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EFFECTS OF BUSINESS ANALYTICS CAPABILITIES ON BUDGET GOAL COMMITMENT: THE MEDIATING ROLES OF FORECAST ACCURACY AND BUDGET ADEQUACY

BY

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ABSTRACT

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Title: Effects of Business Analytics Capabilities on Budget Goal Commitment: The Mediating Roles of Forecast Accuracy and Budget Adequacy

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Budgeting processes rely on the use of existing data to forecast future activities, identify predictable resource consumption and provision patterns, and facilitate resource allocation decisions. Prior research suggests that business analytics capabilities hold some promise in enabling effective budget processes. However, little empirical research examines the processes by which business analytics capabilities are implicated in budget processes and how they translate into performance. This study aims to examine the relationships among business analytics capabilities and budget goal commitment and explore the intervening roles of forecast accuracy and budget adequacy in these relationships. The study adopts a quantitative strategy to collect data through surveys distributed to a sample of managers working in a cross-section of organizations located in the State of Qatar. Results from partial least squares approach to structural equation modelling fails to show a direct positive relationship between business analytics capabilities and budget goal commitment. However, the effects of business analytics capabilities on budget goal commitment are generated by mediating variables; particularly, forecast accuracy and budget adequacy. The study results make theoretical and practical contributions to enhance our understanding of how the recent development in information technology affects budget processes in organizations. Besides, it demonstrated the significant role of business analytics capabilities in forecast accuracy, budget adequacy, and subsequently, budget goal commitment.

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Chapter 1 Introduction

1.1 Background and Statement of Problem

Budget processes are integral to the resource allocation processes within organizations that have significant performance consequences in organizations. The budget processes rely on internal and external data sources to decide on the most efficient ways of allocating scarce organizational resources in ways that motivate effective performance (Henri et al., 2020). In doing so, the budgeting processes rely on the use of existing data to forecast future activities, identify predictable resource consumption and provision patterns, and facilitate resource allocation decisions.

Significant advancement in enterprise information systems have led to the gathering and use of big data (high-volume and high variety data) to influence business decisions (Chen et al., 2016; Rikhardsson & Yigitbasioglu, 2018). While most organizations have developed the capacity to gather large amounts of financial and non-financial data from internal and external sources, research suggests that the benefits of such data may only be realized when organizations develop the analytical capabilities for sorting through such data (Chen et al., 2016; Ramanathan et al., 2017; Rikhardsson & Yigitbasioglu, 2018; Ashrafi et al., 2019). This capability, known as business analytics capability, is said to disaggregate and reassemble large amounts of structured and unstructured data in a manner that allows organizational participants to transform data, identify predictable actions, and make data-driven decisions (Santiago Rivera & Shanks, 2015; Amani & Fadlalla, 2017). This study seeks to examine the impact of business analytics capabilities on the budget processes within organizations.

Prior research suggests that business analytics capabilities hold some promise in enabling effective budget processes (Maisel & Cokins, 2014; Rikhardsson & Yigitbasioglu, 2018). However, little empirical research examines the processes by which business analytics capabilities are implicated in budget processes and how they translate into performance

(Rikhardsson & Yigitbasioglu, 2018). In the context of Qatar, there is limited evidence of the effect of business analytics or application of these data technologies in the budgeting processes. This phenomenon is understandable, with Rikhardsson and Yigitbasioglu (2018) noting that the field of business analytics is still new and will continue to evolve. Thus, this study aims to examine the relationships among business analytics capabilities, forecast accuracy, budget adequacy (BA), and budget commitment.

1.2 Research Aim and Objectives

This study aims to investigate the relationship between business analytics capabilities and budget goal commitment and examine whether this relationship is mediated by forecast accuracy and budget adequacy. Specifically, the study aimed to attain the following objectives:

a) To understand the effect of business analytics capabilities on budget goal commitment.

b) To understand how forecast accuracy mediates the relationship between business analytics capabilities and budget goal commitment.

c) To determine if budget adequacy mediates the relationship between business analytics capabilities and budget goal commitment.

d) To determine whether forecast accuracy affects budget adequacy in the context of business analytics.

1.3 Research Questions

Based on the above objectives, the research developed the following four questions:

a) Do business analytics capabilities affect budget goal commitment?

b) Does forecast accuracy mediate the relationship between business analytics capabilities and budget goal commitment?

c) Does budget adequacy mediate the relationship between business analytics capabilities and budget goal commitment?

d) Does forecast accuracy affect budget adequacy in the context of business analytics?

1.4 Summary of Methodology

A quantitative research design has been employed in this study. Specifically, a survey approach has been used to collect data from a cross-section of entities engaged in the State of Qatar. The target respondents are managers who have responsibilities for the budget of their units or departments. The survey was distributed through email and phone message to the prospective 600 participants, who were all requested to participate in the study. The data collected was analyzed through partial least squares (PLS) structural equation modelling approach.

1.5 Summary of Contribution

The study focused on the direct effects of business analytics capabilities on budget goal commitment and mediating roles of forecast accuracy and budget adequacy in this relationship. The results support the direct relationships between the following: business analytics capabilities and forecast accuracy; business analytics capabilities and budget adequacy; forecast accuracy and budget adequacy; and budget adequacy and budget goal commitment. Further, it provides evidence that forecast accuracy and budget adequacy individually and serially mediate the relationship between business analytics capabilities and budget goal commitment.

The study findings are expected to increase research interest in the role of business analytics in budgeting and management accounting and encourage more organizations to adopt those data capabilities that aid to fully benefit from business analytics capabilities. Theoretically, the findings add to the descriptive literature on the present status of digitalization and the use of business analytics in the budgeting process. In practice, this study signals the management accounting practitioners and organizations that investments in business analytics capabilities are essential to optimize budgeting processes and boost budget goal commitment.

1.6 Dissertation Structure

The study is divided into six chapters. Chapter 2 reviews the literature that is relevant to this study. Chapter 3 presents the theoretical framework and hypotheses development. Chapter 4 discusses the methodological approach adopted in this study. Lastly, chapter 5 presents the findings, while chapter 6 discusses the results and concludes the study.

Chapter 2: Literature Review

2.1 Introduction

This chapter focuses on reviewing literature that is relevant to the research problem under investigation. The first part of the literature review will focus on reviewing the relevant literature related to business analytics. This section will focus on providing a background understanding on business analytics and the capabilities they generate. The second part of the chapter will focus on reviewing the relevant literature related to budget goal commitment. I will examine how the notion of budget goal commitment has been conceptualized in prior studies, its importance for organizations, and how budget goal commitment can be fostered to generate value for the organizations. The third and fourth sections of this chapter will review the literature on budget adequacy and forecast accuracy. The focus will be on how these two variables have been conceptualized and their importance, antecedents, and consequences.

2.2 Business Analytics Capabilities

2.2.1 Business Analytics

The influence of information technology on the managerial accounting function in organizations has been well-documented (Rikhardsson & Yigitbasioglu, 2018). The emergence of ERP systems promised the development of integrated information systems that support organizational decision-making (Cooper & Kaplan, 1997; Davenport, 1998). In view of this, prior management accounting research has examined the effects of ERP systems on management accounting practices (Scapens & Jazayeri, 2003; Rom & Rohde, 2007; Kallunki et al., 2011). Despite the fact that these systems have improved the speed with which accounting data is collected and reported (Cooper & Kaplan, 1997; Davenport, 1998), many have concluded that they frequently stabilize rather than significantly alter the management accounting procedures (Granlund & Malmi, 2002; Rom & Rohde, 2007; Scapens & Jazayeri, 2003). ERP solutionsare found to improve control (Chapman & Kihn, 2009; Granlund &

Malmi, 2002; Rom & Rohde, 2007; Scapens & Jazayeri, 2003; Wagner et al., 2011) and boost organizational performance (Hunton et al., 2003; Nicolaou, 2004; Nicolaou & Bhattacharya, 2006; Velcu, 2007). Moreover, studies have looked at how digitalization of accounting operations, through ERP systems, affects the function of the management accountant. As the roles of management accountants have become more strategic oriented (Granlund & Malmi, 2002; Quattrone & Hopper, 2001), the decentralization of management accounting has led to management accounting tasks being increasingly performed by other functions of an organization due to better access to information. While ERP systems created data warehouses, it was believed that additional information technology would be required to make the information useful to support decisions (Shaikh & Karjaluoto, 2015; Belfo & Trigo, 2013). This resulted in the emergence of business inelegance systems (Elbashir et al., 2011).

Business intelligence systems are tools used to assist firms in managing and refining business information to make better decisions (Gbosbal & Kim, 1986; Gilad & Gilad, 1986). Lönnqvist and Pirttimäki (2006) used the term business intelligence to refer to the information and knowledge that characterizes the business environment, organization itself, and organization's status with regard to its markets, consumers, rivals, as well as economic concerns. Moreover, they used the phrase to describe a structured and systematic method through which businesses obtain, evaluate, and distribute information from internal and external information sources that are significant for their business activities and decision-making. In view of this, Lönnqvist and Pirttimäki (2006) indicated that business intelligence is a process comprising two major activities, namely data input and data output. A conventional term for data input is data warehousing, and it entails the transfer of data from a variety of source systems to a single, integrated data warehouse. The full value of a company's data warehouse can only be realized when its users have access to the data and can utilize it to make decisions. As a result, organizations place the most emphasis on dissemination of data. This is where the second activity follows, and it is referred to as business intelligence (BI), as managers use data from the data warehouse to execute enterprise reporting, OLAP, querying, and predictive analytics. In light of this, Jourdan et al. (2008) indicate that business intelligence is a process as well as a product. The process comprises techniques that organizations utilize to generate meaningful information, or intelligence, that can assist them to thrive in the global economy. The product is the information that enables enterprises to anticipate with a high degree of certainty the behavior of their “competitors, suppliers, customers, technologies, acquisitions, markets, products and services, and the general business environment.”

In more recent times, business analytics have emerged as a powerful source of decision support. It can be differentiated from business intelligence by its emphasis on future predictions that goes well beyond just providing information in the form of figures and graphs, and can be considered an advanced form of business intelligence (Mashingaidze & Backhouse, 2017). There is no consensus in the literature on the definition of business analytics, since definitions have evolved with time. Initially, scholars perceived business analytics from the perspective of the application of statistical methods to analyze data in the organization to gain new insight (Emblemsvåg, 2005). Later, this understanding evolved to include not just statistical methods and tools but also models aimed at generating insight from data (Tribou, 2006). This change is captured by Davenport and Harris (2007, p. 7) who defined it as “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive choices and actions.” Bose (2009) improved on this definition by adding automation. Boss (2009) defined business analytics as a collection of specific activities and technologies that improves human decision-making and provides automated decisions. Later, Evans (2017) included the specific context where business analytics unfolds. The author defined this term as “a process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving” (p. 30). However, this definition failed to capture the automated decisions that are central to business analytics. Considering this limitation, this definition must be combined with an earlier interpretation by Bose (2009) as the application of statistical methods, tools, and technologies to generate insights and automated decisions in an organization based on historical data.

Davenport and Harris (2007) observe that owing to the increasingly complex nature of business problems and a lack of time for decision-making, the role of business analytics is becoming more critical to modern organizations. With the growing availability of massive amounts of data, Evermann and Tate (2016) note that business analytical tools give managers better confidence and visibility to handle uncertainty. Furthermore, such analytics are of tremendous interest and utility to behavioral and social scientists, who are constantly challenged to uncover patterns hidden in dense quantitative data. Hopkins et al. (2007) note that adequate knowledge of business analytics methods can provide the analysts in an organization capabilities that allow them to make quick and informed decisions and offer stable leadership to the organization to effectively compete in the market. Additionally, Hopkins et al. (2007) argue that business analytics could provide a forum for researchers and academicians for theoretical development, as evident in this study.

Business analytics has become even more crucial in recent times due to the large amount of data structured and unstructured gathered from disparate sources by organization. Data storage and processing technology have significantly advanced in recent years, thus allowing managers to incorporate new options for data collection and handling for their decision-making and strategic management (Brynjolfsson & McElheran, 2016). This has led to what has come to be known as big data. The study by Chen, Chiang, and Storey (2012) defined big data as data with greater diversity, higher volumes, and greater velocity. This data is in gigabytes, terabytes, tetra bytes, and quintillion bytes. Advances in information technology and development of data warehouses have been instrumental in generating big data

(Gandomi & Haider, 2015). Individuals can now collect large volumes of data and store them in the cloud or data warehouses (Gandomi & Haider, 2015). In 2018, Forbes Magazine reported that 2.5 quintillion bytes of data was being generated daily, and with the advent of Internet of Things (IoT), this is expected to accelerate over time (Marr, 2018). Google, the biggest search engine, records an average of 3.5 billion searches daily (Marr, 2018). These have led to the generation of large data that standard data processing technologies cannot effectively process (Grover et al., 2018), thus creating the need for business analytics and machine learning techniques. For example, it is not able to handle quintillion bytes of data in MS Excel and other standard data process technologies.

The heterogeneity, pervasiveness, and dynamic nature of the different data generation resources and devices, as well as the enormous scale of data itself, renders the determination, retrieval, processing, integration, visualization, and interpretation of big data a challenging task (Barnaghi et al., 2013). Big data, thus, brings new challenges to data mining techniques and requires contemporary approaches to address those challenges (Zhao et al., 2013).

Big data has the power to fundamentally transform the organizational structure of the management accounting function. This stems from the possibility of a long-term effect on organizational decision-making (Kitchin, 2014). Decision-makers in an organization frequently focus on determining the reasons for occurrences to infer correlations or forecast future events. Variance analysis, for example, focuses on finding the quantity- and price-related reasons for budget discrepancies. Contrastingly, Rikhardsson and Yigitbasioglu (2018) observe that data-driven decision-making emphasizes the links and patterns in data that can inform actions, with the “why” becoming secondary. Managers can make decisions on patterns that exist and are stable throughout time. Phillips (2013) notes that management accounting may even be incorporated into a wider analytical function within the firm, alongside the customer, process analytics, and environmental analytics.

Mayer-Schönberger and Cukier (2013) downplay data quality as a key characteristic in the big data literature because cleaning of the data becomes impossible as data sets become larger and the importance of correctly registering any one item of data is negligible in comparison to the complete set. This is contrary to accounting practice, as it places a premium on data quality assurance in areas like internal controls and management reporting. Mayer-Schönberger and Cukier (2013) note that working with "raw" data in reporting makes data quality issues more critical, especially for individuals in charge of management reporting. Since individuals in more functions want to access accounting data and combine it with other data, for example, combine data from sales and marketing, management accountants must be adept at providing data access and assisting in data combination. In this case, Evans (2017) considered business analytics as a solution to the challenge of large volumes of information caused by big data. Evans (2017) observes that businesses can use business analytics to transform big data into actions through analysis and apply the insight in the decision-making process. In agreement, Grover et al. (2018) observed that businesses apply business analytics techniques and big data to understand consumer behaviors and predict market trends to design effective marketing campaigns and bespoke products and services.

2.2.2. Business Analytics Capabilities (BAC)

Research shows that business analytics has emerged as a solution to the problems posed by big data, including the availability of large volumes of information collected by companies (Davenport & Harris, 2007). The design features of business analytics facilitate the sorting of large datasets into manageable sets, enable the analysis of data for informed decision-making, allow data-driven forecasts, enable the use of simulation to test scenarios, and facilitate the identification of predictable actions (Applebaum et al., 2017; Davenport & Harris, 2007). As noted by Applebaum et al. (2017), inherent in business analytics are four main capabilities, namely *descriptive analytics, diagnostic analytics, predictive analytics*, as well as *prescriptive* *analytics*. A detailed discussion of these capabilities is provided in the next section.

Descriptive analytics

Descriptive analytics capability is the first dimension of business analytics. Raghupathi and Raghupathi (2021) argue that this dimension is the most basic type of data analytics that employs simple statistical and mathematical techniques such as percentages and averages rather than complicated computations. They (2021) add that descriptive analytics is concerned with the fundamental question of what occurred. Similarly, Dilla et al. (2010) observe that this kind of analytics uses dashboards and other kinds of visualization to provide a representation of what happened. For Dilla et al. (2010), descriptive analytics involves the collection, organization, and presentation of historical data in an understandable manner. Unlike other analytics capabilities, descriptive analytics does not lead to reliable forecasts or conclusions as the basic starting point used to inform or prepare data for subsequent analysis Raghupathi and Raghupathi (2021). They serve as feedback mechanisms on past actions but cannot be relied on solely to adequately generate insight about the future from the data.

Several studies have examined the application of descriptive analytics in various fields, including marketing (Griva et al., 2018), education (Daniel, 2015), and budgeting (Bergmann et al., 2020). These studies agree that descriptive analytics can play a big role in understanding what has actually occurred in a firm. For instance, Raghupathi and Raghupathi (2021) show that a business can use descriptive analytics to observe the marketing trends and make appropriate decisions. This view is shared by Grover et al. (2018) who observed the instrumental role of descriptive analytics in understanding the trends and patterns. However, Berman and Israeli (2020) disagree with these studies by stating that there is no clear evidence to suggest that descriptive analytics is beneficial at all. They argue that most previous studies lacked appropriate data or failed to distinguish the four categories of business analytics.

Diagnostic capability

Diagnostic analytics capabilities provide more insight than descriptive analytics, as it conducts in-depth analysis to determine how and why things happen. Raghupathi and Raghupathi (2021) observe that diagnostic analytics focuses on root cause analysis using data finding and mining, as well as drill-down and drill-through methods. According to Holsapple, Lee-Post, and Pakath (2014), these may include questions on why the sales have increased in an area despite no marketing changes or why there has been an unexpected surge in traffic to a website with no evident rationale. Chen et al. (2012) postulate that diagnostic analytics is a technique that modern businesses employ to determine the scope and effect of data-related problems. They observe that the continued use of diagnostic analytics produces a paradigm shift in the way data is used, even in marketing and sales. It is vital for marketing professionals to have a technological mindset and harness technology to maximize the value of business analytics.

Research conducted in the U.S.A reveals that senior executives in the automotive industry use diagnostic analytics 21 to 32% of the time (PWC, 2016). Another research by Sharda, Delen, and Turban (2017) reports that many businesses have started relying on diagnostic analytics tools to uncover the factors behind the trends and patterns in their organization. Similarly, Raghupathi and Raghupathi (2021) noted that analysts are increasingly relying on diagnostic analytics capabilities to explain anomalies in business functions, such as sales and marketing, planning, and decision-making. Aydiner et al. (2019) share this view by supporting the instrumental role of diagnostic analytics in observing trends and evaluating whether they are heading in the right direction. Overall, these studies (Aydiner et al., 2019; PWC, 2016; Sharda et al., 2017) show that diagnostic analytics can be applied in different areas as part of the root cause analysis of issues facing an organization.

