THE USE OF ANALYTICS IN DECISION-MAKING: THE ROLE OF INFORMATION PROCESSING CAPABILITY AND ANALYTICAL-BASED CULTURE

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DEDICATION

I dedicate this thesis work to my family, who have been a source of support and motivation throughout this process.

ABSTRACT

This study examines the role of data quality, organizational analytical structure and bigness of data in the quality of decision making. It investigates the mediating role of information processing capability in the association of data quality, organizational structure and bigness of data with decision quality. Furthermore, the moderating role of analytical-based culture in the relationship of information processing capability and decision quality is investigated. Data was collected from 54 industry professional within the field of analytics. Ordinal linear regression analysis was used to test the hypotheses. The results support that data quality and organizational analytical structure have a positive effect on decision quality. Additionally, the results suggest that information processing capability is a significant and positive predictor of decision quality. Findings from this study contribute to the literature by providing understanding on the structural, process and cultural view of the use of analytics within an organization.

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LIST OF ABBREVIATIONS

AC	Analytical-based Culture
BD	Bigness of Data
BI	Business Intelligence
DQ	Data Quality
IPC	Information Processing Capability
OAS	Organizational Analytical Structure
QD	Decision Quality

CHAPTER 1: INTRODUCTION

The act of decision making is one of the most important functions of a management team. This is so, as every organization depends on navigating proper decision-making to propel them forward in the ever-dynamic business environment (Papadakis, Lioukas, & Chambers, 1998). These types of decisions are often referred to as strategic; and according to Eisenhardt and Zbaracki (1992) strategic decisions are key actions that dictates the general direction of an organization. Additionally, strategic decision addresses complex and vague issues which consumes a large amount of organizational resources (Amason, 1996). Mintzberg, Raisinghani, and Theoret (1976) states that in order for strategic decisions to be successful; all underlying decisions and tasks must be performed effectively. For instance, the launch of a new smart phone requires the organization to determine tech specification, price range, manufacturing timeline, advertisement, etc. based on the target market.

Depending on the nature of the decision, the implementation of strategic decision-making process will differ from organization to organization as well as have a wide range of factors influencing it (Dean Jr & Sharfman, 1996). Based on the literature in strategic management, it can be deduced that effective communication (Dean Jr & Sharfman, 1996), organizational structure (Skivington & Daft, 1991), prior experiences (Kiesler & Sproull, 1982; Walsh, 1995), organizational culture (Kaplan, 2008; Ocasio, 1997) and top management team characteristics (Hambrick & Mason, 1984), are some of the factors that mostly influence the processes behind strategic decision-making. As earlier stated, the intricacies of implementation will vary between organizations but in order for the decision to be successful it will require effective implementation.

With the advancement in technology and availability of enormous volume of consumer data, a lot of organizations are increasingly looking into ways of utilizing this to their advantage and mitigating the uncertainty and ambiguity associated with strategic decisions. One of the effective tools to aid with such decision-making is Analytics (Barton & Court, 2012; Cao, Duan, & Li, 2015; Elgendy & Elragal, 2016). Analytics can be defined as the use of data to generate insightful outcomes that can be employed to inform decision-making in a timely manner (Agrawal, 2014). It is basically the process of converting data into measurable actions that allow for problem solving and business understanding using analytical techniques (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Liberatore, Pollack-Johnson, & Clain, 2017). Likewise, it provides a coherent cushion that helps companies make informed decisions, using data in correspondence with external environmental factors.

The field of analytics has grown exponentially over the past decade, and this has been mainly due to the availability of data in enormous volume, velocity, variety and veracity which has resulted in a big data revolution (G. George, Haas, & Pentland, 2014; Ghasemaghaei, Ebrahimi, & Hassanein, 2018; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). Using data to inform decision-making is increasingly becoming the norm in most industries; and some scholars even believe that the traditional intuitive-based approach towards management decision-making is being overwritten by the data-driven approach (Bose, 2009; Davenport, 2010; Keim et al., 2008; McAfee et al., 2012). The digital era, emergence of big data and advancement in analytical technology has contributed significantly to the birth of this modern phenomenon (McAfee et al., 2012). As a result, the use of analytics as a company-wide strategy to differentiate from competitors is becoming more popular within various industries around the world (Choi, Wallace, & Wang, 2018; LaValle et al., 2011; Tiwari, Wee, & Daryanto, 2018).

