for instance, data from the World Bank (Sahoo, 2022). The disadvantage of using secondary data sources is that they may not directly answer the researcher's specific research questions or contain the precise information they seek. The information might not have been collected from the desired geographical or demographical locations.

Data Organization Technique

Data organization entails the arrangement of data so that they can easily be accessed, retrieved, and managed to improve the quality of the research. Data organization can be conducted by creating a database where the data are recorded systematically. A technique used by researchers involves creating a separate file for each participant, data source, and interview for easy retrieval (Jain, 2021). In this research, the secondary sources can be aligned in a computer with the corresponding video interview to which it relates and the digital recordings stored in an external gadget.

Savin-Baden and Major (2023) emphasized that a consistent approach to data organization simplifies the handling of interview data in subsequent stages. Ensuring consistency in participant interview data is essential to mitigate potential issues in the later stages of the research, as pointed out by Yin (2018). A research log aids in validating and ensuring the reliability of data and can be seen as a strategy for organizing data. The research log is deployed when searching for sources related to data analytics strategies to keep track of their location. Such logs are instrumental in tracking research evolution, as discussed, and Yin highlighted the importance of maintaining a research log to document events or interview data and validate interview research protocols and interactions. Yin also noted the potential of research logs to reduce bias in studies.

According to Walden University's guidelines, I saved the files for all participants in a safe, secure, and password-protected area in my home. Trint software was used for interview recordings and transcribing. Data were transferred to a Microsoft Word document for review and validation, and they were labeled using identifiers and stored alphanumerically in a chronological manner for easy referencing. According to Barocas and Selbst (2016), it is the responsibility of the researcher to safely protect the data from each participant's experience and knowledge. Files were stored in an external drive that was protected with secure passwords and vaulted until the data analysis phase began. Also, other files like reflexive journals, field notes, and copies of publicly available organization documents were saved alongside the interview recordings. All files from the NVivo software were saved on the external hard drive. Files will be saved for 5 years, after which they will be deleted and destroyed permanently.

Data Analysis

During the data analysis phase, the researcher transforms extensive fieldwork and illustrative data into substantive and actionable conclusions. Data analysis has different stages, and in this study, I discussed the steps from form two different authors (see Raskind et al., 2019). One approach was based on the six-step thematic analysis procedures postulated by Braun and Clarke (2014). Braun and Clarke's six-step, inductive thematic analysis procedures regularly given its prevalence in qualitative research and the procedures were conducted based on the following protocol: (a) review the data to gain familiarity with the dataset on a holistic basis to support the identification of patterns spanning the responses of multiple participants; (b) code the data by labeling the codes with a brief, descriptive phrase to indicate the relevant meaning of the data assigned; (c) search for themes in the data by grouping related codes. Codes were identified as related when they converged as various aspects of the same overarching idea; (d) evaluate the themes and compare them to the transcripts to make sure they correspond to the meanings the participants expressed; (e) identify the themes by comparing the data excerpts assigned to each of them to the research questions to assess how they addressed the questions; and (f) create and tabulate the presentation of results organized by each research question, with the results addressing each research question organized by theme.

Another data analysis step for qualitative research was recommended by Yin (2018). These steps include (a) gathering all information, (b) compiling and organizing all data for analysis, (c) conducting a detailed analysis using a coding scheme, (d) grouping the data into a categorization of groups or themes, (e) translating the themes, and (f) drawing conclusions from the data. These steps were followed in this research. Amongst other data analysis strategies, data triangulation was also used for this research as a means to improve reliability and validity.

According to Yin (2018), method triangulation is when a researcher has different sources of data-gathering methods within a research study. In this research, the sources of data were interviews and publicly available organizational data for review on data analytics strategies for management accountants. Data triangulation was important because it reduced bias that comes from a single study and enhanced validity and credibility. Member checking was also utilized to ensure participants checked the transcripts, making sure it was accurate and reflected their recordings. Participants were also given the opportunity to add any additional data to the study. The member-checking process continued until all participants were satisfied with their responses. The Trint app from an Android phone was used for audio recording and transcribing of the responses. The NVivo software organized, compiled, and coded the transcript responses. The NVivo application was useful for gathering similar themes and patterns within the responses. Gehman et al. (2018) stated the importance of connecting the data analysis to the underlying theoretical framework and literature to address the emerging answers to the research question. In this study, I ensured that the data analysis process was being accessed through the lens of the DIT and TAM and also from key themes from the literature to support the findings.

Reliability and Validity

Reliability

In qualitative studies, the concepts of reliability and validity center on credibility, dependability, transferability, and confirmability, as discussed by Savin-Baden and Major (2023). In qualitative research, reliability refers to the consistency of results obtained from a measurement procedure, regardless of when or how it was conducted and the extent to which these findings were not influenced by accidental factors in the research. Bahariniya et al. (2021) suggested that reliability was achieved when every reader of a phenomenological research study can critically assess the investigator's fundamental insights. Also, it refers to the steadiness of the results in a repetitive measurement.

Dependability concerns the consistency of the research, and it was similar to reliability in that the usage of a particular method yielded identical outcomes. Dependability was also defined as a work repeated in the same context with identical participants and methods, and the result would be similar (Janis, 2022). To achieve reliability for this study, I used the Interview Protocol (see Appendix A) to ensure consistency during semi-structured interviews among all participants. Member checking was used to ensure participants could give feedback on their transcribed responses. Feedback was discussed with the participants to resolve any misinterpretation of the transcribed responses. Participants were given the opportunity to add to their responses. I also used a reflexive journal to minimize bias. One major vulnerability for credibility was research bias and collecting insufficient data due to time constraints or nonrepresentative sampling (see Bahariniya et al., 2021). Such bias can arise from the researcher's own beliefs or interpretations. Measures like keeping reflexive journals, pilot testing, and expert panels are recommended to mitigate this. Insufficient data or unrepresentative sampling can hinder a comprehensive understanding of the subject (Savin-Baden & Major, 2023). The application of interview protocol, triangulation, and member checking increases the reliability of qualitative research.

Validity

Validity includes multiple components: credibility, transferability, confirmability, and data saturation. The credibility component reinforces the importance of maintaining integrity and preventing bias through data triangulation. Based on the transferability aspect, I analyzed the data diligently by outlining all the assumptions and constraints to mitigate bias. For the study to remain trustworthy, I ensured that research activities, decisions, interactions, and materials were well-documented and in case of any doubt, other researchers can re-check the details. Data saturation also promotes validation in that the researchers interviewed the qualified participants until they gave consistent information without adding any new details.