Predictive capability

Predictive analytics capabilities facilitate the forecasting of what could happen in the future (Applebaum et al. 2017). Gandomi and Haider (2015) argue that machine learning is central to predictive analytics. Under machine learning, individuals use historical data to develop learning models that consider patterns and trends. They (2015) note that these models are then applied to current data to predict the future. In agreement, Applebaum et al. (2017) indicate that predictive analytics seek to find patterns and links in data to answer the question, “What may happen?” Predictive analytics approaches often include statistical techniques including regression analysis, clustering, and factor analysis, in addition to machine learning approaches such as neural networks (Gandomi & Haider, 2015). Predictive analytics is differentiated by its proactive emphasis on the future, whereas descriptive and diagnostic analytics focus on investigating and reporting previous data (Halper, 2013). Simply put, predictive analytics use inductive reasoning as opposed to deductive reasoning (Huikku et al., 2017).

Devonport and Harris (2007) argued that majority of high-performance work systems or organizations need individuals to be highly analytical, thus highlighting the importance of analytical demands. Businesses that include such tactics into their decision-making processes are better equipped to compete and sustain their competitive edge. Among the various statistical approaches, structural equation models (SEMs), including confirmatory factor analysis, help in theory construction and predictive analysis, and their usefulness has increased, as enormous data sets have been introduced. Managers and scholars get fresh insights into their future endeavors through predictive modelling (Shmueli & Koppius, 2010).

In healthcare, Alonso et al. (2017) noted that predictive analytics help healthcare organizations predict complicated clinical cost structures, discover optimum healthcare practices, and obtain a greater insight into future healthcare trends based on patient knowledge, habits, and illness management. In the marketing sector, Phillips-Wren et al. (2015) observed that predictive analytics can assist businesses to forecast the future, such as possible drop or increase in sales and demand. By analyzing historical data and insights, Raghupathi and Raghupathi (2021) argue that analysts can forecast the future and develop appropriate plans, thus implying that the future of effective planning in organizations lies in predictive analytics. This predictive capability is more evident in the supply chain sector where predictive analytics is used to offer accurate forecasting, particularly demand forecasting, with the goal of lowering the bullwhip impact (Nguyen et al., 2018). The application of business analytics to supply chain demand forecasting has been documented for both supervised and unsupervised learning. In the former, data is connected with labels, thus suggesting that the inputs and outputs are known. By detecting the underlying links between the inputs and outputs, the supervised learning algorithms seek to map the inputs to their matching outputs, given a fresh unlabeled dataset (Han et al., 2013). For example, a supervised learning model for demand forecasting may be used to anticipate future demand based on previous data on product demand. These predictions in the supply chain enable effective product scheduling, demand planning, and inventory management.

Prescriptive analytics

Finally, prescriptive analytics capabilities focus on what is to be done based on the findings in predictive analytics (Gandomi & Haider, 2015). This means that prescriptive analytics extends what has been gained from descriptive and predictive analysis by identifying the best feasible action. In this case, Raghupathi and Raghupathi (2021) observed that prescriptive analytics predicts what will happen, when and why. Research shows that prescriptive analytics is the most sophisticated type of business analytics, and it can provide businesses with the greatest intelligence and value (Lepenioti et al., 2020). The effectiveness of the prescriptions is contingent upon the models' ability to incorporate structured and unstructured data, accurately represent the domain under study, and accurately capture the consequences of the decisions being analyzed (Lepenioti et al., 2020). After analyzing the potential consequences of each choice alternative, suggestions may be given regarding the most ideal option.

In the healthcare sector, research by Phillips-Wren et al. (2015) established that prescriptive analytics such as simulations and machine learning techniques are vital in providing possible courses of action. Besides, this method has been proven in other fields, including marketing (Griva et al., 2018), budgeting (Bergmann et al., 2020), project management, and strategic management (Li et al., 2016). However, critics argue that machine learning techniques are not always capable of accounting for all external variables (Barga et al., 2015). In disagreement with Barga et al. (2015), evidence by Kraus, Feuerriegel, and Oztekin (2020) shows that the application of machine learning significantly decreases the likelihood of human mistakes. Additionally, Berman and Israeli (2020) hold that the present prescriptive methods are inconclusive, such that future research is required to create better prescriptive solutions. Thus, more research may be needed to establish the effectiveness of machine learning techniques that are applied in predictive and prescriptive analytics in accounting for external variables.

2.2.3 Potential application in budgeting

Overall, there is potential for the four capabilities of business analytics, especially diagnostic and predictive analytics, to play a big role in the budgeting processes. Since budgeting comprises a lot of recurrent processes and data, the benefits of digitalization and business analytics might be absorbed into the organizations' budgeting processes rather fast. Furthermore, there is an increasing trend in the use of quantitative modelling; it is likely to enhance the process by producing more accurate forecasts for yearly budgeting. However, there is limited research on how business analytics can be applied in the budgeting process, with most studies being focused on the marketing and retail sector (Bergmann et al., 2020; Berman & Israeli; 2020). To contribute to this area of research, the present research focuses on the impact of business analytics on budget goal commitment.

2.3. Budget Goal Commitment

Budgets are an essential instrument in businesses for short-term planning and control (Anthony et al., 2007). Having a budget helps businesses make judgments about different courses of action (Merchant & Van der Stede, 2012) and enable them to assess their operational capacity usage (Langfield-Smith et al., 2005). Based on this view, budgeting is defined as the full set of procedures that characterize the creation and use of budgets. Research shows that a successful budgeting process depends on various technical aspects that have significant implications on the effectiveness of resource utilization (Lidia, 2014). These aspects include the creation of responsibilities (Morlidge, 2017), goal setting (Lidia, 2014), measuring performance (Wong-On-Wing et al., 2010), and managing interdependencies (Lin & Chang, 2005). While these factors have the potential to enhance performance, Lu, Mohr, and Ho (2015) observe that behavioral factors are crucial in translating the potential benefits into realized benefits. Over the years, researchers (Locke & Schweiger, 1979; Radebe & Radebe, 2014) have identified behavioral factors such as budget goal commitment, budget participation, and budget goal conflict as the keys to a successful budgeting process.

Budget goal commitment is the motivation of a person to do something to help the business succeed by internalizing the budget targets (Wentzel, 2002). Locke et al. (1981) described budget goal commitment as a strong will to endeavor to reach budget targets and persistently strive to attain them all the time. Based on these two definitions, budget goal commitment could imply the strong will by individuals to consistently attain budget targets. Prior research suggests that businesses can foster budget goal commitment by ensuring that all the departments and units in the organization are involved in the budgeting process (Wong-On-Wing et al., 2010). The agency approach presupposes that a key incentive for budget goal commitment is the exchange of knowledge between subordinates and superiors and that both parties stand to benefit (Maiga, 2005). This implies that organizations can enhance budget goal commitment by enhancing the communication between various players. Empirical research by Radebe and Radebe (2014) concluded that organizations must seriously consider the behavioral elements in their budgeting procedures. A strictly quantitative budgeting method ignores, if not undermines, the behavioral factors that may help optimize the resources and maximize the participation of role players. The changing information system landscape has created rich data for understanding these behavioral factors in the budgeting processes (Warren Jr et al., 2015). A business analytic dimension like agonistic analytics can help identify these behavioral factors and use predictive analytics to predict their implication (Raghupathi & Raghupathi, 2021). It is for this reason that the study focuses on the relationship between business analytics capabilities and budget goal commitment.

2.3.1. Antecedents of budget goal commitment

Mathieu and Zajac (1990) emphasized the importance of budget goals in supporting the psychological aspects that encompass individual, professional, and organizational factors and include specific assessments, emotions, and behavior patterns for those under observation. Gómez-Miambres (2012) observes that budget goal commitment is influenced by the interaction between the forms of individual references and goals, with higher references requiring higher goals for individuals to be more dedicated to those goals. Locke and Latham (2004) emphasize the importance of motivation for goal commitment. They argue that motivation is the primary determinant of commitment to a budget target.

In light of self-determination theory, it is suggested that individuals would display specific actions because of motivation. Thus, different motivations will have a distinct effect on an individual's conduct because motivation stems from an inward urge to accomplish something (Deco & Ryan, 2000). As such, the theory of self-determination states that external incentives have a positive effect on a person's commitment to goals (Deco & Ryan, 2000). In this regard, Locke and Latham (2002) argue that external incentives can be used to promote commitment to goals, as a reward is directly related to an employee's engagement to the organization.

Another key antecedent of budget goal commitment is budget participation. Along with being directly impacted by the individual's intrinsic motivation and the potential of participation in the budget process, empirical research reveals that budget goal commitment may be indirectly explained by its engagement in the budgeting process (Stearns, 2016). This finding bolsters the argument that an individual's involvement in the budget process can result in an effective commitment to the goal (Meyer et al., 2004), whether through the increased acceptance of budget goal or the assistance in setting higher targets and improving performance. Participation in the budget process has been found to increase the employees' emotional commitment, as it values their engagement with the budget objective as they assess their involvement and effect on the budget objective (Stearns, 2016).

A study by Baerdemaeker and Bruggeman (2015) shows that participation enables employees to build a greater emotional attachment to the company, thus increasing their motivation to achieve. That way, Wong-On-Wing et al. (2010) noted that employees might be intrinsically motivated to engage in goal creation, particularly when their activities result in personal successes and pleasure. This motivational element has the capacity to affect an individual's commitment to a goal. According to Gómez-Ruiz and Rodrguez-Rivero (2018), consultative involvement by employees increases autonomous motivation, while pseudo-participation reduces it. As a result, the research by Van der Kolk et al. (2019) discovered a positive association between intrinsic and extrinsic motivations and departmental performance. Furthermore, incentives (intrinsic and extrinsic) contribute to the link between management controls and performance in distinct ways. This shows that intrinsic motivation and extrinsic motivation may have a varied effect on the managers' adherence to budget targets.

Given that business analytics enhances information sharing, there is a great potential for it to influence budget goal commitment. However, little is known about the specific roles business analytics play in generating commitment to budget goals although the potential for this may exist. A key question is, would business analytics capability generate budget goal commitment and how will this occur? This study seeks to answer this question.

2.3.2. Consequence of Budget Goal Commitment

The existing research suggests that budget goal commitment leads to high motivation in an organization. Welsh et al. (2020) assert that the desire to avoid failure is the driving factor for people with high commitment. This is because the intended outcomes of goal setting occur due to cognitive processes (Welsh et al., 2020). The budget literature demonstrates that motivation can influence people's behavior when it comes to meeting budget goals (Stearns, 2016) and that allowing employees to participate in setting the budget goals could motivate them to show high levels of commitment (Baerdemaeker & Bruggeman, 2015). These findings imply that the more the employees remain committed to the budget goals, the more is their level of motivation.

Additionally, budget goal commitment is favorably associated with job performance (Marginson & Ogden, 2005). Lin and Chang (2005) argue that highly committed subordinates are driven to communicate with their superiors and peers who may give insight into their work surroundings, performance objectives, task methods, and other topics that have a major influence on their performance. A high level of goal commitment is associated with an improvement in performance (Nguyen et al., 2019). The association between budget goal commitment and employee performance has long been recognized in human resource management and organizational behavior research (Jaramillo et al., 2005). In the context of budgeting, researchers have drawn on goal-setting theory to argue that if employees are committed to budget goals, they will exert additional effort to achieve those goals. This implies that the employees who are committed to their budget targets will work harder and longer, thus resulting in better performance, compared to the less committed employees (Chong & Johnson, 2007). As a result, a favorable association between budget goal commitment and work performance is suggested.

2.4. Budget Adequacy (BA)

The Cambridge English Dictionary defines adequacy as the state of being sufficient or adequate. Based on this, Khaddafi et al (2015) defined budget adequacy[1] as a manager's judgment that a specified budget is adequate for carrying out work activities that support the attainment of business targets. From the above definition, it is evident that budget adequacy involves two major aspects, namely judgment and an element of satisfaction with the budget (Tokilov et al., 2019). A combination of these two antecedents is key to the employees' perceptions of budget adequacy in an organization. The metrics for measuring budget adequacy differ from one organization to the other (Bedford & Speklé, 2018), thus implying that what is adequate in one organization could be inadequate in another one.

As noted, budget adequacy implies an individual's perception that the allocated resources are sufficient to meet the job needs. This concept can be distinguished from the accounting concept of budgetary slack. According to Young (1985), budgetary slack comes in when subordinates purposefully come up with excess budgetary requirements. Thus, the budgetary slack entails excess budgetary resources, which arise as a result of deliberate forecasting biases that are aimed at making the performance goals appear easier to attain. However, Nouri and Parker (1998) revealed that in some instances, budget adequacy and budget slack may coincide. Managers who make erroneous budget estimates, and thus obtain excess resources are more likely to experience high levels of budget adequacy. On the other

[1] Although budget adequacy is an important component of the budgeting process, it has been under researched in the management accounting research.

hand, the levels of fiscal sufficiency and budget slack will vary under a variety of circumstances. Managers may report little budgetary slack and high BA in various instances.

2.4.1. Antecedents of Budget Adequacy

Young (1985) argues that the key antecedent of budget adequacy is the perceived presence of sufficient resources. As noted by Khaddafi et al. (2015), having sufficient resources creates a feeling of adequacy in the organization. Employee participation in the budgeting process is another vital antecedent of perceived budget adequacy. Chow et al. (1988) propose that subordinates have more precise information about the local situations than their superiors. The authors considered subordinates as individuals who have "private" information regarding the local situations within the agency–principal structure. Hence, enabling the subordinates to contribute to the budgeting process might help disclose undisclosed information or department-specific data, thus resulting in more accurate plans and adequate budget allocations. A decade later in agreement with Chow et al. (1988), Nouri and Parker (1998) found that subordinates frequently had more knowledge than their managers did about the degree of budgetary assistance required to do the subordinate's job. Subordinates will then work to integrate this information into the budget, thus ensuring that they have the resources to do their responsibilities correctly. While a participatory budget process provides this information, a non-participatory budget process does not.

Nouri and Parker (1998) note that while budget participation results in budgetary adequacy, fiscal adequacy may result in increased job performance. Zainuddin and Isa (2011) observe that when employees are more involved in the budgeting process, their degree of BA increases as well. This, in turn, will aid in the improvement of job performance. These findings are corroborated by Karakoc and Ozer (2016) who concluded that participation allows employees to contribute toward the formulation of plans, thereby increasing the likelihood of accurate and sufficient budgets.

There is a great possibility of business analytics playing an instrumental role in enhancing these benefits. Against this background, Karakoc and Ozer (2016) argue that business analytics is especially beneficial for improving plan formulation and ensuring that the organization meets their budget requirements. Contemporary improvements in information technology have a great potential to significantly alter the way accounting in general and budgeting, in particular, are conducted (Taipaleenmäki & Ikäheimo, 2013). Besides, research by Brynjolfsson and McElheran (2016) shows that solutions open up new avenues for collecting and leveraging data in support of data-driven decision-making such as budget allocation decisions.

While the prior literature has improved our understanding of the antecedents of budget adequacy, little is known about whether and how business analytics may influence the perceived adequacy of budget allocation. Yet, the theoretical literature on business analytics suggest that business analytics may play significant roles in budget allocation decisions and processes. Given the pervasiveness of business analytics in contemporary organizations, it is crucial to examine the extent to which it influences the employees' judgment of the adequacy of their budgets.

2.4.2. Consequences of Budget Adequacy

Research reveals that budget adequacy motivates employees and other stakeholders (Tokilov et al., 2019). Paters (1971), as cited in the work of Tokilov et al. (2019), identified budget adequacy as a situational factor that affects managerial effectiveness and motivation. Staff and managers who have appropriate budgetary support are motivated to achieve higher performance than managers and employees who do not have adequate budgetary support (Tokilov et al., 2019). With budget adequacy, managers are expected to do their best to execute the planned programs or tasks. However, contrasting results were achieved in Sinuraya's (2011) study; there is no association between budget adequacy and enhanced motivation.

Khaddafi et al. (2015) later disagreed with Sinuraya (2011) and agreed that through budget adequacy, employees will feel that the organization is committed and supportive toward them for the attainment of business targets, which increases satisfaction. Thus, organizations with high budget adequacy should expect a high level of motivation and satisfaction among the employees.

Studies in the management literature have focused on how budget adequacy can either aid or hinder managerial performance, but few empirical studies have been conducted in this area. Studies (Khaddafi et al, 2015; Zainuddin & Isa, 2011) have established a strong connection between budget adequacy and performance in the organization. These studies indicate that budget adequacy improves work performance not just directly, but also indirectly through organizational commitment. This finding is corroborated by Zainuddin and Isa (2011) who observed that there is a positive link between budget adequacy and the performance of employees in an organization. Similarly, Khaddafi et al. (2015) conclude that budget adequacy leads to high performance and satisfaction in the organization. Karakoc and Ozer (2016) had also reached a similar conclusion that budget adequacy promotes high performance in the organization. The findings from these studies confirm that organizations with a high sense of budget adequacy are more likely to perform better than those whose budget seems inadequate.

2.5. Forecast Accuracy

Forecast accuracy is defined as the reliability and precision of the predicted values (Liu & Tan, 2019). Forecast accuracy is also defined as the difference between the forecasts and actual quantities (Hyndman & Koehler, 2006). These two definitions imply that forecast accuracy is the precision of estimates where there is an insignificant or no difference between the predicted and actual values. Koutsandreas et al. (2021) point out that since forecast accuracy is likely the most important criterion for selecting one forecasting approach over another, researchers have concentrated their efforts on developing measures that accurately capture it. Thus, according to Koutsandreas et al. (2021), individuals need to select a forecasting method that will guarantee accurate forecasting. Consequently, research by Trusheim and Rylee (2011) noted that most budgeters use predictive budgeting that involves the utilization of predictive analysis to produce short- and long-term forecasts. This approach, according to Trusheim and Rylee (2011), detects trends and patterns, assesses possible hazards, and projects future outcomes using those methods and data, thus leading to better estimates and decision-making.

2.5.1. Antecedents of forecast accuracy

According to the literature, the most important aspects that affect the accuracy of economic predictions are the forecasters' competence, data and model's quality, unanticipated occurrences and uncertainty, social and political situations, financial stability, and forecast adjustment (Clements & Hendry, 2008; Davydenko & Fildes, 2013). Buturac (2022) observed that accurate prediction is uncomplicated at first glance; simply comparing what was forecasted with what occurred. However, the situation is far more convoluted since all forecasts are based on assumptions that may or may not be validated in reality (Buturac, 2022). The primary difficulty in picking an acceptable metric for evaluating forecast accuracy is that different metric results in various conclusions, thus implying the selection and use of several forecasting methodologies (Koutsandreas et al., 2021). The inconclusiveness of the measurements can be influenced by the particularities of the forecasting methodologies used and the measures themselves. Each forecasting technique has its own characteristics, including strengths and limitations, and its efficacy is dependent on the problem being solved (Koutsandreas et al., 2021). Information sharing is another key antecedent of forecast accuracy. For example, forecasts, according to Avci (2019), are based on the information available at the time of forecasting, and with so many unknowns in demand, supply, and production processes, it is understandable that forecasts might quickly become inaccurate. The collection and dissemination of the most recent information would mitigate the impact of uncertainty and increase the chance of modifying the prediction in near real-time, which might be used to reflect on the current situation. In the supply chain contexts, Yan and Wang (2012) discovered that information sharing boosts prediction accuracy, thus allowing enterprises to adapt to customer demand in real-time in a study of the franchisor-franchisee supply chain. The model developed by Yan and Wang (2012) indicated that by sharing data, forecast accuracy increased dramatically, thus benefiting both parties. Prior literature suggests that business analytics can play an instrumental role in enhancing forecast accuracy.