According to Hsinchun, Chiang, and Storey (2012), many organizations are beginning to seize the opportunities afforded by analytics to create competitive advantage within their industries. Furthermore, it is said that organizations that are data driven are more likely to substantially outperform their peers, hereby becoming leaders in the ever-changing landscape of the business environment (Hsinchun et al., 2012; LaValle et al., 2011; Liberatore et al., 2017; McAfee et al., 2012). This is due to long standing business strategic issues such as concept & product development, or customer segmentation being made with more accuracy using analytical methods (Agrawal, 2014). These methods can be used to perform and understand analysis that determine things such as, what happened? (Descriptive analysis), why it happened? (Diagnostic analysis), what could happen? (Predictive analysis) or how to make things happen? (Prescriptive analysis). Descriptive and Diagnostic analysis typically involves looking at data from the past to understand the business, Predictive analysis uses data to forecast some semblance of the future, while Prescriptive analysis uses some variation of current data along with optimization models to produce possible direction for organizations (Liberatore et al., 2017; Weiss, Indurkhya, Zhang, & Damerau, 2010).

For analytics to function as intended, it is without saying that an organization needs to implement the appropriate analytical tool(s) that fits their needs, as well as have the competency to utilize such tools (Ghasemaghaei, 2019b; Ghasemaghaei et al., 2018; Popovič, Hackney, Coelho, & Jaklič, 2012). This is referred to as organizational analytical structure, as it is the level of analytical competency and technological infrastructure within an organization (Popovič et al., 2012). Additionally, and as previously insinuated, data is what fuels analytical tools, therefore poor-quality data equals mediocre insights. Hence, it is paramount that the quality of data is of high standard which is defined as one that is suitable for use by end-users (R. Y. Wang & Strong, 1996). Lastly, bigness of data refers to the robustness of data (Ghasemaghaei et al., 2018). Having sufficient data that covers the scope of analysis is important in using analytics for decision making. Data quality, organizational analytical structure and bigness of data are addressed from a structural point of view in the literature.

The importance of an organization's ability to process information effectively is quite common within different disciplines (Bender, 1986; Cegielski, Jones-Farmer, Wu, & Hazen, 2012; Jarvenpaa, 1989; Srinivasan & Swink, 2018), most especially in strategic management (Dollinger, 1984). It is implied that the way an organization processes information has an impact on their effectiveness in strategic decision-making (Jansen, Curşeu, Vermeulen, Geurts, & Gibcus, 2013). According to Cao et al. (2015), information processing capability refers to the ability of an organization to effectively capture, implement, analyze data and use the insight gained to inform decision-making. Hence, information processing capability enables organizations to maximize the use of analytics to enhance the quality of decision-making. In contrast, the failure to effectively process information has the potential to have dire consequences for an organization. In the literature, information processing capability is analyzed through the theoretical lens of information processing theory to investigate its effect on organizations (Galbraith, 1974, 2008). Information processing theory states that if there is a fit between an organization's information processing needs and information processing capability, then they are in prime position to achieve optimal performance (Galbraith, 1974). Thus, the importance of information processing capability for an organization cannot be understated in this digital era of voluminous availability of data; as lack of it can lead organizations to use unnecessary data to inform their decision-making. This is addressed in the literature from an organizational process point of view.

The culture of an organization influences the way employees execute their tasks. Hence, according to Hofstede (1980), culture impacts the decision-making process of an organization. Even though a lot of organizations are implementing the use of analytics to guide decision-making, the anticipated benefits might not always be realized if the culture does not support it (Davenport, 2006). Analytical-based culture entails the use of rationale and data/information to always support the decision-making process, while a heuristic approach might be satisfied with experience and intuition to facilitate decision-making (McAfee et al., 2012; Popovič et al., 2012). Even when an organization projects being data-driven, if the culture isn't strong enough, some top management might be able to override or manipulate insights formulated by data to favour their views. Organizations may see different outcomes to decision quality depending on the strength of their organizational culture (Davenport, 2009).