Credibility

Credibility was an important aspect of research as it reinforced the importance of ensuring that the collected data was accurate. Savin-Baden and Major (2023) defined credibility in research as thoroughness and accuracy throughout the study's execution. The researcher, being the primary data collector, must maintain integrity to uphold credibility. The largest threat here was researcher bias. To address this, participant validation of transcriptions and member checking, reflexive journaling, and triangulation were beneficial. Member checking involves sharing findings or interpretations with participants to get their feedback and verify if your interpretations align with their experiences (Johnson et al., 2020; López-Zerón et al., 2021; Riazi et al., 2023). Triangulation was an important part of validity. According to Mtisi (2022), it was the usage of different data sources or multiple methods in order to understand phenomena in qualitative research. Data triangulation uses multiple sources of data, while method triangulation uses multiple methods of data collection within the same study. The method of triangulation was used for the study, and it was the use of structured interviews and publicly available organizational documents to review. Triangulation confirmed the accuracy and increased the credibility of the study.

Transferability

Transferability pertains to the applicability of research results to different contexts (Savin-Baden & Major, 2023). To ensure this in qualitative studies, researchers should outline all assumptions and constraints. The challenges to maintaining trustworthiness include biases, inadequate samples, flawed data collection tools, and potential misinterpretation of data (Miller et al., 2022; Newman et al., 2020). Best practices call for data to be analyzed with multiple coders and presented transparently. In the same setting and data, another researcher should be able to use the results of this research and derive a similar result (Mtisi, 2022). A well-documented methodology, context, and participant selection can mitigate these. Transferability for this study was ensured by analyzing the data collection process, describing the data, recording and analyzing the data, and accurately presenting the findings in the study. Focusing on transferability served as a valuable foundation for future data analytics researchers, facilitating the adoption of similar methodologies in their own research endeavors.

Confirmability

Confirmability was about maintaining a detailed audit trail, as highlighted by Savin-Baden and Major (2023) and elaborated upon by Korstjens and Moser (2018). I documented all research activities, decisions, interactions, and materials in my audit trail. For this study, NVivo software was used for data analysis, and codes, themes, and an audit trail were created to help with the examination of study information. Ensuring bias was avoided through the use of reflexive journals and member checking ensured the study remained trustworthy throughout and the study was consistent and replicable.

Data Saturation

Data saturation can be referred to as the researchers' attaining the final point of data collection without adding anything to the database. Sauder et al. (2018) claimed that data saturation is when data redundancy occurs and no new insights exist. I ensured data saturation by continuously interviewing qualified participants until no new information was found (see Sauder et al., 2018; Sebele-Mpofu, 2020). Using data saturation helped increase the validity of my study.

Transition and Summary

Section 2 described the role of the researcher in this pragmatic inquiry, described the rationale for that choice of methodology and research design, and described the data collection and analysis procedures for conducting the study. The purpose of this qualitative pragmatic inquiry was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. A purposeful sample of 12 SMB chief financial officers (head accountants) were recruited via email in Virginia using Virginia's SMB databases and LinkedIn, available as public records.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this qualitative pragmatic inquiry study was to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. Five themes emerged during data analysis to address this question, as follows: Theme 1: data analytics strategies, Theme 2: data analytics processes, Theme 3: types of data analytics, Theme 4: challenges, and Theme 5: overcoming challenges. The following section is the presentation of the findings.

Presentation of the Findings

The research question used to guide this study was as follows: What data analytics strategies do SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage? The following sections are presentations of these themes with evidence in the form of direct quotes from the data.

Theme 1: Data Analytics Strategies

Table 1 indicates the initial codes grouped to form Theme 1 and the number of data segments assigned to each of them.

Table 1

Theme 1 Initial Codes

Theme code (alphabetized)	*n* of data segments assigned
Theme 1: Data analytics strategies	9
Expense tracking and management	1
Line-by-line analysis	1
Multifaceted data analytics strategy	1
Predictive analytics	2
Risk-based audits	1
Root cause analysis	1
Supply chain analytics	1
Understanding of market trends	1

The first strategy was cost tracking and analysis, which included implementing robust cost-tracking mechanisms to monitor expenses across different departments and processes (see Baig et al., 2019; Nguyen et al., 2022). One participant reported using data analytics for expense tracking and management. P12 said, “It's a religious organization. I wouldn't necessarily then say that it was competitive. But we do use it [data analytics] for things such as expense tracking and management.” Although P12’s organization may not have gained a competitive advantage from data analytics, they found it helpful for managing their expenses. Data analytics have also been used to analyze historical spending patterns, identify cost drivers, and detect any abnormal fluctuations in costs (Akter et al., 2022). This information can enable management accountants to make data-driven decisions on cost-reduction strategies (Moll & Yigitbasioglu, 2019). Budget variance analysis uses data analytics to compare actual financial results against budgeted figures, identify significant variances, and investigate the underlying reasons for deviations (Rialti et al., 2019). Budget variance analysis can help management accountants take corrective actions promptly to control costs effectively (Bergmann et al., 2020). In the present study, P2 discussed their use of line-by-line analysis for tracking and managing expenses:

> For my small-business clients, nothing formalized. It's more so in comparison to prior expenses and budget. When I compile their financial statements, I do a line-by-line analysis to see if there's any significant fluctuations that require data. I also look at their balance sheet to see if there were any major cash fluctuations, either in the cash or an investment section, that would warrant further discussion with the client.

P2 conducted a line-by-line analysis of expenses to identify anomalies that indicated a need for further investigation and discussion with the small-business clients for whom they provided accounting services.

Inventory management uses data analytics to optimize inventory levels and reduce carrying costs, as well as to analyze historical sales data to forecast demand accurately, preventing overstocking or stockouts (Ferraris et al., 2019). Efficient inventory management helps minimize storage costs and potential wastage. One participant described a multifaceted data analytics strategy that involved the application of machine-learning algorithms to identify trends in data and enable fast, competitive decision-making. P4 said this of their data analytics strategy:

> In our organization, we leverage a multifaceted data analytics strategy to maintain a competitive edge. We focus on integrating both internal and external data sources to create a comprehensive view of our business environment. By combining customer data, market trends, and operational metrics, we can identify patterns and insights that drive strategic decisions. We employ advanced machine learning algorithms to predict customer behavior and optimize supply chain operations, ensuring we stay ahead of market demands. Additionally, we emphasize real-time data processing to enable swift decision-making.

Predicting customer behavior enabled P4 to forecast supply needs in real time and ensure that supplies were in place to meet forthcoming demands. Another participant, P7, also discussed the use of predictive analytics to forecast consumer demands:

> In our organization, data-driven decision-making was pivotal to maintaining a competitive edge. We rely heavily on predictive analytics to forecast future trends based on historical data, enabling us to anticipate market shifts and customer behavior proactively. Performance metrics and KPIs were meticulously set and tracked to measure our success and operational efficiency.