2.5.2. Consequences of forecast accuracy

Forecast accuracy can be critical in determining a company's success or failure. At its fundamental level, effective forecasting helps keep prices low by optimizing a business' operations—cash flow, production, human resources, and financial management (Liu & Tan, 2019). Additionally, it is said to assist organizations in increasing their industry expertise. While businesses typically utilize yearly budgets to set goals and inspire staff, they also regularly use predictions to aid in operational decision-making (Sivabalan et al., 2009). These estimates exist for a variety of financial and operational issues, but sales forecasts are particularly relevant in both operational and financial terms. Forecasts of sales give insight into future revenues and are critical for synchronizing the demand and supply actions. Sales forecasting accuracy (in terms of accurately anticipating future states) is a vital part of planning quality, and accurate prediction is a goal shared by many finance and operations managers (O'Mahony & Lyon, 2016). More precisely, Jordan and Messner (2020) argue that forecast accuracy are judged to be consistent with important organizational objectives such as lowering capital costs (by eliminating inventory) and boosting customer satisfaction.

In the context of budgeting, Williams and Calabrese (2016) note that forecasting is a technique that analyzes historical and current operational data, as well as market and industry data, to help predict the allocation of budgets for future expenses. Bogsnes (2016) adds that forecasting boosts the management's confidence in making critical business choices. Previous evidence by Bagdigen (2005) from Turkey had concluded that the outcome of budget forecasting is a vital tool for budget decision-makers. This evidence supports the critical role that forecasting plays in the budgeting and decision-making processes in an organization.

Moreover, forecast accuracy has the potential to impact budget adequacy since, as noted by Davenport and Harris (2007), accurate measures ensure that the organization allocates a sufficient budget for various activities. Prior research substantiates this assumption by noting that forecast accuracy may be a decisive factor for businesses that operate in a highly competitive or unpredictable market (Becker et al., 2016; Palermo, 2018). Additionally, findings by Schäffer and Weber (2016) indicate that the budgeting process takes longer when prediction accuracy is low. This finding implies that business analytics capabilities might assist in shortening the budgeting process while also improving the prediction accuracy. However, while in principle, forecast accuracy is important in the budget process, there is little empirical evidence of whether and how it affects budget adequacy and budget goal commitment. This research seeks to investigate whether forecast accuracy affects budget adequacy and budget goal commitment.

2.6 Summary

Business analytics has arisen as a response to the challenges posed by big data, such as the availability of massive amounts of data gathered by businesses. Business analytics enable the segmentation of enormous datasets into manageable sets, the analysis of data for informed decision-making, the generation of data-driven predictions, the use of simulation to test scenarios, and the identification of predictable actions. Organizations benefit from business analytics through four capabilities namely, descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. This chapter argues that these capabilities can play significant roles in the budgeting process, including influencing the budget goal commitment directly and indirectly through forecast accuracy and budget adequacy. The following chapter develops the theoretical argument underlying this expectation.

Chapter 3: Theory Development

3.1 Introduction

This study investigates the impact of business analytics capabilities on budget goal commitment and whether forecast accuracy and budget adequacy mediate this relationship. This chapter presents the theoretical framework that informs the study and develops testable hypotheses regarding the relationships among the constructs in the study.

3.2 Theoretical Framework

This study draws on goal-setting theory to develop arguments about the relationships among the main constructs of the study. Goal-setting theory emphasizes the relevance of the connection between goals set and the ensuing performance. The fundamental concept is that clear goals motivate individuals to achieve them (Robbins, 2008). If a person makes a commitment to accomplish a goal, then the commitment will affect actions, and, in turn, the organization's performance. The attainment of stated goals (objectives) can be viewed as an indicator of an individual's end/performance levels. In general, objectives establish a strong motivation to perform well. Attainment of goals has an effect on employee behavior and work performance. The theory asserts that the setting of specific and challenging but achievable targets, along with performance feedback, are more effective than having easy and unclear goals (Locke & Latham, 2019). Central to the theory is the employees' commitment to goal, as this is seen as their willingness to dedicate desirable efforts toward achieving these goals (Hirst & Yetton, 1999; Chong & Chong, 2002; Locke & Latham, 2002; Kenno et al., 2018). Besides, the theory argues that to secure the employees' commitment to goals, they need to be confident that they have the required capacity to undertake the necessary tasks to achieve these goals (Locke & Latham, 2006).

In line with goal-setting theory, research shows that when employees are committed to budgetary goals, they are more likely to increase the effort necessary to accomplish the goals

(Locke & Latham, 2006). This suggests that the employees who are devoted to their budget objectives will work harder and endure longer, thus resulting in greater effectiveness, compared to employees who are less committed to goal attainment (Chong & Johnson, 2007).

Given the importance of goal commitment, this thesis draws on goal-setting theory to understand the mechanisms through which business analytics capabilities may influence the employees' commitment to their budget goal. Figure 1 shows the conceptual model adopted in this study.

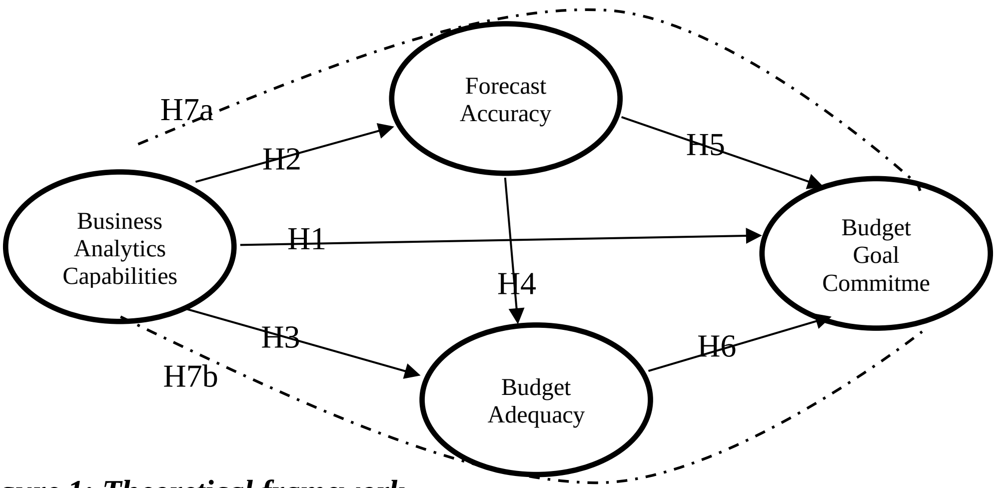

Figure 1: Theoretical framework

3.3. Business Analytics Capabilities and Budget Goal Commitment

Commitment is the driving factor that tethers an individual to a certain path of action. This commitment is based on an individual's motivation, and it can take on a variety of shapes and be aimed toward a variety of objectives, including budget goal (Meyer et al., 2004). It is described as the will to attempt and the persistence with which one pursues a goal through time. In the context of budgeting, the goal-setting theory can suitably explain the link between business analytics capabilities and budget goal commitment. Managers will commit to budget goals if the goals are clear and specific. Developing and communicating clear and specific goals require good quality information because such information reduces ambiguity about the goals and tasks required to achieve those goals. Business analytics have the capabilities to improve the information quality to make goal less ambiguous (Ashrafi et al., 2019). As indicated, the descriptive capabilities embedded in business analytics provide the employee with an analytical base to understand the trends and patterns that inform the setting of budget goal, thereby making the goal clearer. Additionally, the measurability of goals reduces the goal ambiguity and increases the probability that employees see a clear path to achieve such goal, and, thereby, commit to the achievement of such goal. The transformation of structured and unstructured data into quantitative forms and the subsequent statistical analysis of the data allows the goals to be appropriately calibrated and measured, thus facilitating the employees' commitment to the goals. Furthermore, managers will commit to the goals if they understand the link between the tasks they are assigned to and the budget goals that are to be achieved. This thesis argues that the prescriptive capability of business analytics provides specific guidelines of what needs to be achieved, thus detailing the different pathways to meet the goals and specifying the resources required to do so. This provides the employees information on the cause-effect relationships between tasks and goals and the flexibility to choose an appropriate task that will lead to desired outcomes. This is expected to foster a commitment to the goals. The expected relationship between business analytics capabilities and budget goal commitment is reflected in the following hypothesis:

***H_1**: Business analytics capabilities have a direct positive relationship with budget goal commitment.*

3.4 Business Analytics Capabilities and Forecast Accuracy

In the study by Richardson and Yigitbasioglu (2018), quality data is seen as a critical organizational resource or asset that has an effect on the organization's performance. Forecast accuracy is heavily dependent on the availability of quality data for which business analytics is well suited. Business analytics have the capability to improve data quality through its focus on cleaning datasets, organizing unstructured data, sorting through large datasets, detecting and eliminating data outliers, and identifying predictable actions in data (Ashrafi et al., 2019; Nespoli et al., 2021). This leads to good quality database on which forecasting activities can feed. Additionally, forecast accuracy depends on the ability of the forecasting techniques to adequately capture the properties of the data that serves as its input. Conventional forecasting techniques have been criticized for its inability to fully reflect the properties of the data it feeds on due to its assumption of linearity of data distribution (Nespoli et al., 2021). The predictive capabilities inhabited in business analytics relax such linear assumptions, allow the complexity of underlying data to be captured, and facilitate scientific estimates through regression and time-series analysis (Delen & Ram, 2018; Nespoli et al., 2021). These processes generate predictive models that improve forecast accuracy.

In the context of the budgeting process, Applebaum et al. (2017) highlight the predictive capability of business analytics as vital in achieving accurate forecasts. As noted, this capability seeks to find patterns and links in data to answer the question, “What may happen?” By analyzing the historical data and insights, Raghupathi and Raghupathi (2021) argue that analysts are able to forecast the future and develop appropriate plans, thus implying that the future of effective planning and accurate forecasts in organizations lies in predictive analytics. Palermo (2018) anticipates that the more a firm stresses on accuracy, the more probable it is that business analytics will be used. Moreover, it is envisaged that the diagnostic capability of business analytics enables a business to detect past budgeting forecast problems and feed this back into the predictive models for future forecasting, thus improving the forecast accuracy. This analysis shows that business analytics capabilities are vital for forecast accuracy. It is therefore predicted as follows:

H_2: Business analytics capabilities have a positive relationship with forecast accuracy.

3.5 Business Analytics Capabilities and Budget Adequacy

Karakoc and Ozer (2016) suggest that business analytics capabilities are particularly valuable for enhancing the budget plans and ensuring that the organization satisfies its budgetary needs. The descriptive, diagnostic, and predictive capabilities of business analytics capabilities can facilitate the collection and use of data in support of data-driven decision-making through prescriptive analytics that will lead to an adequate budget in the organization. Descriptive capabilities of business analytics provide information on the past budgetary practices of resources allocation and how the sufficiency of the resources allocated. Where inadequacy of budget allocation is detected, the diagnostic capabilities are useful for understanding why the budgets were inadequate, thus providing valuable inputs into future budget allocations to ensure that sufficient resources are provided. The predictive capabilities transform the feedback from descriptive analytics into predictions of future resource requirement, thus improving the probability that future budgets will be adequate. As the future may not necessarily reflect the conditions of the past, the predictive capabilities will facilitate the prediction of future events and their impacts, thus juxtaposing them with the feedback from past data to allow better resource allocation that enhances budget adequacy. Thus,

***H_3**: Business analytics capabilities have a direct positive relationship with budget adequacy.*

3.6 Forecast Accuracy and Budget Adequacy

Given that the budgeting process is future-oriented, organizations need accurate forecasts to set adequate budgets. Davenport and Harris (2007) argue that a key aspect of forecast accuracy is that it leads to proper planning during the budgeting process. In this case, forecast accuracy has the potential to impact budget adequacy since, as noted by Davenport and Harris (2007), accurate measures ensure that the organization allocates a sufficient budget for various activities. Thus, organizations can leverage forecast accuracy to achieve budget adequacy. Based on this background, the researcher hypothesized the following:

***H$_4$**: Forecast accuracy has a direct positive relationship with budget adequacy.*

3.7 Forecast Accuracy and Budget Goal Commitment

Previous studies suggest that the planning and control aspects of budgeting are judged more important than the evaluation function (Sivabalan et al., 2009). Forecasting is particularly important in the budgeting process where the budgeting team works with cost estimates and forecasts to predict future budgetary needs. Managers' perceptions of the probability of achieving their budget goals influence their level of commitment to those goals. Based on this premise, the goal-setting theory by Locke and Latham (2019) proposed that employees were more likely to remain committed to the organization's goals when the goals are clear and easy to achieve. In the case of budgeting, forecasting can play a major role in improving the specificity of goals. Through accurate forecasting, an organization is likely to set clear and realistic goals, which according to Locke and Latham (2019), are instrumental in motivating individuals. Clear and achievable goals will motivate the employees, thus leading to high commitment. This relationship is reflected in the following hypothesis:

***H$_5$**: Forecast accuracy has a direct positive relationship with budget goal commitment.*

3.8 BA and budget goal commitment

As noted by Zainuddin and Isa (2011), an antecedent of budget goal commitment is the feeling of having sufficient resources and management support. In line with the goal-setting theory, BA creates a feeling of having sufficient resources and necessary management support to achieve both individual and organizational goals. This situation is likely to motivate the employees, thus making them more committed toward goal attainment. Moreover, prior studies have shown significant correlation between budget sufficiency and goal commitment in the organization (Khaddafi, 2015; Zainuddin & Isa, 2011). These studies demonstrate that organizations with adequate budget allocations will more likely have a committed workforce that is focused on achieving budget goals. Therefore,

H_6: *BA has a direct positive relationship with budget goal commitment.*

3.9 Mediation effect of Forecast Accuracy and Budget Adequacy

In addition to the direct relationships between business analytics capabilities and budget goal commitment, the literature suggests that there may also be intermediate mechanisms that explain the relationship between these two variables (Bagdigen, 2005; Khaddafi, 2015). This necessitates the examination of possible mediation. Business analytics capabilities are predicted for forecast accuracy. In turn, forecast accuracy is expected to improve budget goal commitment. Thus, through their effect on forecast accuracy, business analytics capabilities influence budget goal commitment. This relationship is reflected in the following hypothesis:

H_{7a}: *The relationship between business analytics capabilities and budget goal commitment is mediated by forecast accuracy.*

Additionally, it was predicted that business analytics capabilities will affect budget adequacy. Moreover, it was argued that budget adequacy will foster budget goal commitment. In juxtaposing these two predictions, it is expected that the influence of business analytics capabilities on budget goal commitment will flow through budget adequacy. Hence,

H_{7b}: *The relationship between business analytics capabilities and budget goal commitment is mediated by perceived budget adequacy.*

Considering that business analytics affects both forecast accuracy and budget adequacy, which in turn influence budget goal commitment, it is anticipated that forecast accuracy and budget adequacy will serially mediate the relationship between business analytics capabilities and budget goal commitment. Hence, the study formulated the following hypothesis:

H_{7c}: *The relationship between business analytics capabilities and budget goal commitment is serially mediated by forecast accuracy and budget adequacy.*

3.10 Summary

This chapter theorizes the potential impact of business analytics capabilities on budget goal commitment. Budget is normally a data-driven process that creates opportunities for budget adequacy. Business analytics could overcome the weaknesses of traditional budgeting by providing accurate forecasts that lead to the setting of an adequate budget and clear budget goals, which the goal-setting theory states will lead to high budget goal commitment. In the chapter, hypotheses have been developed for the expected direct relationships among the focal constructs. Additionally, mediation hypotheses have been developed to reflect the intermediate process through which business analytics capabilities and budget goal commitment are expected to be related. The following chapter will outline the methods followed for collecting the data that is necessary for testing the hypotheses developed in this chapter.

Chapter four: Research Methodology

4.1 Introduction

This chapter outlines the research method of this thesis. Section 4.2 presents the research design. Section 4.3 discusses the sample selection and method for collecting the required data. The following section presents the measurements of the constructs. The statistical approach adopted in the study is presented in section 4.5. Section 4.6 summarizes the chapter.

4.2 Research Design

A quantitative research design was adopted in this study to test the hypotheses and answer the research question of the study. Survey approach was used as instruments for collecting the required data. It has been argued that the survey approach has a unique advantage among other data collection instruments, as it can aid in the estimation of a population percentage with specific attributes by obtaining data from a small fraction of the total population. According to Brownell (1995), surveys are an ideal tool for gathering information on naturally occurring phenomena since respondents reply to questions based on their own personal experiences. Kumar (2018) believes that it is possible to get the most accurate information on self-reported beliefs and behaviors through surveys. As noted by Brownell (1995), survey methodologies account for the vast bulk of organizational, social, and behavioral research undertaken by researchers.

This study used an online survey to research a large target sample. According to Dillman (2011), online surveys represent a more efficient data collection procedure for the following reasons: they eliminate all costs associated with paper and postage, mailing, and data entry; they eliminate international boundaries; they reduce the data collection time from weeks to days or hours; and they provide more flexible survey design options.

4.3 Sample Selection and Data Collection

Data for the study has been collected from a cross-section of organizations that operate in the State of Qatar. This is corroborated by Lillis and Mundy (2005) who suggest that cross-sectional studies enhance the generalizability and external validity of the results. Potential survey participants were drawn from various industries in different sectors of the economy in the State of Qatar. Access to a rich and well-established database of organizations in the State of Qatar facilitated the sample selection. The database from where the participants were identified is considered confidential. The database contained the contact information of managers employed in the organizations. Given this study’s focus on budgeting, the target sample were managers with budgetary responsibilities. A total of 600 potential participants were considered for the study.

Invitation for the online survey was sent to these potential participants through emails and phone massages. To enhance the response rate, the invitation highlighted the background and objectives of the research, as well as the role they can play in improving our understanding of the relationship between business analytics capabilities and budget goal commitment. Furthermore, participants were assured of the confidentiality of their responses and that they would not be identified with their specific responses. They were informed that the data will be aggregated and used only for the purposes of this study. All the potential respondents were notified that the study was approved by the Qatar University Review Board and that the study adheres to all of the university’s ethical standards. Their formal consent to participate was sought through the following statement: “Please, kindly indicate that you have read, understood, and voluntarily agree to participate in this survey. If you wish to participate, kindly select Yes below”. Those who consented proceeded to undertake the survey by clicking a link provided at the end of the invitation letter. Further, potential respondents were assured that they could withdraw from the study at any time. Three reminders were automatically sent to the respondents each week after the initial invitation. This was to ensure a higher response rate.