Even though there is so much buzz about analytics, just about one fourth of organizations say their investments and implementation of analytical technology has been successful (Ghasemaghaei et al., 2018). This could be due to the fact that organizations are yet to figure out the necessary conditions for utilizing analytical technology appropriately (Ghasemaghaei, 2018; McAfee et al., 2012; Vidgen, Shaw, & Grant, 2017). While some studies show empirical evidence that supports the value of analytics to organizations (Brynjolfsson, Hitt, & Kim, 2011; Ghasemaghaei et al., 2018; McAfee et al., 2012; Popovič et al., 2012); others that are specific to the impact of analytics on organizational decision quality have been anecdotal in nature (Agarwal & Dhar, 2014; Mikalef, Pappas, Krogstie, & Giannakos, 2018; Wamba et al., 2017). This could be because there is still a resistance, lack of readiness or acceptance from organizations in mainly utilizing data to inform decision process. According to Liberatore et al. (2017), a lot of organizations are struggling to understand the necessary resources and capabilities needed to utilize analytics appropriately. Therefore, the core factors or conditions that lead to the organizational use of analytics and decision quality deserve close investigation. Hence, this study will add to the literature, as well as attempt to address the question of how the structural, process and cultural view of analytics impose a combined effect over decision-making and quality of decision making. Utilizing empirical approach, this study will investigate the mediating and moderating roles of information processing capability and analytical-based culture respectively on decision quality. The literature and empirical results will be used to understand the following:

1. Does information processing capability have a mediating effect on the impact of using analytics to improve the decision quality of an organization?
2. What is the role of an analytical-based culture on enhancing the decision quality of an organization?

This study examines the interaction of data quality, organizational analytical culture and bigness of data with information processing capability, which leads to data driven decision making and quality. Consistent with (Cao et al., 2015), the study argues that information processing capability can effectively complement the use of analytics in decision-making. To validate this view, the mediating role of information processing capability was tested in the relationship between data quality, organizational analytical structure and bigness of data with decision quality. Furthermore, this study examines the moderating role of analytical-based culture in the relationship of information processing capability and decision quality.

The next section of this paper will focus on literature review of key concepts, theoretical framework and development of hypothesis. Afterwards, the illustration of the study design and data analysis procedure will be described in details; which will be followed by, the presentation of results and discussion of the research findings and limitations.

CHAPTER 2: LITERATURE REVIEW

There are several important factors that influence decision-making within an organization. According to literature, these factors vary between organizations as well as within various industries. However, the most prevalent within the literature include the environment, experience, organizational structure etc. Organizational structure is mostly looked at from the perspective of formalization, and centralization (Fredrickson, 1986). Miller (1987) argues that there is a positive relationship between a formalized organization and rational decision-making but a negative relationship between a centralized organization and rational decision making. While according to Wally and Baum (1994), more formalized organizations make decisions at a slower pace, whereas organizations that are more centralized make decisions at a faster pace. Reliance on experience is based on knowledge of similar situations related to a specific task or environmental context (Prietula & Simon, 1989). This is a heuristic-based approach towards managerial decision-making, where top management make decisions based on the number of years of experience (Wally & Baum, 1994), and rely on judgement and gut feeling to support their decisions (Khatri & Ng, 2000). Even though intuitive-based approach is not supposed to be emotionally charged (Khatri & Ng, 2000), when decisions are made on gut feeling and turns out to be wrong, there is typically no justification to support the rationale behind why the decision was made (Amit & Schoemaker, 1993).

The digital era has ushered in new factors to managerial decision-making by focusing on data to create a powerful source of insight and competitive advantage (Davenport, 2009, 2012; McAfee et al., 2012). The amount of data being generated daily is astonishing, and hence its value continues to grow as it provides a more accurate profile of a consumer base (Barton & Court, 2012; McAfee et al., 2012). It is said that data has become the new business currency, and its continued growth will be key to strategic decision outcomes (Davenport, 2013). The digitalization of business processes has allowed data to evolve in type and volume, hereby influencing factors such as data quality, analytical structure, big data, information processing capability etc. that impacts the quality of an organizational decision-making with the use of analytics. The following sub-section will define this key factors and concepts:

2.1 Key Concepts

2.1.1 Analytics in Decision-making

Analytics has been mainly defined as the process of discovering, explaining and conveying important patterns in data (Davenport, 2013). The term analytics emerged roughly in the 1950's with the invention of tools that mainly identified patterns and trends from small internal data sources (Hsinchun et al., 2012). The rapid rise and use of social media and online platforms in the mid-2000s ushered a new era of data structure which is popularly known today as big data (Hsinchun et al., 2012). Big data can simply be defined as an extremely large set of data that cannot be processed using traditional methods (McAfee et al., 2012). With the arrival of big data, new technology started to emerge that had the ability to process these enormous volumes of data being generated on the internet. These technological advancements assisted organizations with capturing and analyzing large sets of data to gain valuable insights (Hsinchun et al., 2012). More recently, analytics is being paired with artificial intelligence and machine learning to provide customized user experiences. This is said to be the new wave in its evolution, and organizations will begin to seek new opportunities to leverage the predictive and prescriptive nature of analytics (Davenport, 2013; Hsinchun et al., 2012).