P7 added that the use of KPIs enabled their organization to measure success. Data about performance were then analyzed to continue forecasting future trends to facilitate ongoing decision-making. Another participant, P11, described how conducting data analytics to forecast consumer behaviors was a means of optimizing efficiency:

> In terms of data analytics, it helps with decision-making. Typically, we use—and I continue to use—data analytics to understand consumer behavior. That's one big one. Another was to understand market trends. Finally, the third one was to better understand our internal operations because we needed to understand if we were being very competitive in the way we operate internally, and then we needed to see how customers were behaving and what market trends were in order to change our business. So, that's generally the strategy around data analytics. We're trying to just improve our efficiency.

By analyzing internal behavior, P11 indicated that their organization could streamline operations to meet emerging customer needs promptly without supply shortfalls or surpluses.

P9 reported a more hands-on strategy for conducting predictive analytics. Rather than providing data to a machine-learning algorithm, P9 conducted predictive analytics using Microsoft Excel: “I'm just using Excel to do trend and predictive analysis type things. And most of my clients were doing the same.” P10 had conducted data analysis on paper before computers became available to their organization:

> In terms of strategies, data analytics was more advanced now than before. When we started, we were doing a lot on paper. Until we started using the computer, we would spend most of our time testing transactions, getting invoices, and performing compliance testing. It was very, very time-consuming. But now, the audit has evolved and has become more risk-based, and many companies are now moving toward new technology like data analytics. We were trying to cut down

> on costs and cut out delays that we've had previously. I'm actually using some data techniques now.

P10 perceived data analytics as a means of reducing inefficiencies and cutting costs, not only in business operations in general but in accounting and strategic decision-making specifically.

ABC was vital in allocating indirect costs to specific activities or products (Quesado & Silva, 2021). ABC helps managers define and measure the actual cost of products or services, allowing management accountants to identify high-cost activities and explore opportunities for process optimization and cost reduction. In the present study, P1 reported that they conducted root-cause analyses on their clients' data: "We do root-cause analysis for bottlenecks and challenges, both in financial and operations. And we receive a lot of big data for transactions that organizations perform." In explaining how root-cause analyses were conducted, P1 added, "We sort of analyze that data in various ways to better understand where things were wrong, and then either replicate the processes that resulted in good outcomes or mitigate the processes that did not result in good outcomes." Data analytics allowed P1 to help clients identify effective strategies in order to replicate them and ineffective strategies in order to modify them.

P3 applied data analytics to supply chain data to identify efficient shipping options and optimize shipping costs for a pharmaceutical company: "There's a lot of data that we collect that we analyze to basically be able to make smart decisions about ensuring that we can optimize our supply chain." P3 explained how the analysis was conducted:

> We look at our cost and information [across the supply chain], and then, basically, have our teams using all the different tools, basically slice and dice, which routes were more expensive, which routes were costing us way more than we did in the previous years, right? What has changed, right? There was a lot of data visualization that went on. There was a lot of data collection. There was a lot of understanding about information and then using that information to make different choices with regard to what changes we can make, which routes we want to use, and which type of transportation systems we want to use.

P3 analyzed shipping expenses to identify routes and carriers that provided optimum costs, as well as less efficient strategies, in order to streamline the supply chain and secure cost savings for their organization.

The first theme aligns with the conceptual framework for this study, which is the DIT and TAM. The TAM, developed by Davis (1985), focuses on explaining users' acceptance and usage of technology. Davis (1989) asserted that perceived usefulness and ease of use assume that positive behavioral outcomes require less labor. The DIT, proposed by Rogers (1962), focuses on how new ideas, technologies, or innovations spread and are adopted within a social system. The participant's use of some of the data analytics strategies, like the value of tracking expenses, performing line-by-line analysis, and recognizing trends and root cause analysis, confirms with TAM and DIT. They perceived the usefulness of these strategies and how easy it was to implement to increase productivity. Hence, this resulted in the adoption of these strategies within their organizations.

Theme 2: Data Analytics Processes

Table 2 indicates the initial codes grouped to form Theme 2 and the number of data segments assigned to each of them.

Table 2

Theme 2 Initial Codes

Theme code (alphabetized)	*n* of data segments assigned
Theme 2: Data analytics processes used	12
Extract-transform-load process	1
IMPACT	7
Profit and loss comparative analysis	1
Reverse cycle	1
Scientific method for data analytics	1
Scrubbing during analysis	1

Seven of the participants reported that they used the IMPACT cycle data analytics process (i.e., identify the question, master the data, perform test plan, address and refine the result, communicate insights, track outcomes). P2 reported relying primarily on the "identify the question" step of the IMPACT cycle: "IMPACT would be the cycle that I use, especially the first part, which identified a question because I'm looking at financials. The first thing I was asking was trying to see what were the right questions to ask?" P5 also referred to the step of identifying the question, saying, "I have been analyzing data by first identifying what the question was we were trying to answer, then coming up with methodologies to come up with sound decisions. The IMPACT cycle was often used in our organization." This first stage entails identifying a business opportunity or issue that data analytics can solve, resulting in a clear problem statement that serves as the framework for the entire data analytics project (Bharadiya, 2023).

P3 also reported that they used the IMPACT cycle, adding, "The starting point was collecting freight data from our partners and vendors, and analyzing that data, and then—depending on what the issue is, or what situation we're trying to assess—using that data to be able to help." Mastering the data, or finding and cataloging pertinent data area sources that can be used to meet the business case, was also known as data identification. Data may come from external providers, databases, spreadsheets, logs, or APIs (Hung et al., 2020). To construct a single dataset, data extraction may involve joining or merging data from many sources (Houtmeyers et al., 2021). Data quality checks were then conducted to find and fix problems. P12 referred to this process as scrubbing the data: "We have to ensure that the information was clear and concise. We're scrubbing the information as well as analyzing it to make sure that it's accurate." Lastly, to make data appropriate for analysis, it was summarized and compressed (Houtmeyers et al., 2021).

Another participant, P4, said, "While we were a small company, we have built data analytics processes that fit with the workflow. We adhere to the IMPACT cycle for our data analytics process, which ensures a structured and effective approach to data-driven decision-making." P4 referred specifically to the step "analyzing results and refining models." The fundamental step in every data analytics process was data analysis. Several statistical and machine learning approaches must be applied to insights, patterns, and trends from the generated dataset. Data analysts investigate relationships, conduct hypothesis testing, and create prediction models (Houtmeyers et al., 2021). P7 referred in their response to the final steps of the IMPACT cycle:

> Addressing and refining the results allows us to derive actionable insights, which were then communicated to stakeholders. Finally, we track outcomes to monitor the effectiveness of our decisions and make necessary adjustments. This structured approach ensures that our analytics efforts were systematic and yield valuable insights.

Data visualization was a crucial step in communicating results to stakeholders. According to Bharadiya (2023), presenting data visually makes complex information easier to grasp and analyze. The last phase was tracking outcomes. This step could entail developing action plans, carrying them out, and monitoring the effects of choices. Closing the loop in the data analytics process through the monitoring of outcomes ensures that data-driven insights convert into real-world business benefits (Bharadiya, 2023).