They online survey was presented in a manner similar to a regular paper-based self-administered questionnaire, as the respondents feel familiar with that format. Simply put, sections of the survey were separated into multiple screens to simplify the survey and enable the absorption of questions by respondents. To further enhance the response rate, the survey was developed with the intention to keep the response time less than 15 minutes. Additionally, a screening question was asked at the beginning of the survey to ensure that only the employees with budget responsibilities proceeded to undertake the survey. The question was "Do you use budgets to manage your department/unit?" A thank you note appeared for those who answered "No" to this screening question and the survey was automatically terminated for them at that stage. Those who answered "Yes" proceeded with the survey. Although all attempts were made to ensure that appropriate respondents participate in the survey, one cannot rule out the possibility that the recipient delegated to others to respond on his/her behalf.

From the 600 potential respondents who were invited to fill the survey, only 295 actually proceeded to answer the questions. Eight of these respondents answered "No" to the consent question and were screened out. The rest (287) of the respondents consented and were allowed to proceed to the next question, which sought to screen out potential respondents who had no budgetary responsibilities. 86 of the respondents answered "No" to this question and were screened out of the survey. The remaining 197 respondents proceeded with the survey, of which 179 actually completed the survey; constituting 29.83 response rate. Table 1 below summarizes the survey responses and response rate.

Table 1: Survey Responses and Response rate:

Initial list of invited people	600
No. of people who started the survey	295
No. of people who consent for taking the survey	287
No. of people allowed to continue after the screening questions	197
No. of total people who completed the survey	179
Response rate	29.83%

Of the 179 respondents, the highest proportion were from two industries namely, construction (17.32%) and wholesale, retail, and distribution (17.32%). This was followed by other variable industries that had 28 responses. The respondents were asked to specify their industries if they chose other among the industry choices. The lowest number of responses came from manufacturing (6.70%) and hospitality industries (6.70%). Table 2 (Panel A) shows the frequency distribution of respondents by industry. As reported in Table 2 (Panel B), majority of respondents (30.73%) came from organizations where the number of employees (size) ranged between 100 and 250. The lowest number of responses by size came from organizations where the number of employees (8.94% each) were between the ranges 501-750 and 751-1000. As shown in Table 2 (Panel C), the highest number of responses by age (45%) came from the 5-10 years range with the lowest (9%) coming from those over 20 years. As reported in Table 2 (Panel D), 75.42% of the respondents were from the private sector, 24.02% were from semi-governmental organizations, and the remaining 0.56% were from the government sector. Males constituted 77.09% while the females constituted 22.91% of the number of respondents (Table 2, Panel E). Finally, the highest number by respondents' age (29.61%) came from the age group of 30 to 34 years, whereas the lowest (0.56%) were over 60 years old (Table 2, Panel F).

Table 2: Distribution of Respondents by Industry, Size, Organizations' Age, Sector, and Gender

	Frequency	Percentage	Ranking
Panel A: Distribution of Respondents by Industry			
Manufacturing	12	6.70%	8
Oil and Gas	20	11.17%	4
Construction	31	17.32%	1
Financial Services	15	8.38%	6
Wholesale, Retail, and Distribution	31	17.32%	1
Consultancy	13	7.26%	7

Hospitality	12	6.70%	8
Utilities	17	9.50%	5
Other	28	15.64%	3
Total	179	100.00%	
Panel B: Distribution of Respondents by Size (number of employees)			
Fewer than 100 employees	39	21.79%	2
100 – 250 employees	55	30.73%	1
251 – 500 employees	31	17.32%	3
501 – 750 employees	16	8.94%	5
751 – 1000 employees	16	8.94%	5
Over 1,000 employees	22	12.29%	4
Total	179	100.00%	
Panel C: Distribution of Respondents by Organizations' Age			
less than 5 years	20	11.17%	3
5 – 10 years	80	44.69%	1
11 – 15 years	44	24.58%	2
16 – 20 years	18	10.06%	4
more than 20 years	17	9.50%	5
Total	179	100.00%	
Panel D: Distribution of Respondents by Sector			
Governmental	1	0.56%	3
Semi-Governmental	43	24.02%	2
Private	135	75.42%	1
Total	179	100.00%	
Panel E: Distribution of Respondents by Gender			
Male	138	77.09%	1
Female	41	22.91%	2
Total	179	100.00%	
Panel F: Distribution by Respondents' Age			
25-29 years	21	11.73%	4
30-34 years	53	29.61%	1
35-39 years	49	27.37%	2
40-49 years	46	25.70%	3
50-59 years	9	5.03%	5
60+ years	1	0.56%	6
Total	179	100.00%	

4.4 Measurement of Construct

All the constructs in this study were adapted from prior studies and anchored on seven-

point Likert scale.

Business analytics capabilities were measured on a five-item scale adapted from the works of LaValle et al. (2010) and Ashrafi et al. (2019). This construct was measured using reflective indicators. The measures asked each respondent to determine the extent to which their organizations use business analytics capabilities throughout the organization (Davenport & Harris, 2007; Someh & Shanks, 2015). The following were the items: the organization predicts and prepares for the future by proactively evaluating scenarios or potential trade-offs; decision-making is based on rigorous analytic approaches (e.g., quantitative modelling, simulation); the organization manages data to enable the ability to share and aggregate data across departments or business units; business information and analytics differentiate us within the industry; and improving our information and analytics capability is a top priority. Respondents were asked to indicate their level of agreement to the above items using a 7-point Likert-type scale ranging from one 'strongly disagree' to seven 'strongly agree'. Reliability of the scale items for these constructs have been high in prior studies (Ashrafi et al., 2019), as the Cronbach's alpha and composite reliability were 0.93 and 0.94, respectively, and factor loadings exceeded the 0.7 threshold. The validity scores of the scale items were high in prior studies with an average variance extracted (AVE) value of 0.77 and HTMT ratios for each pair being below 0.85.

Budget goal commitment was measured on a four-item scale. The following three items were adapted from the instrument developed by Hollenbeck, William, and Klein (1989): I think the performance goals are good goals to strive for; I am willing to put a great deal of effort into achieving the performance goals; and I am strongly committed to achieving performance goals. A fourth item was added to measure the construct: "I think it is important to attain the budget goals for my responsibility area". The respondents were asked to indicate their level of agreement to the above items using a 7-point Likert-type scale ranging from 'strongly disagree' to ‘strongly agree’. The reported composite reliability coefficients and factor loadings for the scale items in prior studies (Sholihin et al., 2011) were all above the accepted level of 0.70 (Peter, 1979). The AVEs for all the items were above 0.65 and the discriminant validity of the construct was within the levels acceptable under the Fornell-Larcker criterion.

Forecast accuracy was measured using the scale-items developed by Winklhofer and Diamantopoulos (2002). Accuracy was measured in relation to a specific forecasting level (total export sales) and three time horizons, namely short-, medium-, and long-term. Although Winklhofer and Diamantopoulos (2002) developed two horizons (short- and medium-term) to measure the variable, a third horizon (long-term) was added to ensure that the scale-items fully reflected the three time horizons. The specific accuracy measure employed was the mean absolute percentage error (MAPE). MAPE captures the absolute difference between actual and forecasted sales as a percentage of actual sales and shows the extent to which actual sales are under or overestimated by the forecast. According to Makridakis (1993), ‘‘MAPE is a relative measure that incorporates the best characteristics among the various accuracy criteria.” Moreover, Mentzer and Kahn (1995) found that MAPE was the most widely used accuracy measure in their sample of firms, and a strong preference for MAPE was also observed in the exploratory interviews conducted by Winklhofer and Diamantopoulos (2002). Respondents were asked to provide information about their range of forecast errors in relation to short-term (1-3 months) total export sales, medium-term (4-6 months) total export sales, and long-term (7-12 months) total export sales. Errors were recorded in one of the following ranges: 0 – 5%, 6 – 10%, 11 – 15%, 16 – 20%, and > 20%.

Budget adequacy was measured using a three-item scale developed by Nouri and Parker (1998). The scale items measure whether the individuals perceive their budgeted resources as being adequate for the performance of job duties. The items include the following: “My budget allows me to perform what is expected of me;” “What is expected of me is achievable under my budget;" and "I am pretty much confident that I can achieve what is expected of me under my budget." The response scale was a seven-point Likert-type scale ranging from one (strongly disagree) to seven (strongly agree). The reliability and validity of these scale items in prior studies were all at acceptable levels.

Past studies (Seddon et al., 2017; Yeoh & Popovič, 2016) have recommended considering firm size and industry sector as control variables in the context of business analytics. We included firm size, as larger firms may have more resources than smaller firms, and this may affect the relationship between business analytics capabilities and budget goal commitment. Simply put, large firms can invest in different activities that support IT (Subramani, 2004). The size of the firms was measured by the number of employees. We also controlled for industry sub-types, as they can capture different environmental dimensions, and this may impact the focal constructs and relationships in the model. Age of the organization is the third control variable that was included in the model. This is because older organizations tend to be more established and capable of investing in the required infrastructures to have the BAC. It was measured by the number of years the organization has been in existence.

4.5 Statistical Analysis

Data from this thesis was analyzed using partial least squares (PLS) structural equation modelling technique. PLS can be defined as a component-based modelling approach that maximizes the amount of variance and minimizes the number of errors simultaneously (Chin, 1998). PLS facilitates the development of latent construct scores on the basis of cross-products that involve multi-item measures. These latent construct scores may subsequently be used to find patterns (Fornell, 1982). Owing to this, it is possible to test route models that incorporate latent variables that are indirectly assessed using a variety of metrics (Chin et al., 2001). Another feature of the PLS is that it allows for the simultaneous modelling of theory (measurement model) and measurements (measurement model).

The PLS approach is used when dealing with a small sample size, as it makes no assumptions about the distribution of the data. The minimum sample size for PLS modelling, according to Chin et al. (1999), should be ten times bigger than the largest regression in the model. In this study, budget goal commitment is the construct that has the most complex regression, with three independent variables and three control variables affecting it. This suggests that the minimum sample size required is 60. The 179 useable responses from the survey are, therefore, adequate for PLS modelling.

Smart PLS release 3 was used to analyze the data of the measurement and structural models simultaneously. As suggested by Hulland (1999), the analysis and interpretation of results for the measurement and structural models are discussed separately. The results are presented in the next chapter.

4.6 Summary

This chapter discussed the research methodology employed to collect the required data for this study. The survey approach used to collect data was discussed, along with measures taken to improve the response rate. Moreover, the chapter discussed the measurement of the constructs of the study. A description of the statistical technique (PLS-SEM) used in analyzing the data was then presented. The results are discussed in chapter 5.

Chapter 5: Results

5.1 Introduction

This chapter presents the results that the partial least squares (PLS) analysis of the data collected for this study. A descriptive analysis of the data is first presented in section 5.2. This is followed by a discussion of the measurement model results in section 5.3, where the reliability and validity of the data are assessed. In section 5.4, the PLS structural model results are discussed and used in testing the hypotheses of the study. Section 5.5 concludes the chapter.

5.2 Descriptive Statistics

The descriptive statistics provide an insight on the response obtained with respect to the different constructs of business analytics capabilities, forecast accuracy, budget adequacy, budget goal commitment, industry, size, and age. The descriptive statistics are as shown in Table 3 below. The mean values of the scale items that measure the BAC constructs lie between 3.7 and 5.3 with an actual range of 1-7. The standard deviation values for all the indicators of the constructs are between 1.31 and 1.861, thus indicating substantial variability in the data. The mean values of the items that measure the forecast accuracy range from 2.2 to 4.2 with actual range between 1 and 5, and the standard deviation for these items are between 0.952 and 1.18. The mean values for the items that measure budget adequacy range from 4.2 to 6.1 with actual range of 1-7, while the standard deviations for the same range between 1.218 and 1.79. Similarly, the mean values of the items that measure budget goal commitment range from 3.7 to 6.1 with actual range of 1-7 while the standard deviations for the same range between 1.24 and 1.943.

Table 3: Descriptive Statistics

Construct	Indicator	Theoretical Range	Actual Range	Mean	Standard Deviation	Median
BAC	BAC1	1-7	1-7	3.726	1.827	4
	BAC2	1-7	1-7	3.899	1.861	4
	BAC3	1-7	1-7	6.095	1.31	7
	BAC4	1-7	1-7	4.894	1.742	5
	BAC5	1-7	1-7	5.335	1.756	6
Forecast accuracy	FA1	1-5	1-5	4.235	0.952	5
	FA2	1-5	1-5	3.57	1.118	4
	FA3	1-5	1-5	2.235	1.031	2
BA	BA1	1-7	1-7	4.223	1.706	5
	BA2	1-7	1-7	4.073	1.743	4
	BA3	1-7	1-7	6.095	1.218	7
	BA4	1-7	1-7	4.575	1.79	5
Budget goal commitment	BGC1	1-7	1-7	3.777	1.799	4
	BGC2	1-7	1-7	5.771	1.394	6
	BGC3	1-7	2-7	6.123	1.24	7
	BGC4	1-7	1-7	4.173	1.943	4

n = 179

5.3 Results of Measurement Models

As indicated, the data in this study is analyzed using Smart PLS 3.0 (Ringle et al., 2015). The software estimates the parameters of the measurement model by evaluating the relationship between the measures and constructs they are intended to measure. This involves the assessment of reliability (individual item and construct reliability) and validity (convergent and discriminant) of the measurement items.

The PLS model was first run using all items gathered through the survey questionnaire. An initial review of the measurement model results showed that BAC 3, BA3, BGC3, and BGC 5, cross-loaded highly on other constructs. In such situations, Hair et al. (2014) recommend deleting the cross-loaded items and re-running the PLS model. Therefore, these four items were excluded from the model. Since all the constructs in this study were measured with reflective indicators, excluding some items from the construct measurement is acceptable, as any of the indicators are interchangeable since they are equally valid for the constructs they measure (Chen, 1998). Following the exclusion of the cross-loaded items, the model was rerun and the results are reported below.

5.3.1 Reliability

Reliability is the consistency level of a method that measures something (Kimberlin & Winterstein, 2008). Given that the constructs of the study are latent, the reliability of the measurements are assessed through individual item reliability and composite reliability (Hulland, 1999).

Indicator reliability is assessed by examining the output of item loadings. As per Table 4, the loading estimates of all the items lie between 0.812 and 0.937. As all of these loading estimates are higher than 0.7 (Hulland, 1999), the indicator reliability can be said to be satisfactory.

Table 4: Factor Loadings and Cross Loadings

	Construct	Items	1	2	3	4	5	6	7
1	BA	BA1	**0.930**	0.752	0.817	0.793	0.526	0.059	0.531
		BA2	**0.937**	0.750	0.843	0.803	0.494	0.005	0.535
		BA4	**0.903**	0.748	0.837	0.806	0.535	-0.040	0.579
2	BAC	BAC1	0.754	**0.925**	0.778	0.786	0.597	0.024	0.565
		BAC2	0.726	**0.921**	0.761	0.772	0.588	0.029	0.568
		BAC4	0.723	**0.868**	0.753	0.794	0.598	-0.028	0.624
3	Budget goal commitment	BGC1	0.860	0.776	**0.939**	0.809	0.579	0.011	0.591
		BGC2	0.701	0.696	**0.812**	0.739	0.504	-0.002	0.459
		BGC4	0.839	0.784	**0.918**	0.803	0.591	0.051	0.626
4	Forecast accuracy	FA1	0.762	0.711	0.760	**0.880**	0.529	0.004	0.503
		FA2	0.799	0.785	0.816	**0.930**	0.625	-0.016	0.648
		FA3	0.748	0.808	0.766	**0.853**	0.655	-0.037	0.636
5	Age		0.561	0.657	0.628	0.681	**1.000**	-0.084	0.711
6	Industry		0.008	0.009	0.024	-0.019	-0.084	**1.000**	-0.215

7	Size	0.594	0.647	0.631	0.674	0.711	-0.215	**1.000**

n = 179

Construct reliability is said to have been established when the composite reliability, Cronbach's alpha, and Dijkstra's rho_A of each construct are more than 0.7 (Nunnally, 1978). As observed in Table 5, the composite reliability, Cronbach's alpha, and Dijkstra's rho_A for all the constructs in the model are higher than 0.70, thereby indicating that the constructs possess adequate reliability.

Table 5: Construct Reliability and Average Variance Extracted (AVE)

Constructs	Cronbach's Alpha	Dijkstra's rho_A	Composite Reliability	Average Variance Extracted (AVE)
BA	0.914	0.914	0.946	0.853
BAC	0.889	0.889	0.931	0.819
Budget Goal Commitment	0.869	0.879	0.920	0.794
Forecast Accuracy	0.866	0.869	0.918	0.789

n = 179

5.3.2 Validity

Validity is the level of accuracy with which a construct is measured. Considering that the constructs of this study are latent, their validity needs to be assessed. The validity of the construct's measurements is assessed using their convergent validity and discriminant validity (Hulland, 1999).

Convergent validity refers to the extent to which the measures are correlated with other measures of the same construct (Wong, 2013). This is determined using the average variance extracted (AVE) and a value of 0.5 or higher indicates adequate convergent validity (Chen, 1998). As observed in Table 5, the AVE for all constructs in the model are in the range of 0.789-0.853, thus indicating adequate convergent validity.

Discriminant validity refers to the extent to which a construct is related to its own indicators rather than the indicators of other constructs (Zait & Bertea, 2011). This is measured using Fornell-Larcker Criterion (Henseler et al., 2015) and Cross Loadings. As observed in Table 5, the values of square root of AVEs are higher than the respective correlations between the constructs, hence, discriminant validity is established.

Table 6: Discriminant Validity using Fornell-Larcker Criterion

	Constructs	1	2	3	4	5	6	7
1	BA	**0.924**						
2	BAC	0.812	**0.905**					
3	Budget Goal Commitment	0.901	0.845	**0.891**				
4	Forecast Accuracy	0.867	0.867	0.880	**0.888**			
5	Age	0.561	0.657	0.628	0.681	**1.000**		
6	Industry	0.008	0.009	0.024	-0.019	-0.084	**1.000**	
7	Size	0.594	0.647	0.631	0.674	0.711	-0.215	**1.000**

n = 179

The second test for discriminant validity is the assessment of cross loadings. The criterion for discriminant validity using cross loadings data is that every single indicator variable loads the highest on the construct it is meant to measure. As observed in Table 4, this criterion is met, as all items in the final model loaded higher on their respective constructs than on any other constructs. Therefore, discriminant validity is established for the dataset.

Overall, both reliability and validity tests are satisfactory, thereby indicating that the items used to measure constructs in the dataset for this research are fit to be used to estimate parameters in the structural model.

5.4 Results of Structural Model

In this section, the structural model results are used in testing the hypotheses of this study. The PLS structural model generates path coefficients for each relationship being examined. As PLS is a non-parametric approach, bootstrap resampling procedures are used in testing the significance of the path coefficients. In this study, 1,000 bootstrap resamples were used. Prior to using the structural model results to test hypotheses, the model is assessed for predictiveness and multicollinearity.

Model predictiveness is assessed using the coefficient of determination (R^2). The R^2 indicates the extent to which differences or variability in a dependent variable can be explained as a result of the changes in two or more independent variables in a model (Streukens & Leroi-Werelds, 2016). In the PLS, R^2s and adjusted R^2s are generated for all dependent variables. As reported in Table 7, the R^2s for the model ranges between 0.771 and 0.781, while the adjusted R^2s ranges between 0.765 and 0.859. These values indicate that the structural model has strong predictive capability and the model can be used to test the defined hypotheses.