Furthermore, the use of analytics can provide strategic advantages; in that it allows organizations to better understand their business environment, predict trends, and manage risks and opportunities by leveraging the systematic rationale of analytics to inform their decision-making process (Davenport, 2013; Hsinchun et al., 2012; McAfee et al., 2012). For instance, companies began to discover the strategic advantages of collecting data and information about their customers/clients to provide more customizable offerings to consumers. This has especially led to the surge in data collection over the years, which has expanded to big data platforms that collect information in high volume, velocity etc.; involuntarily creating the buzz around big data and analytics in the current business landscape (G. George et al., 2014; Ghasemaghaei & Calic, 2019; McAfee et al., 2012). This new age of data collection has opened up portals of information hubs like social media, banking, applications, POS and other forms of data collection points that has increased the level of information each company can acquire about consumers (McAfee et al., 2012). The increased data pool has also led to an increase in required talent, tools and applications that can store, extract and transform this information into prolific insights. These changes in the business environment to become analytically driven has resulted in the emergence of sophisticated analytical business programs commonly referred to as business intelligence tools (Davenport, 2010; Luhn, 1958; Negash & Gray, 2008). This is not to be confused with the term analytics, as analytics is more of a parent term for computing insights from data, while business intelligence is a tool under the field of analytics.

The term business intelligence (BI) is defined as tools, techniques, and applications that can extract, transform, load and analyze data into actionable information to improve decision-making (Davenport, 2010; Eidizadeh, Salehzadeh, & Chitsaz Esfahani, 2017; Hsinchun et al., 2012; Richards, Yeoh, Chong, & Popovič, 2017; Y. Wang & Byrd, 2017). The crucial functionality of BI empowers decision-makers to make refined decisions on present situations, as well as future projections based on analysis of historical and current data (Davenport, 2012;

Liberatore et al., 2017; Lönnqvist & Pirttimäki, 2006). Furthermore, the use of BI tools to gain advantage varies across organizations and industries as illustrated by various studies. For instance, Chau and Xu (2012) addressed how BI can be used to analyze blog contents to identify critical information such as feedback and new ideas. A possible method to this would be using BI tools to extract insights from strings of text/information provided by customers. Additionally, Park, Huh, Oh, and Han (2012) argues that BI can be used to improve an organization's profitability by understanding and catering to consumer behaviours derived from consumer profile data. Such profiling paves the way for strategic segmentation that allows companies to effectively serve their customers based on potential group behaviours. Also, BI can be useful in mergers and acquisitions as it can assist with identifying patterns of sociocultural and political-economic issues to address post-acquisition concerns (Lau, Liao, Wong, & Chiu, 2012). Lastly, Abbasi, Albrecht, Vance, and Hansen (2012) argues that BI can help with detecting fraudulent activities by acting as a predictive model to notice patterns of historic logs associated with fraud. This can be instrumental to banks and other financial institutions that build their businesses on lending, credit and a host of other services that require proper risk management assessments; such modelling could potentially save them from defaults and high-risk borrowers.

The above discussion on BI shows it is an organizational resource that contributes to strategic advantage in many different business industries and environments. However, despite the numerous advantages that have been previously stated, the literature also emphasizes that in order to take full advantage of the benefits associated with BI, there are more elements to consider than just simply acquiring the technology (Ghasemaghaei et al., 2018). It is important that organizational resources are systematically bundled into matching competencies. For instance, an organization can be equipped with useful BI programs/tools such as SQL, Power BI etc., however, without skilled personnel, the organization would be unable to extract valuable insights from existing data using the aforementioned tools. This illustrates the importance of having valuable analytical competency that matches the analytical structure within an organization, as it can result in the effective use of BI as a whole (Rouhani, Ashrafi, Zare Ravasan, & Afshari, 2016). Also, IşıK, Jones, and Sidorova (2013) echoed similar sentiments – as their study suggests that the successful implementation of BI depends on organizational and technological fit. Organizations typically have an objective; therefore, it is imperative that the right technological tools and proper data that aligns with their goals are implemented for expected outcomes. Likewise, Peters, Wieder, Sutton, and Wakefield (2016) emphasizes the importance of infrastructure integration, how well data is processed and ease of self-serve reporting for high quality of BI output. In other words, integrating the appropriate combination of tools that optimally serves end users could result in advantageous BI findings, that could aid decision making. Others such as Popovič et al. (2012) mentions data integration and analytical capabilities as critical success factors for BI implementation; further stating that the factors will contribute immensely to the improvement of information quality for decision-making.