One participant described using a data analytics process that was similar to IMPACT. P11 stated,

> We typically follow an ETL process. ETL was extract-transform-load. ETL was still very similar to what IMPACT does. Let's say you have a question you're trying to track, customer satisfaction with services. We have to extract the data. Surveys were sent down. Customers have responded that data was sitting somewhere in a database. My job was to calculate the satisfaction score for the last quarter

P11 went on to say that data could be separated to illuminate local trends (e.g., disaggregating customer satisfaction data by state to assess whether the scores varied by geographic area). Another participant, P9, reported conducting cost-benefit analyses:

> It always starts with just the financial statements, a balance sheet and profit and loss comparative analysis, ratio comparisons, and then determining if they were resulting the way they were expected or not. And then we're not identifying what's happening with that data and why. Then, ultimately, you can address that issue. And it could be that you expected something to remain the same, and it did not work.

The cost-benefit analysis approach enables management accountants to prioritize initiatives that offer the most significant competitive advantages and returns on investment (Sharma et al., 2022).

TAM highlights that perceived usefulness and ease of use have a big effect on technology acceptance (Tien, 2020). For instance, the findings by the researcher highly perceived useful processes such as IMPACT and profit and loss comparative analysis, which are being adopted because they produce actionable insights for business decisions. The IMPACT cycle is a structured process involving various steps such as identifying questions, mastering the data, performing tests, addressing and refining results, communicating insights, and tracking outcomes. These steps are vital in reinforcing systematic data analytics which yield actionable insights. TAM theory revolves around the IMPACT cycle’s simplicity suggesting that its ease of use encourages adoption while the structured nature also enhances perceived usefulness. Most SMEs are likely to adopt the IMPACT cycle to avoid excessive complexity since the process provides actionable and clear results.

Theme 3: Types of Data Analytics

Table 3 indicates the initial codes grouped to form Theme 3 and the number of data segments assigned to each of them.

Table 3

Theme 3 Initial Codes

Theme code (alphabetized)	*n* of data segments assigned
Theme 3: Types of data analytics	37
Descriptive analytics	10
Diagnostic analytics	10
Predictive analytics	10
Prescriptive analytics	7

Ten participants reported that they conducted descriptive analytics. Descriptive analytics was the first stage of looking at historical data to gain insights into prior performance. Ge (2018) focused on effectively condensing and presenting material, such as creating reports and dashboards to display KPIs. Trends in sales, production, or consumer behavior may be part of descriptive analytics. In the present study, P12 stated the following about descriptive analytics: “I would say we would use the descriptive data and analytics. And that's mostly for our financial statements to show the current status of the organization.” P2 reported their use of descriptive analytics:

> For me, the biggest one [type of data analytics] was descriptive. I wanted to understand the why behind the numbers. If I see an anomaly, why was this happening? If I am doing a comparison and I see a variance, first of all, did I code in the same manner as I did the previous year? Or did we incur something this year?

P2, therefore, defined descriptive analytics as finding the reason or "why" for anomalies and variances identified in year-to-year data. P6 reported using descriptive analytics because it "allows for the examination of general characteristics and trends."

Ten participants reported that they conducted diagnostic analytics. Diagnostic analytics sifts through data more deeply to determine the reasons behind previous results or trends. The process of diagnostic analytics aids in addressing the "why" issues raised by the patterns that have been noticed (Hung et al., 2020). For instance, diagnostic analytics can entail performing a root cause analysis to determine why sales of a specific product decreased. P1 said of their organization's use of diagnostic analytics, "We do analysis on whether organizations were the best agents of taxpayer dollars and how much more efficiently we can do that. It was primarily diagnostics-type data analytics that we perform." Consistent with the research by Hung et al. (2020), P3 said, "We have used diagnostics typically when we were trying to problem-solve." P4 was also consistent with the previous research in saying, "We use diagnostic analytics to understand the reasons behind a sales dip." By conducting root cause analyses, P4 was able to identify reasons for an alteration in a trend, such as an unanticipated decline in sales.

Ten of the participants reported that they conducted predictive analytics. Predictive analytics forecasts future patterns or outcomes using statistical algorithms and historical data. The method entails creating prediction models that can be applied to decision-making. Predictive analytics can be used, for example, to forecast future sales trends or customer turnover (Rehman et al., 2019). P3 provided a response consistent with this literature in stating,

> When we were doing a lot of forecasting, we utilized more of the predictive stuff, where we were picking up historical information and saying, look, this was the data for the last five years. Now we want to forecast the next five years in terms of, let's say, a specific market that we want to basically play in. We're looking at pricing and other stuff.

P3 discussed the use of historical data to predict future trends. P6 described a specific method for conducting predictive analytics: “After descriptive analysis, we use predictive analysis via means such as LASSO regression to analyze large datasets containing company performance metrics and general characteristics.” P6 noted that predictive analytics were conducted after descriptive analytics. P8 explained predictive analytics: “Predictive analytics was used to forecast future outcomes based on historical data. We apply predictive analytics for budgeting and financial forecasting, using tools like Hadoop and machine learning models to predict future costs and identify potential risks.” P8’s description of predictive analytics was consistent with the definition provided by Rehman et al. (2019).

Seven participants reported that they used prescriptive analytics. Prescriptive analytics goes beyond forecasting to suggest particular actions that should be performed to optimize results. Managers and researchers use the method of prescriptive analytics to make recommendations for tactics or actions to take to get the intended effects (Rehman et al., 2019). In the present study, consistent with the previous research, P11 said of prescriptive analytics that it was as follows:

> Basically, analytics allows you to provide recommendations. To optimize outcomes that come after you have been able to forecast the future. It was like that last frontier where every analytics team wanted to get to, which was to prescribe.

P4 said that they used "prescriptive analytics to devise strategies to boost sales." P8 also provided a response consistent with the literature in saying, "Prescriptive analytics provides recommendations on actions to take. We use prescriptive analytics to optimize resource allocation and cost management strategies. Advanced optimization models and scenario analysis tools like Solver in Excel were utilized for this purpose." The participants' descriptions were consistent with the definition of prescriptive analysis by Rehman et al. (2019).

This theme aligns with TAM and DIT. TAM offers a strong theoretical foundation for understanding the adoption of various types of data analytics (Malatji et al., 2020). As restated by the researchers' findings, the emphasis is on perceived usefulness and ease of use as major factors of technology acceptance. According to the respondents of the research, management accountants often tend to take up descriptive and diagnostic analytics first as their methodologies are straightforward and easy to use when dealing with summarizing and analyzing past data to understand the performance and identify an issue. DIT offers a comprehensive overview of how early adopters and innovators adopt more advanced analytics like prescriptive and predictive tools, while others do not use them until their effectiveness has been determined. TAM can help to understand how management accountants in SMEs give more priority to ease of use initially, but as they realize that such analytics offer substantial benefits, they increasingly accept more complicated analytics (Malatji et al., 2020).