Table 7: Coefficient of Determination (R^2)

	R^2	Adjusted R^2
BA	0.771	0.765
Budget Goal Commitment	0.864	0.859
Forecast Accuracy	0.781	0.776

n = 179

Multicollinearity was assessed using the structural model variance inflation factors (VIFs). VIF values not exceeding 10 are considered adequate. As reported in Table 8, the VIFs values range between 1.093 and 6.615, thus indicating that multicollinearity is not a threat.

Table 8: Structural Model Variance Inflation Factors (VIFs)

Independent Variable	Dependent Variables BA	Budget Goal Commitment	Forecast Accuracy
BA		4.369	
BAC	4.240	4.532	2.052
Forecast Accuracy	4.560	6.615	
Age	2.417	2.464	2.338
Industry	1.094	1.095	1.093
Size	2.546	2.554	2.463

n = 179

5.4.1 Hypothesis Testing

As indicated, the results of PLS structural model are used in testing the hypotheses of this study. The structural model results are reported in Table 9 (direct results are in Panel A and indirect effects are in Panel B).

Table 9: PLS Structural Model Results – Path Coefficients, T-Statistics, and P-Values

Panel A: Direct Effects

Hypotheses	Paths	Path Coefficient	T Statistics	P-Values
H1	BAC -> BGC	0.182	1.239	0.108
H2	BAC -> FA	0.693	10.053	0.000
H3	BAC -> BA	0.26	1.925	0.027
H4	FA -> BA	0.683	5.635	0.000
H5	FA -> BGC	0.223	1.599	0.055
H6	BA -> BGC	0.515	4.51	0.000
Control Variables				
	Age -> BA	-0.104	2.101	0.018
	Age -> BGC	0.049	1.19	0.117
	Age -> FA	0.131	2.925	0.002
	Industry -> BA	0.019	0.551	0.291
	Industry -> BGC	0.032	0.945	0.172
	Industry -> FA	0.014	0.292	0.385
	Size -> BA	0.044	0.937	0.175
	Size -> BGC	0.029	0.721	0.236
	Size -> FA	0.134	1.963	0.025

Panel B: Indirect Effects

Hypotheses	Paths	Path Coefficient	T Statistics	P-Values
H7a	BAC -> FA -> BGC	0.154	1.662	0.049
H7b	BAC -> BA -> BGC	0.134	2.357	0.009
H7c	BAC -> FA -> BA -> BGC	0.244	2.729	0.003
	BAC -> FA -> BA	0.473	4.998	0.000
	FA -> BA -> BGC	0.352	2.871	0.002

n = 179

Results for direct relationships

Hypothesis 1 predicted that business analytics capabilities have a direct positive relationship with budget goal commitment. The structural model results of Table 9 (Panel A) indicate that the direct path coefficient is positive (0.182), but not statistically significant *(p = 0.108)*; indicating that there is no direct relationship between business analytics capabilities and budget goal commitment. The hypothesis is therefore not supported.

While Wong-On-Wing et al. (2010) show that business analytics could enhance the budget goal commitment by ensuring that all departments and units in the organization are involved in the budgeting process, this is not entirely reflected in the findings of the present study. The insignificant results for hypothesis 1 indicate that business analytics capabilities do not directly influence budget goal commitment. The findings suggest the need to investigate whether the impact of intermediate variables on the relationship between business analytics capabilities and budget goal commitment. This will be examined in hypotheses 7a, 7b, and 7c.

Hypothesis 2 predicted that business analytics capabilities have a positive effect on forecast accuracy. The direct path coefficient for this relationship (reported in Table 8, Panel A) is positive (0.693) and statistically significant ($p < 0.01$). Therefore, the hypothesis is supported.

Furthermore, the above findings are supported in academic literature where Raghupathi (2021) argued that analysts are able to forecast the future and develop appropriate plans when organizations have business analytics. This view is also supported by research using the resource-based theory, which states that organizations have unique resources or assets that contribute to the differentiation of their performance and competitive advantage (Barney et al., 2011). By using the business analytics capabilities, organizations are able to generate accurate forecasts. Similarly, Palermo (2018) anticipated that the more a firm stresses on accuracy, the more probable it is that business analytics will be used, thereby emphasizing on the direct and positive influence of business analytics capabilities on forecast accuracy.

Hypothesis 3 predicted that business analytics capabilities have a direct positive relationship with budget adequacy. This hypothesis is supported. The direct path coefficient for this relationship is positive (0.26) and statistically significant at the 0.01 level (See table 9, Panel A).

Further, the results for hypothesis 3 are well supported in the literature. Karakoc and Ozer (2016) suggested that business analytics capabilities are particularly valuable for enhancing the budget plans and ensuring that the organization satisfies its budget adequacy criteria. This aspect is also evident in the context of the current research where there is a direct impact of business analytics capabilities on budget adequacy. This implies that business analytics capabilities can facilitate the collection and use of data in support of data-driven decision-making through prescriptive analytics that will lead to an adequate budget in the organization.

Hypothesis 4 predicted that forecast accuracy has a positive effect on budget adequacy. As shown in Table 9 (Panel A), the direct path leading from forecast accuracy to budget adequacy has a statistically significant ($p < 0.01$) positive coefficient (0.683). These significant results provide support for the hypothesis.

The result for H4 is consistent with the findings in the existing literature that emphasizes the importance of forecast accuracy in influencing budget adequacy. In this regard, Becker et al. (2016) and Palermo (2018) note that forecasting with a high degree of accuracy can be a considerable advantage for organizations that operate in a highly competitive or uncertain setting and can contribute toward budget adequacy without the need for constant revisions. This is based on the argument that budgeting process is future-oriented, hence, organizations need accurate forecasts to set proper budgets. Besides, this view is supported by Davenport and Harris (2007) who stated that a key aspect of forecasting accuracy is that it leads to proper planning during the budgeting process, such that it ensures budget adequacy. Hence, the findings of this study are consistent with the prior literature that examined the impact of forecast accuracy on budget adequacy.

Hypothesis 5 predicted that forecast accuracy has a direct positive relationship with budget goal commitment. The results reported in Table 9 (Panel A) show a positive path coefficient of 0.223 that is not statistically significant ($p < 0.055$). The results do not support the hypothesized relationship.

The findings from academic literature indicate that employees were more likely to remain committed to the organization's goals when they were clear and easy to achieve (Locke & Latham, 2019). In the case of budgeting, accuracy in forecasting can play a big role in the proper planning of budgets and conveying them to the employees so that they can stay motivated and committed to the budgetary goals. However, the findings of this study do not support a direct impact of forecast accuracy on budget goal commitment. Rather, the relationship between forecast accuracy and budget goal commitment is indirect (0.352; $p < 0.01$) through budget adequacy (see Table 9, Panel B).

Hypothesis 6 predicted that budget adequacy has a direct positive relationship with budget goal commitment. The results reported in table 9 (Panel A) indicate that the path coefficient is positive (0.515) and statistically significant at the 0.01 level. Thus, the results support the hypothesis.

The findings from this study are consistent with the existing literature, where it has been reported that focusing on budget adequacy creates a feeling among employees that the organization is devoted to their success and is assisting them in meeting business objectives (Zainuddin & Isa, 2011). Further, this view is supported by Khaddafi (2015) who reported a substantial correlation between budget sufficiency (i.e., adequacy) and goal commitment.

Results for mediation hypothesis

For mediation to be present, the indirect paths between the independent variable and dependent variable through the mediator(s) must be statistically significant (Nitzl et al., 2016). If both the direct and indirect paths are significant, it indicates partial mediation. However, if the indirect path is significant, but the direct path is not significant, then there is full mediation. The results for the indirect effects in the model are reported in Panel B of Table 9.

Hypothesis 7a predicts that the relationship between business analytics capabilities and budget goal commitment is mediated by forecast accuracy. As shown in the Table 9 (Panel B), the indirect effect of business analytics on budget goal commitment through forecast accuracy is positive (0.154) and statistically significant ($p < 0.05$). As reported, however, the direct effect (see H1) is insignificant. This implies that forecast accuracy fully mediates the relationship between business analytics capabilities and budget goal commitment. Hypothesis 7a is, thus, supported.

In hypothesis 7b, it was predicted that budget adequacy will mediate the relationship between business analytics capabilities and budget goal commitment. As reported in the Table 8 (A), the direct effect (H1) is not statistically significant. However, the indirect effects (0.134), as reported in Table 9 (Panel B), is statistically significant ($p < 0.01$) Therefore, hypothesis 7b is supported. Thus, budget adequacy fully mediates the relationship between business analytics capabilities and budget goal commitment.

Hypothesis 7c predicts that the relationship between business analytics capabilities and budget goal commitment will be serially mediated by forecast accuracy and budget adequacy. The indirect coefficient for the path from business analytics through forecast accuracy, and thence budget adequacy to budget goal commitment is positive (0.244) and significant at the 0.01 level. However, as reported, the direct path is insignificant. This implies that the relationship between business analytics capabilities and budget goal commitment is fully serially mediated by forecast accuracy and budget adequacy.

A summary of the results for the hypotheses tests are in table 10 below.

Table 10: Summary of Results for Hypotheses Tests

Hypotheses	Results
H1	Not Supported
H2	Supported
H3	Supported
H4	Supported
H5	Not Supported
H6	Supported
H7a	Supported
H7b	Supported
H7c	Supported

5.5 Summary

SmartPLS 3.0 was used to examine the effects of business analytics capabilities on budget goal commitment and the mediating roles of forecast accuracy and budget adequacy. The descriptive statistics presented in section 5.2 indicates substantial variability in the data. As discussed in section 5.3, the measurement model results support the reliability and validity of the data used in the model. The structural model results provide support for four direct relationships (H2, H3, H4, and H6), but not for H1 and H5. However, all the mediation hypotheses (H7a, H7b, and H7c) are supported by the results. The implications of these findings are discussed in chapter 6.

Chapter 6: Conclusion

6.1 Introduction

This last chapter discusses the results and concludes the study. The chapter is divided into various sections. Section 6.2 summarizes the findings of the study. Section 6.3 highlights the implications and contribution of this study to the literature and management accounting practices. Section 6.4 highlights the study limitations, with section 6.5 providing direction for future research.

6.2 Summary and Finding

The primary objective of this study was to examine the relationships among business analytics capabilities, forecast accuracy, budget adequacy, and budget commitment. A substantial amount of research has focused on business analytics as a response to the big data challenges that the businesses face and specifically, the budgeting process (Warren et al., 2015; LaValle et al., 2011; Zhao et al., 2020). This study extends and contributes to the current literature on the behavioral aspect of budgeting by examining the impact of business analytics capabilities on budget goal commitment. The focus on this relationship and the mediating role of budget adequacy and forecast accuracy was motivated by the increased use of analytic capabilities in enhancing the business processes (Aydiner et al., 2019; Shankararaman & Gottipati, 2015).

As observed in the literature review, organizations benefit from business analytics through four capabilities, namely descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. This thesis examined whether budget goal commitment will be impacted directly by business analytics capabilities or whether the impact will flow through the intermediation of forecast accuracy and budget adequacy. The study attained this objective by demonstrating how budget adequacy and forecast accuracy mediate the positive relationship between business analytics capabilities and budget goal commitment.

It was predicted that business analytics capabilities have a direct positive relationship with budget goal commitment. However, the findings from the PLS structural model show that rather than being direct, the relationship is fully mediated individually and serially by forecast accuracy and budget adequacy. Consequently, this study concludes that organizations that increasingly use business analytics capabilities, including descriptive, diagnostic, predictive, and prescriptive analytics, are more likely to experience a high level of budget goal commitment among managers. Thus, failure to use these capabilities could explain the lack of or low level of budget goal commitment among managers with budgetary responsibilities in the organization.

From a behavioral perspective, the results are explained by goal-setting theory that suggests that clear and achievable goals motivate the employees more than unclear goals. In this regard, business analytics capabilities assist organizations in creating clear budgetary goals through its impact on forecast accuracy, and thence adequate budget allocations, which, in turn, enhance their commitment. The findings indicate that, by impacting forecast accuracy, business analytics contribute to setting clear and achievable goals (reflecting the forecast), and with clear goals come improved allocations of resources through the budget process, thus ensuring that the managers have adequate budgets to execute the task expected of them. Adequate budgets then increase the confidence of employees that they can achieve their budget goals, and thus enhance budget goal commitment. These results highlight the need for management accounting professionals to continually employ data and business analytics in the budgeting process.

Further, the study had predicted that business analytics capabilities have a positive relationship with forecast accuracy and budget adequacy. The PLS results show a positive relationship between business analytics capabilities and forecast accuracy. There is also a strong positive relationship between business analytics capabilities and budget adequacy. Based on these results, the study concludes that increased use of business analytics in an organization will increase forecast accuracy and budgets adequacy. Likewise, the study concludes that organizations with poor analytical capabilities experience challenges when making accurate forecasts, thus leading to high incidences of inadequate budgets.

Furthermore, it was predicted that forecast accuracy has direct positive relationships with budget adequacy and budget goal commitment. As expected, the results support this prediction. The PLS results indicate a positive relationship between forecast accuracy and budget adequacy but not for the relationship between forecast accuracy and budget goal commitment. Rather, the results show that forecast accuracy influences budget goal commitment through budget adequacy. Consequently, the results imply that having accurate forecasts will enhance the organization's ability to set an adequate budget that ensures that the workforce remains committed to budget goals. From a behavioral perspective, the results show that adequate budgets, as a consequence of forecast accuracy, will motivate the employees to remain highly committed to the set budget goals.

Overall, the theoretical model developed in this study is supported by the findings except for the direct hypotheses implied in H1 and H5. However, it is worth noting that the impact of business analytics capabilities is much stronger for forecast accuracy than budget adequacy. The results also establish budget adequacy as a significant variable in the model, as it acts as an important conduit through which both business analytics and forecast accuracy affect budget goal commitment. In conclusion, the findings implies that business analytics has potential to enhance budgeting processes and outcomes in organizations.

6.3 Implications and Contributions

This study contributes to research and budgeting practice in numerous ways. First, by analyzing the application of business analytics in the budgeting process, the study responds to previous literature's demands to investigate how technology influences management accounting (Santiago Rivera & Shanks, 2015; Rikhardsson & Yigitbasioglu, 2018). By investigating the impact of business analytics on budget goal commitment, this study uncovered an essential role of technology-driven changes in the field of management accounting.

Second, the study looks at how business analytics affects one of the most critical management accounting tools, budgeting. As a result, the findings contribute to the descriptive literature that examines the current state of digitalization and the application of business analytics in the budgeting process. In practice, this study informs management accounting practitioners and organizations that investments in business analytics are required to optimize budgeting processes and increase budget goal commitment. Considering that budget goal commitment is a behavioral factor (Mathieu & Zajac, 1990), organizations whose employees are unsatisfied with the budgeting process may want to consider whether analytics might help solve their problems.

6.4 Limitations

Whereas the above results offer invaluable information on the mediating role of budget adequacy and forecast accuracy in the relationship between business analytics capabilities and budget goal commitment, the findings should be interpreted cautiously due to potential limitations. First, the study is based on a survey of 179 managers from the State of Qatar. This limits the generalizability of the results across different country contexts. Second, there is a risk of potential self-selection bias since it is possible that individuals that have achieved significant success in analytics would have responded to this survey. As a result, the study may exaggerate the present status of business analytics utilization in the budgeting process. Third, the study is limited by the small sample size. Initially, the researcher targeted 600 participants and only 295 responded to the invite. After the initial screening, only 197 were allowed to participate in the study, with 179 completing the survey. This figure represents a 29.8% response rate. While this sample size is similar to that obtained in prior literature, the current study could have benefited from a higher response rate. Future research should aim at a larger sample size drawn from different business backgrounds and industries. Fourth, it was not possible to examine the mediating role of other variables, with the study being focused only on budget adequacy and forecast accuracy. Future research should explore other mediating variables. Fifth, although business analytics capabilities were measured as first order reflective indicator model, the results could have been enhanced if it was measured as a second order construct with each of the four capabilities serving as its first order construct. Future research may measure this as second order construct of the four capabilities.

6.5 Implications for Future Research

This research presents several opportunities for future research. The current research explored the possible influence of business analytics capabilities in the budgeting process. The risks posed by budgeting automation and business analytics tools might be investigated. The findings could help understand whether business analytics capabilities could be counter-productive in enhancing budget goal commitment. Additionally, future research could extend this study by examining the potential effects of business analytics on other management accounting practices. Furthermore, it will be interesting if future studies can explore the individual and organizational factors that encourage or discourage budget goal commitment when an organization applies business analytics in the budgeting process.

References

Abbasi, A., Sarker, S., & Chiang, R. H. (2016). Big data research in information systems: Toward an inclusive research agenda. *Journal of the association for information systems, 17*(2), pp. 1-32.

Abernethy, M. A., Bouwens, J., & Van Lent, L. (2010). Leadership and control system design. *Management Accounting Research, 21*(1), pp. 2-16.

Alonso, S. G., de la Torre Diez, I., Rodrigues, J. J., Hamrioui, S., & Lopez-Coronado, M. (2017). A systematic review of techniques and sources of big data in the healthcare sector. *Journal of medical systems, 41*(11), pp. 1-9.

Amani, F. A., & Fadlalla, A. M. (2017). Data mining applications in accounting: A review of the literature and organizing framework. *International Journal of Accounting Information Systems, 24*, pp. 32-58.

Anthony, R. N., Govindarajan, V., & Dearden, J. (2007). Management control systems (Vol. 12). New York, NY: McGraw-Hill.

Applebaum, D., Kogan, A., Vasarhelyi, M., & Zhaokai, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems, 25*, pp. 29-44.

Asadi Someh, I., & Shanks, G. (2015, January). How business analytics systems provide benefits and contribute to firm performance?. In 23rd European Conference on Information Systems, ECIS 2015 (Vol. 2015). Association for Information Systems. https://core.ac.uk/download/pdf/301366865.pdf

Ashrafi, A., Ravasan, A. Z., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management, 47*, pp.1-15.

Autor, D. H. (2013). The "task approach" to labour markets: an overview. *Journal for Labour*

Market Research, *46*, pp. 185-199.

Avci, Ö. (2019). A study to examine the importance of forecast accuracy to supply chain performance: A case study at a company from the FMCG industry. The University of Twente.

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of business research*, *96*, pp. 228-237.

Baerdemaeker, J. D., & Bruggeman, W. (2015). The impact of participation in strategic planning on managers' creation of budgetary slack: The mediating role of autonomous motivation and affective organizational commitment. *Management Accounting Research*, *29*(1), pp. 1-12.

Bagdigen, M. (2005). An empirical analysis of accurate budget forecasting in turkey. Dogus Universitesi Dergisi, 6(2), pp. 190-201.

Baiman, S. (1982). Agency research in managerial accounting: A survey. *Journal of Accounting Literature*, pp. 154-213.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, *84*(2), p. 191.

Bandura, A. (1999). Social cognitive theory: An agentic perspective. *Asian journal of social psychology*, *2*(1), pp. 21-41.