Although BI tools in general have the potential to identify insightful data patterns to enhance decision-making processes, in practice, the outcome derived from BI will be impacted by other factors involved such as data quality, organizational analytical structure, bigness of data, information processing capability, and analytical-based culture. In the following section, the characteristics of these factors and their potential impact will be discussed.

2.1.2 Data Quality

Data is the power source that propels BI tools. However, not just any form of data can become the powerhouse of BI, high quality data is the best form that fits the bill. Hence, Data quality can be defined as accurate data suitable for use by an end-user (Ghasemaghaei & Calic, 2019; R. Y. Wang & Strong, 1996). Over the past decades, various scholars have proposed different data quality dimensions (Cai & Zhu, 2015; Rieh & Danielson, 2007; Stvilia, Gasser, Twidale, & Smith, 2007; R. Y. Wang & Strong, 1996; Webb & Webb, 2004). One of the earliest accepted frameworks in this field is developed by Wang and Strong (R. Y. Wang & Strong, 1996). The framework developed argued that data quality is dependent on four main categories namely – Intrinsic, Contextual, Representational, and Accessibility. Intrinsic is defined by the correctness of data, in that data have quality in their own right. This includes accuracy, objectivity, believability and reputation. Contextual refers to the quality of data defined by context of the particular task at hand, such as the timeliness, completeness and relevancy of data. Representational data quality is defined by showing data in a clear and detailed manner such as consistent representation and ease of understanding. Lastly, accessibility refers to the ease in which data is obtained.

2.1.3 Organizational Analytical Structure

An organization's approach towards the use of analytics is defined by the level of their analytical competence and the tools used as these are important factors in reaping benefits associated with implementing analytics (Ghasemaghaei, 2019a; Popovič et al., 2012). Analytical organizational structure is the ability of an organization to deploy and combine data analytics resources for action-oriented analysis of data (Ghasemaghaei et al., 2018). The importance of analytical structure cannot be understated, as it contributes immensely to the appropriate use of analytics in organizational decision quality. It would be difficult to navigate the world of analytics and its benefits without the proper tools and competence to support it (Ghasemaghaei, 2020). Various scholars have conducted research on organizational structural competence from varying aspects regarding the use of analytics. Some such as Kiron, Prentice, and Ferguson (2014), argued that competence in big data analytics are categorized as organizational culture, advanced tools, and employee analytical skills. Similarly, Wamba et al. (2017) using IT capabilities as a model identified three dimensions namely management, infrastructure and personnel capabilities. Furthermore, Barton and Court (2012); Davenport (2012) pointed out very similar sentiments that – management, people and technology are dimensions that are very important in the big data environment. Additionally, they argued that management is important for improving decision processing models; technology for extracting, transforming, and loading varieties of data from various sources; and analytical skills to understand, develop and apply analytical models. Others defined analytical structure in four dimensions – Big data utilization, data quality, analytics capability and tools sophistication (Ghasemaghaei, 2019b).

2.1.4 Big Data

The characteristics of big data varies from scholar to scholar. Some such as Ghasemaghaei et al. (2018) have characterized big data by four V's namely: volume, veracity, velocity and variety. Others such as, McAfee et al. (2012); Russom (2011); Tsai, Lai, Chao, and Vasilakos (2015) characterize big data via three V's – volume, velocity and variety. Gandomi and Haider (2015) also defined big data via the three V's, but with additional dimensions such as veracity, variability, and value. All the dimensions of big data are defined below:

Volume – is defined as the enormity of data, which basically classifies the size of data. Big data is reported to reach astronomical levels in size, as it is reported that about 2.5 exabytes of data is generated each day. To put this in perspective, an exabyte equals 1000 petabytes; a petabyte is one quadrillion byte or the equivalent of 20 million filing cabinets worth of text. Also, the size of data is relative and varies across industries (Gandomi & Haider, 2015; Ghasemaghaei et al., 2018; McAfee et al., 2012; Russom, 2011; Tsai et al., 2015).