Theme 4: Challenges

Table 4 indicates the initial codes grouped to form Theme 4 and the number of data segments assigned to each of them.

Table 4

Theme 4 Initial Codes

Theme code (alphabetized)	*n* of data segments assigned
Theme 4: Challenges	22
Data quality	11
Inconsistent data formats	6
Learning curve	2
Scarcity of skilled data analysts	3

Quality assurance and data integrity were among the major challenges facing the implementation of data analytics in SMEs. Côrte-Real et al. (2020) demonstrated that organizations face various data analytics implementation barriers, including incompatibility, inaccurate data entry, duplication, and silos. In the present study, 11 participants cited data quality as a significant challenge in implementing data analytics for SMEs. P11, for example, said,

> By far, ask any data analysts, the biggest challenge was always data quality. Because we always say garbage in, garbage out. So, usually, the data was being inputted by other people. For example, you have people who work directly with customers. They were the ones collecting customer names, customer address; if they enter wrong customer address, you ended up with bad data on the backend. Data quality and data integrity were usually the biggest problem with data analysis.

Similarly, P6 stated in another representative response, "Sometimes quality data wouldn't be a guarantee since most of the data used in our organization were hand-recorded by a human being." P8 noted the potential consequences of low data quality in stating, "Inaccurate, incomplete, or inconsistent data can lead to incorrect insights." The participants' responses were consistent with the discussion in Côrte-Real et al. (2020) of data quality being negatively affected by incomplete and inconsistent data entry.

Raut et al. (2019) analyzed linking big data analytics and operation practices for business management in organizations; the findings suggested that integrating data from different sources raised security and privacy concerns, as well as a lack of standardization in data formats or units across different systems, making it hard to implement data analytics in organizations. In the present study, P1 said of data in inconsistent formats,

> We receive data in many forms and from many systems. And one data would be standard, readable data. When they come in different forms, you can standardize how the data was laid out. And that's usually a time-consuming process. And there's risk in altering the data, since you need to change it from different forms.

P1 described the time-consuming process of manually modifying data from one format to another in order to ensure standardization. P4 agreed with P1, saying, "Accessing relevant and high-quality data was often challenging due to data silos and inconsistent data formats." Like P1, P5 reported a potentially labor-intensive, manual process for standardizing data that came in incompatible formats:

> The export feature on Capsule and Google Analytics generally allows us to obtain the data we need. But sometimes, the data gets exported in a format that's hard to work with, including inconsistent rows and columns, wrong number formats, and other export-related errors. Our statisticians review the data for missing entries and entries that may have been recorded incorrectly.

P8 agreed with P5 and added a mention of data silos: "One of the biggest challenges in gaining access to relevant quality data was dealing with data silos. Different departments often maintain their own data systems, leading to fragmented and inconsistent data." Consistent with P8's response, Côrte-Real et al. (2020) demonstrated that silos were a data analytics implementation barrier that organizations face.

A lack of talent and skilled staff was a key challenge faced by organizations when implementing data analytics, a challenge that was multifaceted and impacted several aspects of data analytic adoption (Butt, 2020). Kumar et al. (2020) conducted a quantitative study to explore the barriers to data analytics adoption and found that an inadequately skilled workforce hindered the implementation of data analytics in organizations. Ghadge et al. (2020) confirmed that without competent employees in organizations with skills in data analytics, organizations could struggle to gain important insights from their data, resulting in opportunities and uninformed decision-making. Two participants in the present study referred to the learning curve, or the effort and time required to learn to conduct data analytics, as a challenge to adoption. P12 said of data analytics, “Some of its challenges probably were learning curves or a new process. That was something that's a challenge to each individual.” P9 indicated that data analytics might take up to two years for an organization to adopt, and added, “It requires a timeline, and some training upfront and support during the process, and a very positive outlook as to why this was going to benefit the organization to edge off some of people not wanting to adopt it.” Implementing data analytics involves the introduction of new work processes, methodologies, and technologies, which can disrupt the existing working procedures, and this can be met with resistance among staff and other stakeholders within the organization because of fear of the unknown (Mikalef et al., 2021; Rialti et al., 2019), as P9 suggested. Three participants in the present study referred to a lack of skilled employees and data scientists as a challenge to using data analytics effectively. P5 stated in a representative response, “The biggest challenge was in people not understanding statistical models and testing, given they don’t have ample data analysis backgrounds.” Similarly, P7 said, “A significant challenge was the scarcity of skilled data analysts and scientists.” The participants’ responses confirmed the findings of Kumar et al. (2020) and

Ghadge et al. (2020) that a lack of employees with sufficient expertise in data analytics was a significant implementation challenge.

This theme is also in alignment with the two theories. The DIT teaches about how new ideas, new products, and new technologies diffuse through various adopter categories, from the early adopter to the laggard (Mbatha, 2024). The main challenges facing SMEs include inconsistent data formats and data quality. The issues influence SMEs negatively as they influence reduced confidence during the decision-making processes and data analysis effectiveness. DIT suggests that the challenges contribute toward reduced innovation as SMEs become resistant to adopting new technologies because of concerns surrounding data quality and also resources for cleaning and standardizing data. TAM reinforces the impact of the challenges on SMEs, claiming that on the aspect of perceived ease of use, unreliable data management difficulties may result in increased struggles, leading to SMEs considering advanced data analytics tools invaluable.

Theme 5: Overcoming Challenges

Table 5 indicates the initial codes grouped to form Theme 5 and the number of data segments assigned to each of them.

Table 5

Theme 5 Initial Codes

Theme code (alphabetized)	*n* of data segments assigned
Theme 5: Overcoming challenges	8
Collaboration and support	4

Four participants indicated that they used collaboration with coworkers as a means of overcoming the challenge of poor data quality and incompatible data formats. P12 said in a representative response,

> We overcome that [challenge], I would say, through teaching, through collaborations, and through coworker support. The more that we do it and we support each other—I guess teamwork, you would say—is how we try to overcome some of those challenges.

Through coworkers working together, P12 indicated that the labor-intensive process of standardizing data into consistent and usable formats could be accomplished. This finding was an addition to the previous literature, in which no studies were found that indicated collaboration and teamwork as a means of overcoming challenges related to data quality and formatting consistency. P4 described a different type of support, in which the organization relied on a centralized database to collect and standardize its data: "We address these challenges by implementing a centralized data warehouse and using data cleaning tools to ensure data accuracy and consistency. Regular audits and validation processes were also in place to maintain data integrity." P4 reported the use of data cleaning tools to address the challenge of poor data quality, and a process involving audits and validation to address standardization issues. P4's response was consistent with the previous literature. Data cleaning, a past study has indicated, involves removing or correcting these issues to ensure data accuracy and reliability (Ridzuan & Zainon, 2019).