Barga, R., Fontama, V., Tok, W. H., & Cabrera-Cordon, L. (2015). Predictive analytics with Microsoft Azure machine learning (pp. 221-241). Berkeley, CA: Apress.

Barney, J. B., Ketchen Jr, D. J., & Wright, M. (2011). The future of resource-based theory: revitalization or decline? *Journal of Management*, *37*(5), pp. 1299-1315.

Becker, S. D., Mahlendorf, M. D., Schäfer, U., & Thaten, M. (2016). Budgeting in times of economic crisis. *Contemporary Accounting Research*, *33*(4), pp. 1489–1517.

Bedford, D. S., & Speklé, R. F. (2018). Construct validity in survey-based management accounting and control research. *Journal of Management Accounting Research, 30*(2), pp. 23-58.

Belfo, F., & Trigo, A. (2013). Accounting information systems: Tradition and future directions. *Procedia Technology, 9*, pp. 536-546.

Bergmann, M., Brück, C., Knauer, T., & Schwering, A. (2020). Digitization of the budgeting process: determinants of the use of business analytics and its effect on satisfaction with the budgeting process. *Journal of Management Control, 31*(1), pp. 25-54.

Berman, R., & Israeli, A. (2020). The Value of Descriptive Analytics: Evidence from Online Retailers. Harvard Business School Marketing Unit Working Paper, (pp. 21-067). Retrieved from: https://www.hbs.edu/ris/Publication%20Files/21-067_2c65c0b0-9f10-476f-8e4b-bbf5b56a57e0.pdf[Accessed 22 February 2022].

Berners-Lee, T., & Shadbolt, N. (2011). There's gold to be mined from all our data. The Times, London 1:1–2. Online Available at: http://www.thetimes.co.uk/tto/opinion/ columnists/article3272618.ece

Bogsnes, B. (2016). Implementing beyond budgeting: unlocking the performance potential. New Jersey, NJ: John Wiley and Sons.

Bose, R. (2009). Advanced analytics: opportunities and challenges. *Industrial Management and Data Systems, 109*(2), pp. 155-172.

Brands, K., & Holtzblatt, M. (2015). Business Analytics: Transforming the Role of Management Accountants. *Management Accounting Quarterly, 16*(3).

Brown, D. E., Famili, F., Paass, G., Smith-Miles, K., Thomas, L. C., Weber, R., ... & Maldonado, S. (2011). Future trends in business analytics and optimization. *Intelligent Data Analysis, 15*(6), pp. 1001-1017.

Brownell, P. (1995). Research methods in management accounting. Coopers and Lybrand and

Accounting Association of Australia and New Zealand.

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review, 106*(5), pp. 133-39.

Buturac, G. (2022). Measurement of Economic FA: A Systematic Overview of Empirical Literature. *Journal of Risk and Financial Management, 15*(1), pp. 1-28.

Carillo, K. D. A., Galy, N., Guthrie, C., & Vanhems, A. (2019). How to turn managers into data-driven decision makers: Measuring attitudes towards business analytics. Business Process Management Journal, 25(3), 553-578. https://doi.org/10.1108/BPMJ-11-2017-0331

Ceccucci, W., Jones, K., Toskin, K., & Leonard, L. (2020). Undergraduate Business Analytics and the Overlap with Information Systems Programs. Information Systems Education Journal, 18(4), 22-32. https://eric.ed.gov/?id=EJ1258206

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*(4), pp. 1165-1188.

Chen, J., Chen, Y., Du, X., Li, C., Lu, J., Zhao, S., & Zhou, X. (2013). Big data challenge: a data management perspective. *Frontiers of Computer Science, 7*(2), pp. 157-164.

Cheng, M. T. (2012). The joint effect of budgetary participation and broad-scope management accounting systems on management performance. Asian Review of Accounting.

Chiang, R. H., Grover, V., Liang, T. P., & Zhang, D. (2018). Strategic value of big data and business analytics, *Journal of Management Information Systems, 35*(2), pp. 383-387. https://doi.org/10.1080/07421222.2018.1451950

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research, 295*(2), pp. 295-336.

Chin, W. W. Mathieson, K., & Peacock, E. (2001). Extending the technology acceptance model: the influence of perceived user resources. *ACM SIGMIS Database: the*

DATABASE for Advances in Information Systems, 32(3), pp. 86-112.

Chin, W. W., & Newsted, P. R. (1999). Structural equation modeling analysis with small samples using partial least squares. *Statistical strategies for small sample research, 1*(1), pp. 307-341.

Chong, V. K., & Chong, K. M. (2002). Budget goal commitment and informational effects of budget participation on performance: A structural equation modeling approach. *Behavioral Research in Accounting, 14*(1), pp. 65-86.

Chong, V. K., & Johnson, D. M. (2007). Testing a model of the antecedents and consequences of budgetary participation on job performance. *Accounting and business research, 37*(1), pp. 3-19.

Chow, C. W., Cooper, J. C., & Waller, W. S. (1988). Participative budgeting: Effects of a truth-inducing pay scheme and information asymmetry on slack and performance. *Accounting Review*, pp. 111-122.

Christensen, F. M. M., Solheim-Bojer, C., Dukovska-Popovska, I., & Steger-Jensen, K. (2021). Developing new forecasting accuracy measure considering Product's shelf life: Effect on availability and waste. *Journal of Cleaner Production, 288*, 125594.

Clements, M. P., and Hendry, D. F. (2008). Economic forecasting in a changing world. *Capitalism and Society, 3*(2), pp. 1-18.

Cokins, G. (2009). Performance management: Integrating strategy execution, methodologies, risk, and analytics (Vol. 21). John Wiley & Sons.

Cokins, G. (2017). Strategic business management: From planning to performance. John Wiley & Sons.

Cooper, R. & Kaplan, R.S., (1997). The promise–and peril–of integrated cost systems. *Harv. Bus. Rev. 76* (4), pp. 109-119.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of Big Data

Analytics in European firms. *Journal of Business Research, 70*, pp. 379-390.

Coyne, J. G., Coyne, E. M., & Walker, K. B. (2016). A model to update accounting curricula for emerging technologies. *Journal of Emerging Technologies in Accounting, 13*(1), pp. 161-169. https://doi.org/10.2308/jeta-51396

Dalrymple, D. J. (1987). Sales forecasting practices: Results of a United States survey. *International Journal of Forecasting, 3*, pp. 379±392.

Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British journal of educational technology, 46*(5), pp. 904-920.

Davenport, T. (1998). Putting the enterprise into the enterprise system. *Harv. Bus. Rev. 76*, pp. 121-131.

Davenport, T. H. & Harris, J. G. (2007). Competing on analytics: The new science of winning. Boston: Harvard Business Press

Davenport, T. H., Harris, J. G., Jones, G. L., Lemon, K. N., Norton, D., & McCallister, M. B. (2007). The dark side of customer analytics. *Harvard business review, 85*(5), p. 37.

Davydenko, A. & Fildes, R. (2013). Measuring forecasting accuracy: The case of judgmental adjustments to SKU-level demand forecasts. *International Journal of Forecasting, 29*(3), pp. 510-522.

Deco, E. L. & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychology Inquiry, 11(4), pp. 227-268.

Dillman, D. A. (2011). Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide. John Wiley & Sons.

Duan, L., & Xiong, Y. (2015). Big data analytics and business analytics. *Journal of Management Analytics, 2*(1), pp. 1-21. https://doi.org/10.1080/23270012.2015.1020891

Elbashir, M. Z., Collier, P. A. & Sutton, S. G. (2011). The role of organizational absorptive capacity in the strategic use of business intelligence to support integrated management control systems. *The Accounting Review, 86*(1), pp. 155-184.

Elbashir, M. Z., Collier, P. A., Sutton, S. G., Davern, M. J. & Leech, S. A. (2013). Enhancing the business value of business intelligence: The role of shared knowledge and assimilation. *Journal of Information Systems, 27*(2), pp. 87-105.

Emblemsvåg, J. (2005). Budget adequacy: getting behind the numbers. *International Journal of Productivity and Performance Management, 541*, pp. 47-58.

Etemadi, H., Dilami, Z.D., Bazaz, M.S. & Parameswaran, R. (2009), "Culture, management accounting and managerial performance: focus Iran", Advances in Accounting. *Incorporating Advances in International Accounting, Vol. 25* No. 2, pp. 216-25.

Evans, R. J. (2017). Business analytics - Methods, Models and Decisions. 2nd edition. London, England: Pearson Education Limited

Evans, J. R. & Mathur, A. (2005). The value of online surveys. Internet research.

Evermann, J. & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators. *Journal of Business Research, 69*(10), pp. 4565-4582.

Fahlevi, H., Irsyadillah, I., Indriani, M. & Oktari, R. S. (2021). DRG-based payment system and management accounting changes in an Indonesian public hospital: exploring potential roles of big data analytics. Journal of Accounting & Organizational Change.

Fernandes, E. & Pacheco, R. R. (2018). Managerial performance of airports in Brazil before and after concessions. *Transportation Research Part A: Policy and Practice, 118*, pp. 245-257.

Fisher, J., Frederickson, J. R. & Peffer, S. A. (2002). The effect of information asymmetry of negotiated budgets: An empirical investigation. Accounting, Organizations and Society, 27(January), pp. 27-43.

Fornell, C. (1982). A second generation of multivariate analysis: An overview. Methods, pp.

1-21.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G. & Gnanzou, D. (2015). How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics, 165,* pp. 234-246.

Fotr, J., Špaček, M., Souček, I. & Vacík, E. (2015). Scenarios, their concept, elaboration and application. *Baltic Journal of Management, 10*(1), pp. 73-97.

Gamage, P. (2016). Big Data: are accounting educators ready? *Journal of Accounting and Management Information Systems, 15*(3), pp. 588-604. https://www.ceeol.com/search/article-detail?id=517553

Gandomi, A. & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management, 35*(2), pp. 137-144.

Gbosbal, S. & Kim, S. K. (1986). Building effective intelligence systems for competitive advantage. *Sloan Management Review (1986-1998), 28*(1), p. 49.

Gilad, T. & Gilad, B. (1986). SMR forum: business intelligence-the quiet revolution. *Sloan Management Review (1986-1998), 27*(4), p. 53.

Gneiting, T. (2011). Making and evaluating point forecasts. *Journal of the American Statistical Association, 106*(494), pp. 746-762.

Gómez-Ruiz, L. & Rodríguez-Rivero, E. (2018). The motivational role of consultative participation in a multi-period target setting: An experimental study. *Spanish Journal of Finance and Accounting, 47*(3), pp. 329-351.

Gray, G. L. & Alles, M. (2015). Data fracking strategy: Why management accountants need it. *Management Accounting Quarterly, 16*(3).

Griva, A., Bardaki, C., Pramatari, K. & Papakiriakopoulos, D. (2018). Retail budget adequacy: Customer visit segmentation using market basket data. *Expert Systems with Applications, 100,* pp. 1-16.

Grover, V., Chiang, R. H., Liang, T. P. & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems, 35*(2), pp. 388-423

Gružauskas, V., Gimžauskienė, E., & Navickas, V. (2019). Forecasting accuracy influence on logistics clusters activities: The case of the food industry. *Journal of Cleaner Production, 240,* 118225.

Gul, F.A. and Chia, Y.M. (1994), "The effects of management and accounting systems, perceived environmental uncertainty and decentralization on managerial performance. A test of three-way interaction", *Accounting, Organization and Society, Vol. 19* Nos 4-5, pp. 413-26.

Gunarathne, A. N. & Alahakoon, Y. (2016). Environmental management accounting practices and their diffusion: the Sri Lankan experience. *NSBM Journal of Management, 2*(1), pp. 1-26. DOI: http://doi.org/10.4038/nsbmjm.v2i1.18

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B. & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*, pp. 308-317.

Hair Jr, J. F., Sarstedt, M., Hopkins, L. & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. European business review.

Halper, F. (2013). Predictive analytics for business advantage. Best practice report: TDWI Research.

Han, J., Kamber, M. & Pei, J. (2013). Data Mining: Concepts and Techniques. USA: Morgan Kaufmann Publishers

Hansen, S. C., Otley, D. T. & Van der Stede, W. A. (2003). Practice developments in budgeting: An overview and research perspective. *Journal of Management Accounting*

Research, 15(1), pp. 95-116.

Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A. & Khan, S. U. (2015). The rise of "big data" on cloud computing: Review and open research issues. *Information systems, 47,* pp. 98-115.

Henseler, J., Ringle, C. M. & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), pp. 115-135.

Henttu-Aho, T. (2018). The role of rolling forecasting in budgetary control systems: Reactive and proactive types of planning. *Journal of Management Control, 29*(3-4), pp. 327-360.

Hollenbeck, J. R. & Brief, A. P. (1987). The eVects of individual diVerences and goal origin on the goal setting process. *Organizational Behavior and Human Decision Processes, 40*, pp. 392-414.

Hollenbeck, J. R. & Klein, H. J. (1987). Goal commitment and the goal setting process: Problems, prospects and proposals for future research. *Journal of Applied Psychology, 72*, pp. 212-220.

Hollenbeck, J. R., Klein, H. J., O'Leary, A. M. & Wright, P. M. (1989). Investigation of the construct validity of a self report measure of goal commitment. *Journal of Applied Psychology, 74*, pp. 951-956.

Hollenbeck, J. R., Williams, C. R. & Klein, H. J. (1989). An empirical examination of the antecedents of commitment to diYcult goals. *Journal of Applied Psychology, 74*, pp. 18-23.

Holsapple, C., Lee-Post, A. & Pakath, R. (2014). A unified foundation for budget adequacy. *Decision Support Systems, 46*, pp. 130-141.

Hope, J. & Fraser, R. (2003). New ways of setting rewards: The beyond budgeting model. *California Management Review, 45*(4), pp. 104-119.

Hopkins, M. S., LaValle, S., Balboni, F., Kruschwitz, N. & Schockley, R. (10). Insights: A first look at the new intelligent enterprise survey. *MIT Sloan Management Review, 52*(1), pp. 22-31.

Hsu, M. F., Hsin, Y. S. & Shiue, F. J. (2021). Business analytics for corporate risk management and performance improvement. *Annals of Operations Research*, pp. 1-41.

Huang, C. L. & Chen, M. L. (2009). Relationships among budgetary leadership behavior, managerial budgeting games, and budgetary attitudes: Evidence from Taiwanese corporations. *Journal of International Accounting, Auditing and Taxation, 18*(1), pp. 73-84.

Huikku, J., Hyvönen, T. & Järvinen, J. (2017). The role of a predictive analytics project initiator in the integration of financial and operational forecasts. *Baltic Journal of Management, 12*(4), pp. 427-446.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal, 20*(2), pp. 195-204.

Hyndman, R. J. & Koehler, A. B. (2006). Another look at measures of FA. *International journal of forecasting, 22*(4), pp. 679-688.

Işık, Ö., Jones, M. C. & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management*, *50*(1), pp. 13-23.

Jaramillo, F., Mulki, J. P. & Marshall, G. W. (2005). A meta-analysis of the relationship between organizational commitment and salesperson job performance: 25 years of research.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D. & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management, 29*(2), pp. 513-538.

Jordan, S. & Messner, M. (2020). The use of forecast accuracy indicators to improve planning quality: Insights from a case study. *European Accounting Review, 29*(2), pp. 337-359.

Joseph, R. C. & Johnson, N. A. (2013). Big data and transformational government. *IT Professional, 15*(6), pp. 43-48.

Jourdan, Z., Rainer, R. K. & Marshall, T. E. (2008). Business intelligence: An analysis of the literature. *Information systems management, 25*(2), pp. 121-131.

Jukić, N., Sharma, A., Nestorov, S. & Jukić, B. (2015). Augmenting data warehouses with Big Data. *Information Systems Management, 32*(3), pp. 200-209.

Kallunki, J. P., Laitinen, E. K. & Silvola, H. (2011). Impact of enterprise resource planning systems on management control systems and firm performance. *International Journal of Accounting Information Systems, 12*(1), pp. 20-39.

Kaplan, S. N., Klebanov, M. M. & Sorensen, M. (2012). Which CEO characteristics and abilities matter? *The Journal of Finance, 67*(3), pp. 973-1007.

Karakoc, E. Y. & Ozer, G. (2016). An investigation of budget-related antecedents of job performance. *International Journal of Research in Business and Social Science, 5*(3), pp. 38-53.

Khaddafi, M. (2015). Effect of Budgetary Participation and budget adequacy on Individual Performance with Job Satisfaction as an Intervening Variable. *International Journal of Economics, Commerce and Management, 3*(2), pp. 1-15.

Kimberlin, C. L. & Winterstein, A. G. (2008). Validity and reliability of measurement instruments used in research. *American journal of health-system pharmacy, 65*(23), pp. 2276-2284.

Kitchin, R. (2014). Big data, new epistemologies and paradigm shifts. [Online] available at: http://bds.sagepub.com/content/1/1/ 2053951714528481[Accessed 2 March 2022].

Koutsandreas, D., Spiliotis, E., Petropoulos, F. & Assimakopoulos, V. (2021). On the selection of forecasting accuracy measures. *Journal of the Operational Research Society*, pp. 1-

18.

Kraus, M., Feuerriegel, S. & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications and managerial implications. *European Journal of Operational Research, 281*(3), pp. 628-641.

Kraus, M., Feuerriegel, S. & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications and managerial implications. *European Journal of Operational Research, 281*(3), pp. 628-641.

Krishnan, R. (2015). Management accountant—What ails thee? *Journal of Management Accounting Research, 27*(1), pp. 177-191. https://doi.org/10.2308/jmar-10461

Kristoffersen, E., Mikalef, P., Blomsma, F. & Li, J. (2021). Towards a business analytics capability for the circular economy. *Technological Forecasting and Social Change, 171*, 120957.

Kumar, R. (2018). Research methodology: A step-by-step guide for beginners. Sage.

Langfeld-Smith, K., Thorne, H. & Hilton, R. W. (2005). Management accounting: Information for managing and creating value (4th Ed.). Sydney, NSW: McGraw-Hill-Irwin

LaValle, S., Hopkins, M. S., Lesser, E., Shockley, R. & Kruschwitz, N. (2010). Analytics: The new path to value. *MIT Sloan Management Review, 52*(1), pp. 1-25.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S. & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), pp. 21-32.

Lawrence, M., O'Connor, M. & Edmundson, B. (2000). A field study of sales forecasting accuracy and processes. *European Journal of Operational Research, 122*(1), pp. 151-160.

LeClair, D. (2018). Integrating business analytics in the marketing curriculum: Eight recommendations. *Marketing Education Review, 28*(1), pp. 6-13.

Lee, T. W., Locke, E. A. & Phan, S. H. (1997). Explaining the assigned goal-incentive interaction: The role of self-efficacy and personal goals. *Journal of Management*, *23*(4), pp. 541-559.

Lepenioti, K., Bousdekis, A., Apostolou, D. & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management, 50*, pp. 57-70.

Li, Y., Thomas, M. A. & Osei-Bryson, K. M. (2016). A snail shell process model for knowledge discovery via data analytics. *Decision Support Systems, 91*, pp. 1-12.