Variety – refers to the form in which data is presented. Data can be presented in structured, semi-structured, as well as unstructured form. Examples of various form of data include – structured: data in databases; semi-structured: extensible markup language (XML); and unstructured: text, images, video, audio etc. (Gandomi & Haider, 2015; Ghasemaghaei et al., 2018; McAfee et al., 2012).

Velocity – is defined as the rate of data creation, as well as the speed at which data is extracted, transformed and loaded. Data is being generated at an unparalleled level because of the rapid increase in digital devices which is driving the growing need for analytics-based tools (Gandomi & Haider, 2015; McAfee et al., 2012; Tsai et al., 2015).

Veracity – refers to the unreliability in some data source. As data comes from various sources including subjective views of human, hence, there is potential for data to be uncertain and imprecise (Gandomi & Haider, 2015).

Variability – defined as the disparity in the flow rate of data. Sometimes the velocity of data can be high or low depending on current situations (Gandomi & Haider, 2015).

Value – which was coined by Oracle, refers to relative low value substance of data when it is originally collected. However, the value of data can become high when it is mined and processed (Gandomi & Haider, 2015).

The above concludes the discussion on the structural viewpoint; emphasizing the importance and characteristics of factors such as data quality, organizational analytical structure and bigness of data, as well as their impact on the use of analytics within an organization. The following sections will focus on the process (information processing capability) and cultural (analytical-based culture) views respectively.

2.1.5 Information Processing Capability

Information processing capability is usually examined in the literature through the theoretical framework of information processing theory. The theory of information processing addresses three key concepts; information processing needs, information processing capability, and the fit between information processing needs and capability (Galbraith, 1974). Information processing needs refers to the possession of adequate data/information to complete a specific task. On the other hand, information processing capability refers to the ability of an organization to competently gather, interpret, and synthesize information to inform decision-making (Cao et al., 2015). In other words, it is not enough to have access to information; it is important to be able to process information in a manner that is advantageous and strategic to decision-making.

Lastly, the theory emphasises the need for a fit between information processing needs and information processing capability to gain maximum outcome. According to Mani, Barua, and Whinston (2010), when there is a purposeful design of the information processing capability of an organization to perfectly align with its information processing needs, the output of this relationship is usually one of efficient performance and advantage for the organization. To further expatiate, the value herein does not revolve around the volume of data an organization is able to capture, but how well they are able to effectively process, and utilize the data (Davenport, 2009; McAfee et al., 2012). If an organization can gather enormous amount of data but lack the ability or infrastructure to appropriately process it, then the data is essentially rendered useless to inform any organizational level decisions (Bughin, 2016; Elgendy & Elragal, 2016). Therefore, it is important that every organization collects data according to its needs as well as its processing capability.

2.1.6 Analytical-based Culture

A lot of studies have been conducted on organizational culture and most scholars broadly define it as a set of shared beliefs, values, norms, assumptions, and behavioural patterns that govern an organization (J. B. Barney, 1986; Deshpandé & Farley, 2004; Ravasi & Schultz, 2006; Schein, 1985). Since culture governs how an organization operates, it has been argued that it plays a very integral role in the decision-making processes adapted by the organization (Hofstede, 1980). Hence, the power of culture in an organization cannot be overstated as it influences how various processes are implemented and adopted. Also, J. B. Barney (1986) argues that an organizational culture can be a source of sustainable competitive advantage; in using the resource-based view (RBV) framework, the scholar determined that culture can be valuable, rare, non-substitutable and imitable. An organization’s analytical culture could have an important role in encouraging the use of analytical outcomes to improve decision quality within the organization.

2.1.7 Decision-making Quality with Analytics

The act of decision-making is something that is common to everyone. Every day we all make decisions consciously or unconsciously that leads to specific outcomes. According to Rachel Dinur (2011), decision-making can be defined as a process which involves the selection of an option from various alternatives to arrive at a specific outcome. Furthermore, Rachel Dinur (2011) states that decision-making has long been considered the essential building block in management. Even though decision making can be a complex task, some scholars have identified steps or processes to the act of making decisions. For example, Simon (1979) states that we recognize a problem, generate alternatives, evaluate these alternatives based on intended criteria, and select the best option that satisfies the criteria. Others such as, Wierenga, Van Bruggen, and Staelin (1999) identified three factors in which a decision situation can be characterized as follows: The problem to be solved, the decision environment, and the decision-maker.