Preprocessing involves transforming and standardizing the data to make it suitable for analysis (Baig et al., 2019).

Four participants reported that they overcame challenges related to data quality through data validation. P10 said of data collected in other countries, “We try to validate data by working with employees from those countries. We also work with external auditors to make sure that the external auditors have validated that data for us to actually use for our analysis.” P10’s response was consistent with the previous literature. For data to be accurate and reliable, cleansing and validating the data was essential. Data were meticulously checked for mistakes, missing numbers, and inconsistencies throughout this process. Data quality checks were conducted to find and fix problems (Houtmeyers et al., 2021). P6 also described a data validation process:

> When missing entries were observed, the person who recorded the data would be contacted to clarify that there was no bias or errors in recording the numbers or information. There were routine quality checks to ensure that data at our organization were accurately and properly managed.

P6’s use of data validation to address the challenge of low-quality data was also consistent with the description in Houtmeyers et al. (2021) of data quality checks. P9 provided further corroboration, saying of data validation: “If the data going in isn't good, then you're not going to get good information. That’s the way to address what was to be determined, why was it not going in the right way? And how do we fix that?” As Houtmeyers et al. also found, imputing missing numbers, fixing data mistakes, and ensuring data integrity were all examples of cleaning processes, and working with high-quality data was the goal to prevent skewed or incorrect analytical outcomes.

The last theme ties in with TAM and DIT. Analytics are likely to be embraced by innovative and early adopters, who are tech savvies and innovators and who are willing to make investments into new technologies (Mbatha, 2024). The most significant way of overcoming challenges associated with data quality is through validation and collaboration processes. Working as a team and the integration of tools such as data cleaning tools and centralized databases enhance data accuracy and consistency. The TAM theory supports the approach claiming that most businesses adopt technologies simplifying data quality improvement processes. DIT reinforces that organizations that have invested heavily in overcoming these challenges, easily become innovation leaders due to creating systems that make the use of new technologies easier.

How the Findings Relate to the Literature Review

This study's findings contribute to previous literature suggesting that cost-tracking management is important in monitoring expenses and costs by management accountants (see Baig et al., 2019). Using data analytics for expense tracking and management can address the challenges faced by SME organizations as cost tracking and analysis include implementing robust cost-tracking mechanisms to monitor expenses across different departments and processes (Baig et al., 2019; Nguyen et al., 2022). The current study also confirmed previous research findings, which indicated that data analytics have also been used to analyze historical spending patterns in large organizations by identifying cost drivers and detecting abnormal fluctuations in costs

(Akter et al., 2022). The current study findings also established that data analytics could help forecast supply needs in real time and ensure that supplies are in place to meet forthcoming demands in organizations. This finding aligns with previous literature, which revealed that inventory management uses data analytics to optimize inventory levels and reduce carrying costs, as well as to analyze historical sales data to forecast demand accurately, preventing overstocking or stockouts (Ferraris et al., 2019; Quesado & Silva, 2021).

Based on the data analyzed, descriptive analytics helps managers look at historical data to gain insights into prior performance and trends including trends in sales. Effectively condensing and presenting material, such as creating reports and dashboards, can help display KPIs showing important trends in sales, production, or consumer behavior, which may be part of descriptive analytics (Ge, 2018). Diagnostic analytics sifts through data more deeply to determine the reasons behind previous results or trends (Hung et al., 2020). Predictive analytics forecasts future patterns or outcomes using statistical algorithms and historical data that can help management forecast future sales and expected cost of production (Rehman et al., 2019). One of the challenges facing the use of data analytics, as demonstrated in the current study, is the quality of data and data integrity. Organizations face various data analytics implementation barriers, including incompatibility, inaccurate data entry, duplication, and silos (Côrte-Real et al., 2020). Integrating data from different sources raised security and privacy concerns, as well as a lack of standardization in data formats or units across different systems, making it hard to implement data analytics in organizations (Raut et al., 2019).

Current research results demonstrated a lack of talent and skilled staff, a key challenge that organizations face when implementing data analytics. The results support those of previous studies, which revealed that an inadequately skilled workforce hindered the implementation of data analytics in organizations (Ghadge et al., 2020; Kumar et al., 2020). Without competent employees in organizations with skills in data analytics, organizations could struggle to gain important insights from their data, resulting in opportunities and uninformed decision-making (Kumar et al., 2020). To address the challenges faced when adopting data analytics, the current study revealed the need to implement a centralized data warehouse and use data cleaning tools to ensure data accuracy and consistency. Regular audits and validation processes should also be in place to maintain data integrity, including data cleaning, which involves removing or correcting these issues to ensure data accuracy and reliability (Ridzuan & Zainon, 2019).

Contribution of the Findings to Theory

The TAM was adopted in this study. TAM is a three-stage process to assess whether an individual can adopt or reject a technology. In TAM, the cognitive responses of an individual, including perceived usefulness and perceived ease of use, are triggered by external factors that inform their affective responses or attitude and intention towards using a particular technology (Davis, 1989, 1993). The current study findings support the concept of perceived usefulness and perceived ease of use. The perceived usefulness of data analytics was demonstrated in the current study by establishing cost-tracking management to help SMEs in the management of costs and expenses. Using predictive analytics, data analytics is helpful in forecasting sales trends and cost management and control in organizations including SMEs. This study's findings support the TAM concept of perceived ease of use by revealing the need for collaboration and data cleaning for enhanced implementation of data analytics in cost management. By leveraging these TAM concepts, organizations can gain insights into the factors that influence adoption and acceptance, ultimately aiding in the effective implementation of data analytics to maintain a competitive advantage in the competitive business landscape.

The second theory that helped frame this study was the DIT. The DIT links performance indicators to the rate of adoption and the factors influencing that serve as barriers and facilitators (Takahashi et al., 2024). The current study contributes to the adoption of innovation by revealing the challenges associated with adopting data analytics. The uncertainties associated with an innovation might be reduced by ensuring everyone is informed of the consequences, including the drawbacks and benefits of adopting an innovation by communicating to create and share information between people to achieve a shared understanding of data analytics. The results of the current study also support the element of the social system. Rogers (2002) asserted that the social system's nature influences an individual's innovative capabilities. Individual innovativeness is the main criterion for categorizing adopters. This study's results demonstrated the need for collaboration in cleaning data to promote data quality for the adoption of data analytics.

Applications to Professional Practice

Business leaders in SMEs and other sectors may apply this study's findings in the cost management plan by implementing robust cost-tracking mechanisms to monitor expenses across different departments and processes. Cost tracking and analysis may help management accountant leaders in expense tracking management and budgeting to ensure the minimum cost of operation and production in businesses. Cost-tracking mechanisms can help in monitoring expenses across different departments and processes (Baig et al., 2019; Nguyen et al., 2022).