Libby, T. & Lindsay, R. M. (2010). Beyond budgeting or budgeting reconsidered? A survey of North American budgeting practice. *Management Accounting Research*, *21*(1), pp. 56-75.

Lidia, T. G. (2014). Difficulties of the budgeting process and factors leading to the decision to implement this management tool. *Procedia Economics and Finance, 15*, pp. 466-473.

Lillis, A. M. & Mundy, J. (2005). Cross-sectional field studies in management accounting research—closing the gaps between surveys and case studies. *Journal of management accounting research, 17*(1), pp. 119-141.

Lin and Chang (2005). Goal orientation and Organizational commitment as explanatory factors of employee mobility. *Personnel Review, 34*(2), pp. 282-291.

Liu, B. & Tan, M. (2019). Overconfidence and FA: An experimental investigation on the hard–easy effect. *Studies in Economics and Finance, 38*(3), pp. 601-618.

Liu, X. & Li, X. (2015). What Motivates Online Disagreement Expression?: The Influence of SelfEfficacy, Mastery Experience, Vicarious Experience, and Verbal Persuasion. In Emerging Media (pp. 215-239). Routledge.

Locke, E. A. & Latham, G. P. (2012). Goal setting theory. In Motivation: Theory and research (pp. 23-40). Routledge.

Locke, E. A. & Latham, G. P. (2004). What should we do about motivation theory? Six recommendations for the twenty-first century. *The Academy of Management Review, 29*(3), pp. 388-403.

Locke, E. A. & Latham, G. P. (2006). New directions in goal-setting theory. *Current Directions in Psychological Science, 15*(5), pp. 265-268.

Locke, E. A. & Latham, G. P. (2019). The development of goal-setting theory: A half-century retrospective. Motivation Science, 5(2), p. 93.

Locke, E. A., Latham, G. P. & Erez, M. (1988). The determinants of goal commitment. *Academy of management review, 13*(1), pp. 23-39.

Locke, E. A., Shaw, K. N., Saari, L. M. & Latham, G. P. (1981). Goal setting and task performance: 1969–1980. *Psychological Bulletin, 90*(1), pp. 125-152.

Locke, E. & Schweiger, D. M. (1979). Participation in decision-making: One more look. In B. Staw (Ed.), Research in organizational behaviour (Vol. 1, pp. 265–339). Greenwich, CT: JAI Press

Lönnqvist, A. & Pirttimäki, V. (2006). The measurement of business intelligence. *Information Systems Management., 23*(1), pp. 32-40.

Lu, E. Y., Mohr, Z. & Ho, A. T. K. (2015). Taking stock: Assessing and improving performance budgeting theory and practice. *Public Performance and Management Review, 38*(3), pp. 426-458.

Macinati, M. S. & Rizzo, M. G. (2014). Budget goal commitment, clinical managers' use of budget information and performance. *Health Policy, 117*(2), pp. 228-238.

Mahmoud, E., Rice, G. & Malhotra, N. (1988). Emerging issues in sales forecasting and decision support systems. *Journal of the Academy of Marketing Science, 16*, pp. 47±61.

Maiga, A. S. (2005). Antecedents and consequences of budget participation. In Advances in management accounting. Emerald Group Publishing Limited.

Maisel, L. & Cokins, G. (2013). Predictive business analytics: Forward looking capabilities to improve business performance. John Wiley & Sons.

Makridakis, S. (1993). Accuracy measures: theoretical and practical concerns. *International journal of forecasting, 9*(4), pp. 527-529.

Marginson, D. & Ogden, S. (2005). Coping with ambiguity through the budget: the positive effects of budgetary targets on managers' budgeting behaviours. *Accounting, Organizations and Society*, *30*(5), pp. 435-456.

Marr, B. (2018, May 21). How Much Data Do We Create Every Day? The Mind-Blowing Stats Everyone Should Read. Forbes [Online] Available at: https://www.forbes.com/sites/bernardmarr/2018/05/21/how-much-data-do-we-create-every-day-the-mind-blowing-stats-everyone-should-read/?sh=6c4f5f6860ba[Accessed 4 January 2022].

Mashingaidze, K. & Backhouse, J. (2017). The relationships between definitions of big data, business intelligence and business analytics: a literature review. *International Journal of Business Information Systems*, *26*(4), pp. 488-505.

Mathieu, J. E. & Zajac, D. M. (1990). A review and meta-analysis of the antecedents, correlates, and consequences of organizational commitment. *Psychological Bulletin, 108*(2), pp. 171-194.

Mayer-Schönberger, V. & Cukier, K. (2013). Big data: A revolution that will transform how we live, work, and think. Houghton Mifflin Harcourt.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J. & Barton, D. (2012). Big data: the management revolution. *Harvard business review, 90*(10), pp. 60-68.

Mentzer, J. T. & Kahn, K. B. (1995). Forecasting technique familiarity, satisfaction, usage, and application. *Journal of forecasting, 14*(5), pp. 465-476.

Merchant, K. A. & Van der Stede, W. A. (2012). Management control systems: Performance measurement, evaluation and incentives (Vol. 3). Harlow: Pearson.

Meyer, J. P., Becker, T. E. & Vandenberghe, C. (2004). Employee commitment and motivation: A conceptual analysis and integrative model. *Journal of Applied Psychology, 89*(6), pp. 991-1007.

Mohamad, M. M., Sulaiman, N. L., Sern, L. C. & Salleh, K. M. (2015). Measuring the validity and reliability of research instruments. *Procedia-Social and Behavioral Sciences, 204*, pp. 164-171.

Morlidge, S. (2017). The little book of beyond budgeting: A new operating system for organizations: What it is and why it works. Matador.

Mortenson, M. J., Doherty, N. F. & Robinson, S. (2015). Operational research from Taylorism to Terabytes: A research agenda for the analytics age. *European Journal of Operational Research, 241*(3), pp. 583-595.

Mosavi, N. S. & Santos, M. F. (2020). How prescriptive analytics influences decision making in precision medicine. *Procedia Computer Science, 177*(2020), pp. 528-533.

Mowen, J. C., Middlemist, R. D. & Luther, D. (1981). Joint effects of assigned goal level and incentive structure on task performance: A laboratory study. *Journal of applied psychology, 66*(5), p. 598.

Narayanan, V. G. & Davila, A. (1998). Using delegation and control systems to mitigate the trade-off between the performance-evaluation and belief-revision uses of accounting signals. *Journal of Accounting & Economics, 25*(3), pp. 255-282.

Nguyen, N. P., Evangelista, F. & Kieu, T. A. (2019). The contingent roles of perceived budget fairness, BGC and vertical information sharing in driving work performance. *Journal of Asian Business and Economic Studies, 26*(1), pp. 98-116.

Nguyen, T. T., Mia, L., Winata, L. & Chong, V. K. (2017). Effect of transformational-leadership style and management control system on managerial performance. *Journal* *of Business Research, 70*, pp. 202-213.

Nguyen, T., ZHOU, L., Spiegler, V., Ieromonachou, P. & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers and Operations Research, 98*, pp. 254-264.

Nitzl, C., Roldan, J. L. & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. Industrial management & data systems.

Nouri, H. & Parker, R. J. (1998). The relationship between budget participation and job performance: the roles of budget adequacy and organizational commitment. *Accounting, Organizations and society, 23*(5-6), pp. 467-483.

Nunnally, J. C. & Bernstein, I. H. (1978). Psychometric Theory McGraw-Hill New York. The role of university in the development of entrepreneurial vocations: a Spanish study, pp. 387-405.

O'Mahony, J. & Lyon, J. (2016). Planning, Budgeting and Forecasting: An eye on the future. KPMG and ACCA Thought Leadership Report.

Palermo, T. (2018). Accounts of the future: A multiple-case study of scenarios in planning and management control processes. *Qualitative Research in Accounting and Management, 15*(1), pp. 2-23.

Pan, X. & Tang, H. (2021). Are both managerial morality and talent important to firm performance? Evidence from Chinese public firms. *International Review of Financial Analysis, 73*, 101602.

Peter, J. P. (1979). Reliability: A review of psychometric basics and recent marketing practices. *Journal of marketing research, 16*(1), pp. 6-17.

Phillips, J. (2013). Building a digital analytics organization: Create value by integrating analytical processes, technology, and people into business operations. Pearson education.

Phillips-Wren, G., Iyer, L.S., Kulkarni, U. & Ariyachandra, T. (2015), “Business analytics in the context of big data: a roadmap for research”, Communications of the Association for *Information Systems, Vol. 37,* pp. 448-472.

Priyadarshi, R., Panigrahi, A., Routroy, S. & Garg, G. K. (2019). Demand forecasting at retail stage for selected vegetables: a performance analysis. Journal of Modelling in Management.

Pröllochs, N. & Feuerriegel, S. (2020). Business analytics for strategic management: Identifying and assessing corporate challenges via topic modeling. *Information & Management*, *57*(1), 103070.

Provost, F. & Fawcett, T. (2013). Data Science for Business: What you need to know about data mining and data-analytic thinking. " O'Reilly Media, Inc.".

PwC. (2016). PwC’s global data and analytics survey: Big decisions. Retrieved from https://www.pwc.com/us/en/services/consulting/analytics/big-decision-survey.html [Accessed 15 February 2022].

Qasim, A. & Kharbat, F. F. (2020). Blockchain technology, business data analytics, and artificial intelligence: Use in the accounting profession and ideas for inclusion into the accounting curriculum. *Journal of Emerging Technologies in Accounting, 17*(1), pp. 107-117.

Radebe, L. Z., and Radebe, P. Q. (2014). Behavioural factors as determinants of effective budgeting process in public secondary schools. *Mediterranean Journal of Social Sciences, 5*(23), pp. 205-205.

Raffoni, A., Visani, F., Bartolini, M. & Silvi, R. (2018). Business performance analytics: exploring the potential for performance management systems. *Production Planning & Control, 29*(1), pp. 51-67. https://doi.org/10.1080/09537287.2017.1381887

Raghupathi, W. & Raghupathi, V. (2021). Contemporary budget adequacy: An Overview. *Data, 6*(8), p. 86.

Ramakrishnan, T., Jones, M. C. & Sidorova, A. (2012). Factors influencing business intelligence (BI) data collection strategies: An empirical investigation. *Decision support systems*, *52*(2), pp. 486-496.

Ramanathan, R., Philpott, E., Duan, Y. & Cao, G. (2017). Adoption of business analytics and impact on performance: A qualitative study in retail. *Production Planning & Control, 28*(11-12), pp. 985-998.

Ramos, T. B., Caeiro, S., Van Hoof, B., Lozano, R., Huisingh, D. & Ceulemans, K. (2015). Experiences from the implementation of sustainable development in higher education institutions: Environmental Management for Sustainable Universities. *Journal of Cleaner Production, 106*, pp. 3-10.

Rehman, M. H., Chang, V., Batool, A. & Teh, Y. W. (2016). Big data reduction framework for value creation in sustainable enterprises. *International Journal of Information Management* (Accepted).

Rikhardsson, P. & Yigitbasioglu, O. (2018). Business intelligence & analytics in management accounting research: Status and future focus. *International Journal of Accounting Information Systems*, *29*, pp. 37-58.

Ringle, C., Da Silva, D. & Bido, D. (2015). Structural equation modeling with the SmartPLS.

Bido, D., da Silva, D. & Ringle, C. (2014). Structural Equation Modeling with the Smartpls. *Brazilian Journal Of Marketing*, *13*(2).

Rom, A. & Rohde, C. (2007). Management accounting and integrated information systems: A literature review. *International Journal of Accounting Information Systems, 8*(1), pp. 40-68.

Santiago Rivera, D. & Shanks, G. (2015). A dashboard to support management of business analytics capabilities. *Journal of Decision Systems, 24*(1), pp. 73-86.

Scapens, R. W. & Jazayeri, M. (2003). ERP systems and management accounting change: opportunities or impacts? A research note. *European accounting review, 12*(1), pp. 201-233.

Seddon, P. B., Constantinidis, D., Tamm, T. & Dod, H. (2017). How does business analytics contribute to business value? *Information Systems Journal, 27*(3), p. 2

Shaikh, A. A., & Karjaluoto, H. (2015). Making the most of information technology & systems usage: A literature review, framework and future research agenda. *Computers in Human Behavior, 49,* pp. 541-566.

Shankararaman, V. & Gottipati, S. (2015, July). A Framework for embedding analytics in a business process. In 2015 IEEE 17th Conference on Business Informatics (Vol. 2, pp. 49-54). IEEE.

Sharda, R., Delen, D. & Turban, E. (2016). Business intelligence, analytics, and data science: a managerial perspective. London: Pearson.

Sharma, R., Mithas, S. & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems, 23*(4), p. 43

Sheldon, Mary (1971). Investments and involvements as mechanisms producing commitment to the organization. *Administrative Science Quarterly, 16*, pp. 143-150.

Shmueli, G. & Koppius, O. (2010). What is Predictive about Partial Least Squares? In Sixth Symposium on Statistical Challenges in eCommerce Research (SCECR). [Online] https://www.galitshmueli.com/system/files/SCECR2010%20PLS%20NEW%20ShmueliKoppius.pdf [Accessed 3 March 2022].

Sholihin, M., Pike, R., Mangena, M. & Li, J. (2011). Goal-setting participation and goal commitment: Examining the mediating roles of procedural fairness and interpersonal trust in a UK financial services organization. *The British accounting review, 43*(2), pp. 135-146.

Sinuraya, C. (2011). The Effect of budget adequacy Intervening Variables and Organizational Commitment on the Relationship between Budgetary Participation and Manager Performance in Indonesia. *Journal of Indonesian Economy and Business, 1*(1), pp. 17-39.

Sivabalan, P., Booth, P., Malmi, T. & Brown, D. A. (2009). An exploratory study of operational reasons to budget. *Accounting and Finance, 49*(4), pp. 849-871.

Sivarajah, U., Kamal, M. M., Irani, Z. & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, pp. 263-286.

Someh, I., Shanks, G. & Davern, M. (2019). Reconceptualizing synergy to explain the value of business analytics systems. *Journal of Information Technology, 34*(4), pp. 371-391. https://doi.org/10.1177/0268396218816210

Sprinkle, G. B. (2003). Perspectives on experimental research in managerial accounting. *Accounting, Organizations and Society, 28*(2-3), pp. 287-318.

Stearns, J. J. P. (2016). The moderating effects of personality on the relationship between budget participation and motivation to reach the budget goal. *International Journal of Business, Accounting, and Finance, 10*(1), pp. 144-165.

Streukens, S. & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. *European Management Journal, 34*(6), pp. 618-632.

Subramani, M. (2004). How do suppliers benefit from information technology use in supply chain relationships? *MIS Quarterly, 28*(1), pp. 45-73.

Taipaleenmäki, J. (2017). Towards Agile Management Accounting: A Research Note on Accounting Agility. Turunkauppak kea, 175.

Taipaleenmäki, J. & Ikäheimo, S. (2013). On the convergence of management accounting and financial accounting–the role of information technology in accounting change. International *Journal of Accounting Information Systems, 14*(4), pp. 321-348.

Tanaka, M., Bloom, N., David, J. M. & Koga, M. (2020). Firm performance and macro forecast accuracy. *Journal of Monetary Economics, 114*, pp. 26-41.

Tang, J. J. & Karim, K. E. (2017). Big data in business analytics: implications for the audit profession. *The CPA journal, 87*(6), pp. 34-39.

Tokilov, D. U., Suputra, I. D. G. D. & Rasmini, N. K. (2019). Effect of budgetary participation in managerial performance with environmental uncertainty, leadership style, and budgetary adequacy as a moderating variable. *International Research Journal of Management, IT and Social Sciences, 6*(6), pp. 50-57.

Tribou, S. (2006). Evolution in business forecasting: Experts share their journey. *Journal of Business Forecasting, 25*(1), pp. 6-28.

Trusheim, D., and Rylee, C. (2011). Predictive modelling: Linking enrolment and budgeting. *Planning for Higher Education, 40*(1), pp. 12-17.

Tsui, J. S. L. (2001), "The impact of culture on the relationship between budgetary participation, management accounting systems, and managerial performance: an analysis of Chinese and western managers", *The International Journal of Accounting, Vol. 36* No. 2, pp. 125-46.

Van der Kolk, B., Van Veen-Dirks, P. M. G. & Bogt, H. J. T. (2019). The impact of management control on employee motivation and performance in the public sector. *European Accounting Review, 28*(5), pp. 901-928.

Van der Stede, W. A. (2000). The relationship between the consequences of budgetary controls: Slack creation and managerial short-term orientation. *Accounting, Organizations and Society, 25*(August), pp. 609-622.

Vanani, I. R. & Jalali, S. M. J. (2018). A comparative analysis of emerging scientific themes in business analytics. *International Journal of Business Information Systems*, *29*(2), pp. 183-206. https://www.inderscienceonline.com/doi/abs/10.1504/IJBIS.2018.094692

Viaene, S. & Van den Bunder, A. (2011). The secrets to managing business analytics projects. *MIT Sloan Management Review*, *53*(1), p. 65.

Waller, M. A. & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), pp. 77-84.

Warren Jr, J. D., Moffitt, K. C. & Byrnes, P. (2015). How big data will change accounting. *Accounting Horizons*, *29*(2), pp. 397-407.

Weber, J. & Schäffer, U. (2018). Digitalisation ante portas. *Controlling, 30* (1), pp. 5-11.

Welsh, D. T., Baer, M. D., Sessions, H. & Garud, N. (2020). Motivated to disengage the ethical consequences of goal commitment and moral disengagement in goal setting. *Journal of Organizational Behaviour, 41*(7), pp. 663-677.

Wentzel, K. (2002). The Influence of Fairness Perceptions and Goal Commitment on Managers Performance in a Budget Setting. *Behavioural Research in Accounting, 14*, pp. 247-271.

Williams, D. W. & Calabrese, T. D. (2016). The status of budget forecasting. *Journal of Public and Nonprofit Affairs, 2*(2), pp. 127-160.

Winklhofer, H. M. & Diamantopoulos, A. (2002). Managerial evaluation of sales forecasting effectiveness: A MIMIC modeling approach. *International journal of research in marketing*, *19*(2), pp. 151-166.

Wofford, J. C., Goodwin, V. L. & Premack, S. 1992. Meta-analysis of the antecedents of personal goal level and of the antecedents and consequences of goal commitment. *Journal of Management, 18*: pp. 595-615.

Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24*(1), pp. 1-32.

Wong-On-Wing, B., Guo, L. & Lui, G. (2010). Intrinsic and extrinsic motivation and participation in budgeting: Antecedents and consequences. *Behavioural Research in Accounting, 22*(2), pp. 133-153.

Wright, P. M. (1992). An examination of the relationship among monetary incentives goal level goal commitment and performance. *Journal of Management, 18*: pp. 677-693.