According to Rachel Dinur (2011), there are two core types of decisions: structured and unstructured. Structured decisions are routine-like decisions which are mostly programmable and predictable – these types of decisions have little to no level of complexity associated with them and have certainty regarding the cause and effect. While unstructured decisions are complex in nature meaning they are non-programmable and not routine-like; hence there is unpredictability regarding cause and effect (Rachel Dinur, 2011). Scott and Bruce (1995) identified five types of decision-making namely: rational, intuitive, dependent, avoidant, and spontaneous. Rational decision-making is defined as making decisions with facts, and intuitive is based on making decisions on gut feelings (Scott & Bruce, 1995). Furthermore, Stanovich and West (2000) argued that most of human decisions are based on intuitive as these decisions are usually: fast, automatic, implied and emotional. Kahneman (2003) on the other hand argued that rational decision is slower, conscious, direct, and logical which is based on an analytical process.

In regards to analytical based decision-making decisions, outcomes are mainly based on facts rather than intuition (McAfee et al., 2012). With the enormous availability of data in this digital age, organizations are more inclined to make decisions based on potentially insightful data than ever before (Ghasemaghaei et al., 2018; Van Bruggen, Smidts, & Wierenga, 2001). Brynjolfsson et al. (2011) also echoed this sentiment by defining analytical based decision-making as a practice of making decisions based on insightful data rather than pure intuition. Scholars such as Brynjolfsson et al. (2011); Davenport (2010, 2013); McAfee et al. (2012) have argued that analytical based decisions are better than intuitive decisions; as it is more practical to measure, understand and manage for specific business situation. LaValle et al. (2011) also noted that organizations will benefit enormously from the overwhelming availability of data in this era to aid their decision-making process. But on the contrary, having access to vast amount of data can become an issue for organizations – as it might become difficult for them to make adequate sense of it (Hsinchun et al., 2012). This could become a challenge as data of this size could result in information overload, and lead to decision fatigue for an organization.

Furthermore, Davenport (2010); McAfee et al. (2012) argue that analytical decisions tend to produce better results as they usually reduce human bias and emotions in decision-making. Additionally, the knowledge gained from the results are way easier to reproduce, transfer and apply to similar business cases or strategic actions. Therefore, organizations can convert these analytical based outcomes into predictive and prescriptive models to ensure timely response to future needs within their business environment (Liberatore et al., 2017). It is also said that organizations that implement analytics in decision-making increase their productivity than those who do not (Brynjolfsson et al., 2011; Ghasemaghaei, Hassanein, & Turel, 2017). Hence, the appropriate use of analytics and an analytical based culture will not only encourage the use of data to inform decisions, but also produce higher quality decisions. Also, it can foster the use of Machine learning (supervised and unsupervised learning), modelling and other data science techniques to produce analytical insights and strategies that could be advantageous to an organization in the current data driven climate.

2.2 Theoretical Framework

According to the resource-based view (RBV) framework, an organization should utilize their strategic resources which are valuable, rare, inimitable and non-substitutable; to achieve competitive advantage (J. Barney, 1991). Similarly, Teece, Pisano, and Shuen (1997) states that organizations need to leverage specific assets to create value and competitive advantage. These strategic organizational resources are typically categorized into tangible, human capital and intangible (J. Barney, 1991; Grant, 1991). The scholar further emphasize that tangible resources are physical in nature e.g., infrastructure, tools, equipment's etc.; human capital resources classified as knowledge; and intangible resources are not physical such as values, intellectual property. J. Barney (1991) asserts that valuable resources may be utilized to execute new strategic initiative to enhance efficiency and effectiveness, as well as reduce cost and improve performance.

According to J. B. Barney (1996), in the context of Information technology (IT), organizations are utilizing technology in an attempt to develop a capability; which in this instance is using analytics to inform decision-making in order to gain competitive advantage. Adopting the RBV framework, some scholars have identified the implementation of Information Technology (IT) resources as a source of potential competitive advantage for organizations (Ghasemaghaei et al., 2018). Drawing from Grant's categorization of organizational resources and for the purpose of this study, tangible resources in the field of IT will comprise of computing infrastructure and analytical tools used to extract, transform and load large amount data in real time (Davenport, Barth, & Bean, 2012). Human capital is established as the competency of employees to use analytical tools to produce insights, hence generating value Popovič et al. (2012); while intangible resources will comprise of non-physical infrastructure such as analytical-based culture; as the implementation of a technology needs to align with the norms and beliefs of an organization (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). Even though analytical tools are freely available to any organization which in turn brings about competitive parity, the value is in the way it's implemented and utilized. That being said, for an organization to create sustainable competitive advantage, it needs to properly integrate its resources to produce organizational capabilities.