Businesses in the SME sector may use the findings of my study to understand the need to implement data analytics in operations. This study finding may not only be used by management accountants in the SME sector but also can be applied by independent professional financial analysts such as auditors who may use data analytics to compare actual financial results against budgeted figures. Financial analysts may thus make informed decisions by conducting a line-by-line analysis of expenses to identify anomalies that indicate a need for further investigation and discussion with small business clients for whom they provide accounting services. Data analytics have also been used to analyze historical spending patterns, identify cost drivers, and detect any abnormal fluctuations in costs (Akter et al., 2022).

The current study findings provided important insight into the need to use data analytics strategies such as descriptive analytics using historical data to gain insights into the prior performance of the business. Additionally, the findings demonstrated predictive analytics for forecasting future patterns or outcomes using statistical algorithms and historical data for informed decision-making by leaders. Managers and researchers can thus use these strategies in their businesses, especially in predicting future business performance. The use of different data analytic strategies, such as prescriptive analytics, can help organizations make recommendations for tactics or actions to take to get the intended effects (Rehman et al., 2019).

Data quality and lack of skills among employees were a significant challenge facing the use of data analytics in SMEs as demonstrated in this study. Learning from the insights of this study, SME leaders may make informed decisions such as implementing training development programs in data analytics among employees. Such training programs can help enhance the knowledge and skills that would foster the adoption of different data analytics strategies to improve performance. SMEs have a shortage of internal data analytics knowledge, resulting in the need to train more staff in data analytics, which may be costly but worth it (Dubey et al., 2019).

Implications for Social Change

The current study's findings have several implications for social change as business leaders can employ these strategies to bolster confidence in financial statements. Managers in SMEs may adopt different data analytic strategies, such as predictive analytics, to enhance cost management efforts for improved performance. Data analytics may promote accuracy in financial statements and cost analysis that leads to trust in financial records by the business stakeholders, including investors, employees, customers, and management. As a result, the professional ethics of management accountant leaders would be improved within the profession.

The use of data analytics can benefit auditors who may conduct higher-quality audits at lower costs leading to improved trust in financial reporting backed by data analytics. Increased confidence in financial statements can result in greater leverage, which, in turn, opens up new business opportunities and enhances employment prospects. Additionally, great confidence in financial statements may attract more investors to the company, stimulating increased capital spending, job creation, and local tax base growth. Overall, these positive social changes can have a broader impact on the business community and society at large.

Employees in SMEs and other organizations may also find this study's results important and may consider adopting different strategies as outlined in this study to improve their data analytics skills. The insights gained from this study on the lack of skills in data analytics may motivate staff in SMEs to attend various training programs to learn different data analytic techniques for enhancing how to use data to improve efficiency and performance in organizations. Implementing data analytics strategies can require substantial updates to an organization's technological infrastructure, including training employees, as a lack of knowledge can make it difficult to fully leverage data analytics and hinder adoption (Côrte-Real et al., 2020).

Recommendations for Action

Various recommendations are suggested for actions to enhance the use of data analytics strategies. These recommendations are suggested for decision-making purposes to maintain a competitive advantage in SMEs and other organizations. The recommendations are based on the study's results.

The first recommendation for action is for the management of SME organizations and other sectors to implement training and development programs about data analytics. As demonstrated in the current study, the lack of knowledge and skills in data analytics has been a challenge for most SMEs, which leads to limited use of data analytics strategies for improved competitive advantage. Organizations could struggle to gain important insights from their data, resulting in opportunities and uninformed decision-making. In this regard, management accountant leaders need to ensure the availability of continuous data analytic training programs for their staff to improve knowledge and skills in data analytic techniques in SME organizations.

The second recommendation is that SME organizations should implement a centralized data warehouse and use data cleaning tools to ensure data accuracy and consistency. Regular audits and validation processes are also in place to maintain data integrity. Regular data audits and validation ensure that the data used for cost-benefit analysis are accurate and can provide accurate results that are effective for informed decision-making to enhance competitive advantage in business operations and performance. Auditors play a critical role in assuring stakeholders that controls are effective and that financial reporting is accurate; thus, they need accurate and validated data (Willetts et al., 2022).

The third suggestion is to establish a collaborative and teamwork environment as a means of overcoming challenges related to data quality and formatting consistency. Teamwork and collaboration help in sharing ideas on how to use data analytics to predict future demand and supply in the market and how data can be used to minimize overhead costs and other expenses. Early detection of inconsistencies improves audit efficiency and decreases review costs, directly impacting operational expenses and this can be effectively achieved through collaboration and teamwork among employees (Hallikainen et al., 2020).

Recommendations for Further Research

The rapid change in technology and data analytics may impact the value of the study results over time. This change in data analytics and technological advancement may indicate a change in strategies needed to implement data analytics in accounting and other financial services in different sectors, including SMEs. Therefore, future researchers are encouraged to consider replicating this study in the future by focusing on the impact of continuous training and development programs on the adoption of data analytics in SMEs and organizations in other sectors.

This study is delimited to only SME management accountant leaders in Virginia, excluding other regions. The focus on SME management accountant leaders in Virginia limits the transferability of the findings across different sectors and locations. Future research should be conducted using data from other settings in the United States and different sectors to determine the transferability of the study findings across diverse sectors. Concentrating on data analytics strategies related to maintaining a competitive advantage, excluding other decision-making purposes or strategies, limited this study to data analytics strategies and competitive advantage, excluding other important factors. There is a need to further explore diverse aspects of data analytics to expand the applicability of the study findings. Based on these limitations, future researchers may consider conducting another study to include diverse aspects of data analytic strategies and general organizational performance not only in SMEs but also within other sectors.

Reflections

In this research, I have self-reflected on data analytics strategies used by management accountant leaders to enhance competitive advantage in SMEs. I investigated data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. Using a qualitative pragmatic inquiry approach, diverse data analytics strategies were demonstrated for SME leaders to consider implementing such strategies in promoting data analytics. Such strategies can lead to effective cost-management practices for enhanced competitive advantage. I understood the need for collaboration and teamwork in any workplace and the importance of continuous training to promote skills among employees. I believe that this qualitative pragmatic inquiry study will be valuable to my colleagues, SME organizations, and other sector organizations in promoting their competitive advantage.

Conclusion

This study addressed the research problem, which aimed to inquire into the data analytics strategies of management accountant leaders for effective decision-making purposes to maintain a competitive advantage. The problem was that management accountant leaders in SMEs in Virginia lacked strategies to use data analytics for decision-making purposes to maintain a competitive advantage. The results of this study provided significant insight into the data analytic strategies and how they can be applied in practice to promote competitive advantage for SMEs in Virginia. The current research has offered significant insight into the need for more training, data quality validation, collaboration, and teamwork to enhance the adoption of data analytics in SMEs by management accountant leaders.