Xiao, M., Xiaoli, H. & Gaojin, L. (2010). Research on application of data mining technology in financial decision support system. Proceeding of the International IEEE Conference on Information Management, Innovation Management and Industrial Engineering (ICIII), Kunming, China November 381-384. 10.1109/ICIII.2

Yan, R. & Wang, K. Y. (2012). Franchisor–franchisee supply chain cooperation: Sharing of demand forecast information in high-tech industries. *Industrial Marketing Management, 41*(7), pp. 1164-1173.

Yeoh, W. & Popovič, A. (2016). Extending the understanding of critical success factors for

Yi, X., Liu, F., Liu, J. & Jin, H. (2014). Building a network highway for big data: architecture and challenges. *IEEE Network, 28*(4), pp. 5-13.

Yigitbasioglu, O. M. & Velcu, O. (2012). A review of dashboards in performance management: implications for design and research. *International Journal of Accounting Information Systems, 13* (1), pp. 41-59.

Young, S. M. (1985). Participative budgeting: the effects of risk aversion and asymmetric information on budgetary slack. *Journal of Accounting Research* (autumn), pp. 829-842.

Zainuddin, S. & Isa, C. R. (2011). The role of organizational fairness and motivation in the relationship between budget participation and managerial performance: A conceptual paper. *Australian Journal of Basic and Applied Sciences, 5*(12), pp. 641-648.

Zaiţ, A. & Bertea, P. S. P. E. (2011). Methods for testing discriminant validity. *Management & Marketing Journal, 9*(2), pp. 217-224.

Zhao, Y., Wang, F., Qin, X., Zhu, X., Wu, N. & Chen, X. (2020, March). Research on Enterprise’s Total Budgeting Management in the Era of Big Data. In IOP Conference Series: Materials Science and Engineering (Vol. 768, No. 5, p. 052028). IOP Publishing.

Cooper, R. & Kaplan, R. S. (1997). The promise–and peril–of integrated cost systems. *Harvard Business Review, 76* (4), pp. 109-119.

Davenport, T. (1998). Putting the enterprise into the enterprise system. *Harvard Business Review, 76*, pp. 121-131

Granlund, M. & Malmi, T. (2002). Moderate impact of ERPS on management accounting: a lag or permanent outcome? *Management Accounting Research, 13*, pp. 299-321

Rom, A. & Rohde, C. (2007). Management accounting and integrated information systems: a literature review. *International Journal of Accounting Information Systems, 8*, pp. 40-68.

Scapens, R. W. & Jazayeri, M. (2003). ERP systems and management accounting change: opportunities or impacts? A research note. *European Accounting Review, 12* (1), pp. 201-233

Chapman, C. S. & Kihn, L.-A. (2009). Information system integration, enabling control and performance. *Accounting, Organizations & Society, 34* (2), pp. 151-169.

Wagner, E. L., Moll, J. & Newell, S. (2011). Accounting logics, reconfiguration of ERP systems and the emergence of new accounting practices: a sociomaterial perspective. *Management Accounting Research, 22* (3), pp. 181-197.

Hunton, J. E., Lippincott, B. & Reck, J. L. (2003). Enterprise resource planning systems:

comparing firm performance of adopters and nonadopters. *International Journal of Accounting Information Systems, 4* (3), pp. 165-184.

Nicolaou, A. I. (2004). Firm performance effects in relation to the implementation and use of Enterprise resource planning systems. *Information Systems Journal*, *18* (2), pp. 79-105

Nicolaou, A. I. & Bhattacharya, S. (2006). Organizational performance effects of ERP systems usage: the impact of post-implementation changes. *International Journal of Accounting Information Systems, 7* (1), pp. 18-35.

Velcu, O. (2007). Exploring the effects of ERP systems on organizational performance: evidence from Finnish companies. *Industrial Management & Data Systems, 107* (9), pp. 1316-1334.

Quattrone, P. & Hopper, T. (2001). What does organizational change mean? Speculations on a taken for granted category. *Management Accounting Research, 12* (4), pp. 403-435

Caglio, A. (2003). Enterprise resource planning systems and accountants: towards hybridization? *European Accounting Review, 12*, pp. 123-153.

Appendix A: Consent Form for the Survey

Dear Respondent,

We would like to invite you to participate in this research study titled "**Effects of Business Analytics Capabilities on Budget Goal Commitment and Managerial Performance: The Mediating Roles of Forecast Accuracy and Budget Adequacy".** The study is approved by the Qatar University Institutional Review Board with the approval number QU-IRB 1660-E/22. If you have any questions related to the ethical compliance of the study, you may contact them at (QUIRB@qu.edu.qa).

The purpose of the study is to investigate if there is a relationship among business analytics capabilities, budget goal commitment, and managerial performance, in addition to whether the relationships are mediated by forecast accuracy and budget adequacy. This study expects to present insight about whether and how business analytics capabilities in budgeting processes affect commitment to budgeted goals, and, subsequently, performance of managers. It is expected that insights from the study can be used to improve the commitment to budgeted goals and the performance of managers in organizations, especially in the State of Qatar.

This survey should be completed by persons who are in managerial and supervisory positions. There are no associated risks or harms involved through participating in this survey. The survey should take about fifteen minutes of your time. The information collected will be kept strictly confidential and secure, where only the researchers have access to it. Your participation is completely voluntary and anonymous. If you would like to obtain the results of the study, you may provide your e-mail address at the end of the survey, however this is entirely optional.

You may withdraw from this study at any time.

If you have any questions, you may contact Mr. Rashid Murad (rm1403553@qu.edu.qa and 00974 5500 7729) or Prof. Habib Mahama (h.mahama@qu.edu.qa).

Kindly indicate that you have read, understood, and voluntarily agreed to participate in this survey. If you wish to participate, kindly select Yes below:

☐ Yes ☐ No

Thank you for your valuable time.

نموذج الموافقة على المشاركة في الاستبيان

عزيزي المشارك:

نود دعوتك للمشاركة في هذا البحث بعنوان "**أثر إمكانيات وقدرات تحليلات الأعمال على الالتزام بهدف الميزانية والأداء الاداري: دور دقة التنبؤ وكفاية الميزانية في العلاقة**". هذه البحث مصادق عليه من طرف لجنة المصادقة على البحوث بجامعة قطر تحت رقم (QU-IRB 1660-E/22) ، إذا كان لديك أي سؤال يتعلق بالالتزام بأخلاقيات الدراسة ، يمكنك التواصل معهم من خلال البريد الالكتروني: QUIRB@qu.edu.qa

الهدف من هذه الدراسة هو التحقق ما إذا كان هناك علاقة بين إمكانيات وقدرات تحليلات الأعمال والالتزام بهدف الميزانية والأداء الإداري و ما إذا كانت هذه العلاقة تتم من خلال متغيرات وسيطة مثل دقة التنبؤ وكفاية الميزانية. يتوقع أن تقدم هذه الدراسة رؤية حول كيفية تأثير قدرات تحليلات الأعمال في الموازنة على الالتزام بهدف الميزانية والأداء الإداري. يتوقع أن تسهم الرؤى المنبثقة عن هذه الدراسة في تحسين الالتزام بأهداف الميزانيات وأداء المدراء في المنشآت ، خاصة في دولة قطر.

هذا الاستبيان يجب أن يملئ بواسطة الأشخاص الذين يشغلون وظائف إدارية أو إشرافية. كما أنه لا يوجد أي مخاطر أو اضرار ترتبط بالمشاركة في هذا الاستبيان. هذا الاستبيان سوف يستغرق من وقتك ما معدله خمسة عشر دقيقة. سيتم التعامل مع المعلومات التي يتم جمعها بسرية تامة ، حيث أن الباحثين هم فقط المخولين بالاطلاع على هذه المعلومات. بالطبع فإن مشاركتك طوعية و مجهولة الهوية. إذا كنت ترغب بالحصول على نتائج هذه الدراسة ، يرجى كتابة بريدك الالكتروني في نهاية هذه الاستبيان ، و هذا بالطبع اختياري. كما يمكنك الانسحاب من هذه الدراسة في أي وقت.

إذا كان لديك أي أسئلة حول هذه الدراسة ، فلا تتردد في التواصل مع السيد / راشد محمد مراد من خلال البريد الالكتروني rm1403553@qu.edu.qa أو الاتصال على هاتف 00974 5500 7729 أو البروفيسور / حبيب مهامه من خلال البريد الالكتروني h.mahama@qu.edu.qa

يرجى الإشارة إلى أنك قرأت و فهمت ، و وافقت طواعية على المشاركة في هذا الاستبيان. إذا كنت ترغب في المشاركة ، يرجى اختيار (نعم) أدناه:

☐ نعم ☐ لا

شكرا لك على وقتك الثمين.

Appendix B: Questionnaire

Instruction

In this questionnaire, we are interested in the relationships among business analytics capabilities, budget commitment, and managerial performance, and whether these relationships are mediated through forecast accuracy and budget adequacy. Though you may feel that it is difficult to generalize, we would like you to answer the questions that follow as accurately as you can. Please answer the attached questions independently of anyone else whom you know may have received the questionnaire. For each of the questions, please tick the box on the scale that best corresponds your understanding. It is important that you complete all questions.

Part A: Personal and professional data

Please answer the following questions. (Note: Responses will be kept strictly confidential)

1. Please indicate which of the following industries best reflect your organization.
   a. Manufacturing ❑
   b. Oil and Gas ❑
   c. Construction ❑
   d. Financial Services ❑
   e. Wholesale, Retail, Distribution ❑
   f. Consultancy ❑
   g. Hospitality ❑
   h. Agriculture ❑
   i. Utilities ❑
   j. Other (Please specify)__________________

2. Please, indicate which of the following sectors best describes your organization:
   a. Governmental ❑
   b. Semi-Governmental ❑
   c. Private ❑

3. Approximately, how many full-time employees do you have in your organization? (Please indicate as appropriate)

Fewer than 100	100 - 250	251 - 500	501 - 750	751 - 1000	Over 1,000

4. Please indicate how many years this organization has been in existence:_______________

5. Please indicate how long you have been working for this organization:_______________

6. Please indicate how long you have been in your current position:____________________

7. Please indicate your job title:____

8. Please, indicate you gender: Female ❑ Male ❑

9. Please, indicate your age group (in years):

24 or less	25-29	30-34	35-39	40-49	50-59	60+

Part B: Business analytics capabilities

This part measures your organization's business analytics capabilities. Please answer the following questions on the scale from 1 to 7 (1 is very little and 7 is very much):

For each of the following questions, please <u>tick the box</u> on the scale that best corresponds your understanding.		**Very Little ___ Very Much**						
		1	**2**	**3**	**4**	**5**	**6**	**7**
1	The organization predicts and prepares for the future by proactively evaluating scenarios or potential tradeoffs							
2	Decision-making is based on rigorous analytic approaches (e.g., quantitative modelling, simulation)							
3	The organization manages data to enable the ability to share and aggregate data across departments or business units							
4	Business information and analytics differentiate us within the industry							
5	Improving our information and analytics capability is a top priority							

Part C: Forecast Accuracy

This part measures the extent of forecast accuracy that exists within planning and budgeting processes. Please choose the degree of mean absolute percentage error on the scale:

For each of the following questions, please <u>tick the box</u> on the scale that best corresponds your understanding.		0 - 5%	6 - 10%	11 - 15%	16 - 20%	> 20%
1	Mean absolute percentage error of short-term (1-3 months) sales/service forecasts					
2	Mean absolute percentage error of medium-term (4-6 months) sales/service forecasts					
3	Mean absolute percentage error of long-term (7-12 months) sales/service forecasts					

Part D: Budget Adequacy

This part measures the extent to which you find your budget adequate. Please answer the following questions on the scale from 1 to 7 (1 is strongly disagree and 7 is strongly agree):

For each of the following questions, please <u>tick the box</u> on the scale that best corresponds your understanding.		**Strongly Disagree**						**Strongly Agree**
		1	**2**	**3**	**4**	**5**	**6**	**7**
1	My budget allows me to perform what is expected of me							

2	What is expected of me is achievable under my budget							
3	I am pretty much confident that I can achieve what is expected of me under my budget							
4.	I find my budget to be adequate							

Part E: Budget Goal Commitment

This part measures the extent of your commitment to your organization's budget goal. Please answer the following questions on the scale from 1 to 7 (1 is strongly disagree and 7 is strongly agree):

For each of the following questions, please tick the box on the scale that best corresponds your understanding.		**Strongly Disagree**						**Strongly Agree**
		1	**2**	**3**	**4**	**5**	**6**	**7**
1	I think the budget goals for my responsibility area are good goals to strive for							
2	I am willing to put a great deal of effort into achieving the budget goals for my responsibility area							
3	I am strongly committed to achieving budget goals for my responsibility area							
4	I think it is important to attain the budget goals for my responsibility area							

Thank you for your participation in this study.

الارشادات

في هذا الاستبيان ، نحن مهتمون بالعلاقة بين المشاركة في الموازنة و الأداء الإداري. على الرغم من أنك قد تشعر أنه من

الصعب التعميم ، إلا أننا نود أن تجيب على الأسئلة بأكبر قدر ممكن من الدقة. يرجى الإجابة على الأسئلة المرفقة بشكل مستقل عن أي شخص آخر تعرفه ربما يكون قد تلقى الاستبيان . لكل سؤال من الأسئلة ، يرجى وضع علامة على الخانة التي قد تتوافق مع فهمك على أفضل وجه. من الضروري إكمال جميع الأسئلة.

الجزء الأول: البيانات الشخصية و المهنية

يرجى الاجابة على جميع الأسئلة التالية: (ملحوظة: سيتم التعامل مع هذه الاجابات بسرية تامة)

1. يرجى تحديد أي من الصناعات التالية يعبر من منشأتك بأفضل ما يمكن:
   - أ. التصنيع ❑
   - ب. النفط و الغاز ❑
   - ت. البناء ❑
   - ث. الخدمات المالية ❑
   - ج. البيع بالجملة أو التجزئة أو التوزيع ❑
   - ح. الاستشارات ❑
   - خ. الضيافة ❑
   - د. الزراعة ❑
   - ذ. الخدمات ❑
   - ر. أخرى (يرجى ذكرها) ______________

2. يرجى تحديد أي من القطاعات التالية يصف منشأتك بشكل جيد:
   - أ. القطاع الحكومي
   - ب. قطاع شبه حكومي
   - ت. القطاع الخاص

3. تقريبا ، كم عدد الموظفين الذين يعملون في منشأتك بدوام كامل (يرجى الاشارة إلى العدد الملائم).

أكثر من 1000	751 - 1000	501 - 750	251 - 500	100 - 250	أقل من 100

4. يرجى ذكر عدد سنوات عمر هذه المنظمة: ______________
5. يرجى ذكر المدة التي تعمل فيها في هذه المنشأة : ______________
6. يرجى ذكر المدة التي تشغل فيها وظيفتك الحالية: ______________
7. يرجى ذكر مسماك الوظيفي: ______________
8. يرجى ذكر الجنس: أنثى ❑ ذكر ❑
9. يرجى ذكر فئتك العمرية (بالسنوات):

+60	50-59	40-49	35-39	30-34	25-29	24 أو أقل

الجزء الثاني: إمكانيات / قدرات تحليلات الأعمال

هذا الجزء يقيس مدى إمكانيات / قدرات تحليلات الأعمال في المنظمة. من فضلك ، اختر على المقياس أدناه من 1 إلى 7 (1 قليل جدا - 7 كثير جدا).

في كل من الأسئلة التالية ، ضع علامة على المقياس الذي يتوافق مع فهمك على أفضل وجه.		منخفض جدا						مرتفع جدا
		1	2	3	4	5	6	7
1	تتنبأ المنظمة وتستعد للمستقبل من خلال التقييم الاستباقي للسيناريوهات أو المفاضلات / المقايضات المحتملة							
2	يعتمد اتخاذ القرار على مناهج تحليلية صارمة (مثل النمذجة الكمية والمحاكاة)							
3	تدير المؤسسة البيانات لتمكين القدرة على مشاركتها وتجميعها عبر الأقسام أو وحدات الأعمال							
4	المعلومات وتحليلات الأعمال تميزنا في القطاع التجاري الذي نعمل فيه							
5	يعد تحسين المعلومات والقدرات / الإمكانيات التحليلية أولوية قصوى							

الجزء الثالث: دقة التنبؤ

هذا الجزء يقيس مدى دقة التنبؤ الموجودة في عمليات التخطيط والموازنة. من فضلك ، اختر درجة متوسط نسبة الخطأ المطلق على المقياس.

في كل من الأسئلة التالية ، ضع علامة على المقياس الذي يتوافق مع فهمك على أفضل وجه.		0%-5%	6%-10%	11%-15%	16%-20%	>20%
1	متوسط نسبة الخطأ المطلق لتوقعات المبيعات / تقديم الخدمات على المدى القصير (1-3 أشهر)					
2	متوسط نسبة الخطأ المطلق لتوقعات المبيعات / تقديم الخدمات متوسطة المدى (4-6 أشهر)					

3	متوسط نسبة الخطأ المطلق لتوقعات المبيعات / تقديم الخدمات طويلة المدى (7-12 أشهر)					

الجزء الرابع: كفاية / ملاءمة الميزانية

هذا الجزء يقيس مدى كفاية الميزانية في المنظمة. من فضلك ، اختر على المقياس أدناه من 1 إلى 7 (1 قليل جدا - 7 كثير جدا).

في كل من الأسئلة التالية ، ضع علامة على المقياس الذي يتوافق مع فهمك على أفضل وجه.		منخفض جدا						مرتفع جدا
		1	2	3	4	5	6	7
1	الميزانية الخاصة بي تسمح لي بأداء ما هو متوقع مني							
2	ما هو متوقع مني يمكن تحقيقه في ظل الميزانيتية الخاصة بي							
3	أنا على ثقة تامة من أنني أستطيع تحقيق ما هو متوقع مني في ظل الميزانية الخاصة بي							
4	أجد الميزانية الخاصة بي كافية / ملائمة							

الجزء الخامس: الالتزام بهدف الميزانية

هذا الجزء يقيس مدى التزامك بأهداف الموازنة في المنظمة. من فضلك ، اختر على المقياس أدناه من 1 إلى 7 (1 قليل جدا - 7 كثير جدا).

في كل من الأسئلة التالية ، ضع علامة على المقياس الذي يتوافق مع فهمك على أفضل وجه.		منخفض جدا						مرتفع جدا
		1	2	3	4	5	6	7
1	أعتقد أن أهداف الميزانية في نطاق مسؤولياتي هي أهداف جيدة يجب السعي لتحقيقها							

2	أنا على استعداد لبذل قدر كبير من الجهد لتحقيق أهداف الميزانية في نطاق مسؤولياتي							
3	أنا ملتزم بشدة بتحقيق أهداف الميزانية في نطاق مسؤولياتي							
4	أعتقد أنه من المهم تحقيق أهداف الميزانية في نطاق مسؤولياتي							

الجزء السادس: الأداء الاداري

هذا الجزء يقيس أدائك كمدير(ة). من فضلك ، قيم(ي) نفسك من خلال ثمانية أبعاد بالإضافة إلى التقييم العام على مقياس من 1 إلى 7 (1 قليل جدا - 7 كثير جدا).

شكرا لك لمشاركتك في هذه الدراسة.