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Appendix A: Interview Protocol

Interview Protocol	
What you will do	**What you will say—script**
Introduce the interview and set the stage—often over a meal or coffee	Script: I appreciate your time for this discussion on data analytics strategies for management accountants in Virginia SMEs. Over coffee, let's explore your experiences with decision-making and maintaining a competitive advantage. I'm eager to hear your insights and delve into the specifics of your practices.
• Watch for non-verbal queues • Paraphrase as needed • Ask follow-up probing questions to get more in depth	1. What data analytics strategies do you use in your organization for decision-making purposes to maintain a competitive advantage? 2. What type of data analytics software/tools does your organization use for your cost analysis, and what other tools and data sources were lacking to improve data? 3. What data analytics process does your organization follow? (i.e. IMPACT cycle - identify the question, master the data, perform test plan, address and refine the result, communicate insights, track outcomes). 4. What types of data analytics were being used, and when do you use them? (descriptive, diagnostic, predictive, and prescriptive analytics). 5. What were some other data analytics strategies being used? How do you describe the use of these strategies, and what were the reasons for selecting these strategies? 6. What were some of the challenges faced during the implementation of data analytics strategies? How did you overcome these challenges? And how do you measure success?

	7. What were the biggest challenges you have faced gaining access to relevant quality data, and how did you and your team effectively resolve them? 8. What other comments do you have in regard to management accountants' use of data analytics for reporting and management support?
Wrap up interview thanking participant	Script: I want to extend my sincere gratitude for your invaluable contribution to my research on data analytics strategies among SME management accountants in Virginia. Your insights and experiences have added significant depth to my understanding. Your willingness to share your expertise and engage in our discussion was greatly appreciated. Your perspectives will undoubtedly enhance the quality of my research findings. Thank you once again for your time and valuable insights. I look forward to potentially sharing the results of the study with you in the future.
Script: I hope this message finds you well. I am reaching out to express my gratitude for your participation in our recent interview on data analytics strategies for SME management accountants in Virginia. Your insights were incredibly valuable, and I am in the process of member-checking to ensure the accuracy and completeness of my findings. I would like to schedule a follow-up interview with you to review and discuss the preliminary results. Please let me know a time that suits you for this follow-up conversation. Your input during this phase was crucial, and I am eager to ensure that your perspectives were accurately reflected in the final research.	

Thank you once again for your time and contribution. I look forward to our continued collaboration. Best regards,	
Introduce follow-up interview and set the stage	Script Dear Participant I trust this message finds you well. I am reaching out to express my sincere appreciation for your insightful contributions to our recent interview on data analytics strategies for SME management accountants in Virginia. As we move forward in the research process, I would like to invite you to participate in a follow-up interview. The purpose of this session was to share and discuss the preliminary findings derived from our initial conversation. Your perspectives were integral to ensuring the accuracy and relevance of the research. **Follow-Up Interview Details:** - **Date:** [Proposed Date] - **Time:** [Proposed Time] - **Location/Platform:** [In-person or virtual, and specific details if applicable] During our follow-up, we will delve into the preliminary results, allowing you to provide valuable feedback and insights. This collaborative discussion will help refine the research and ensure that your experiences were accurately represented. Your expertise was immensely valued, and I look forward to our continued collaboration. Please confirm your availability for the proposed date and time, or suggest an alternative that suits you. Thank you once again for your time and dedication to this research. I am confident that our follow-up discussion will further enrich the depth of our findings. Best regards,
Share a copy of the	Script; synthesis here for each interview and below every question.

succinct synthesis for each individual question	
Bring in probing questions related to other information that you may have found— note the information must be related so that you were probing and adhering to the IRB approval. Walk through each question, read the interpretation and ask: Did I miss anything? Or, What would you like to add?	1. What data analytics strategies do you use in your organization for decision-making purposes to maintain a competitive advantage? 2. What type of data analytics software/tools does your organization use for your cost analysis, and what other tools and data sources were lacking to improve data? 3. What data analytics process does your organization follow? (i.e. IMPACT cycle - identify the question, master the data, perform test plan, address and refine the result, communicate insights, track outcomes). 4. What types of data analytics were being used, and when do you use them? (descriptive, diagnostic, predictive, and prescriptive analytics). 5. What were some other data analytics strategies being used? How do you describe the use of these strategies, and what were the reasons for selecting these strategies? 6. What were some of the challenges faced during the implementation of data analytics strategies? How did you overcome these challenges? And how do you measure success? 7. What were the biggest challenges you have faced gaining access to relevant quality data, and how did you and your team effectively resolve them? 8. What other comments do you have in regard to management accountants' use of data analytics

for reporting and management
support?

Appendix B: Interview Questions

1. What data analytics strategies do you use in your organization for decision-making purposes to maintain a competitive advantage?
2. What type of data analytics software/tools does your organization use for your cost analysis, and what other tools and data sources were lacking to improve data?
3. What data analytics process does your organization follow? (i.e. IMPACT cycle - identify the question, master the data, perform test plan, address and refine the result, communicate insights, track outcomes).
4. What types of data analytics were being used, and when do you use them? (descriptive, diagnostic, predictive, and prescriptive analytics).
5. What were some other data analytics strategies being used? How do you describe the use of these strategies, and what were the reasons for selecting these strategies?
6. What were some of the challenges faced during the implementation of data analytics strategies? How did you overcome these challenges? And how do you measure success?
7. What were the biggest challenges you have faced gaining access to relevant quality data, and how did you and your team effectively resolve them?
8. What other comments do you have in regard to management accountants' use of data analytics for reporting and management support?

Appendix C: Invitation Letter

Date:

Subject: Request for Management Accountants Leaders to participate in a research study

Dear Management Accountants,

Hello, my name is Katty N Nkem, and I am a Doctoral candidate in the Doctor of Business Administration (DBA) program at Walden University. I am currently conducting a research study to explore data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. This academic research study only supports a doctoral degree and was unrelated to any business program. I got participants from SMB databases and LinkedIn available as public records.

This letter was to invite management accountant leaders to be a part of this study.

Participation in the study will consist of a 30-minute audio-recorded interview with eight questions on data analytics strategies that SME management accountant leaders in Virginia use for decision-making purposes to maintain a competitive advantage. I also have attached the Consent Form to provide additional information about the study, including confidentiality. Please let me know if you require modification to the planned procedures before you consent to participate in the study. Also, please note that if you choose to be a part of the study and find that you no longer want to participate, you are free to withdraw from the study at any time.

Management accountant leaders that meet the participant criteria and would like to take part in the study (as outlined in the attached Consent Form), please send an "I Consent" e-mail to [redacted] by "date." Also, if you have any questions or concerns, please feel free to contact me by e-mail [redacted] or phone [redacted].

Thanks for your time and consideration.

Sincerely,

Katty N Nkem

DBA Doctoral Candidate, Walden University