From a RBV perspective, any IT resources that enables an organization to share insightful information in a timely manner represents an invaluable organizational resource (Reed & DeFillippi, 1990). Information is a very valuable resource as it is able to have a multiplier effect wherein it can facilitate other competitive advantages in various areas of an organization (Lubit, 2001; Porter & Millar, 1985). It allows an organization to detect, mitigate and respond to opportunities and threats in a timely manner (Wade & Hulland, 2004). However, for organizations in extremely dynamic environments, the sustainability of insightful information as a competitive advantage may be a challenge in the near future (McGrath, 2013). Any organization that is not agile enough to detect and respond to changes may face difficulty in the landscape (McGrath, 2013). The reasoning behind this is that technological advancement such as artificial intelligence may reduce sustainability of current organizational capabilities; hereby compelling organizations to rely on seeking temporary competitive advantage based on the timeliness and completeness of information in a dynamic environment (McGrath, 2013).

From an information processing view, information is considered a very valuable organizational resource. Information processing capability is often understood through the lens of information processing theory which dictates that in order for an organization to obtain optimal performance, there must be a fit between their information processing needs and information processing capability (Galbraith, 1974, 2008). The external business environment is often very unpredictable because of constant changes within the environment facilitated by various factors (Duncan, 1972). Organizations usually have little to no influence on these factors, hence they require quality information to cope with environmental uncertainty and improve their decision making (Premkumar, Ramamurthy, & Saunders, 2005). According to Galbraith (1974); Greiner, Böhmann, and Krcmar (2007), uncertainty generally stems from lack of sufficient information required to perform a task. Therefore, organizations that face high degree of uncertainty are usually presumed to require more information to lower the degree of uncertainty (Zack, 2007).

Drawing from IPT, one of the ways organizations can mitigate uncertainty is by implementing structures and processes to enhance the use of information for decision-making (Galbraith, 1974; Tushman & Nadler, 1978). In the context of this research paper, the structural view (data quality, organizational analytical structure and bigness of data) facilitates the process view (information processing capability) in order to improve decision quality. By aligning the structural and process view, organizations will be able to assess their information needs with their information processing capability (Galbraith, 1974). The core benefit of this is that decision-makers will only be provided with information within the scope of their current task in order to make strategic decisions. On the contrary, if decision-makers are overwhelmed with unnecessary/excessive information, their ability to make quality decision is likely to diminish. As stated by Zack (2007), the structural mechanisms implemented are supposed to streamline the amount of information available to decision-makers, hereby using their information processing capability to process and interpret the information gathered for decision-making. Furthermore, some studies have demonstrated the impact of information processing theory and information processing capability on organizational performance. Studies such as, E. T. Wang (2003) showed that there is a relationship between information processing capability and organizational performance. Likewise, Premkumar et al. (2005) posit that information processing needs and information processing capability has a positive effect on performance.

2.3 Research Model & Hypothesis

The proposed research model is shown in **Figure 1** which shows the hypothesized relationships between data quality, organizational analytical structure, and bigness of data, Information processing capability, analytical-based culture and decision quality.

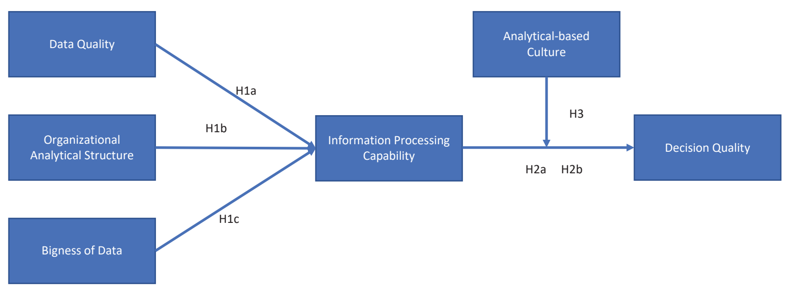

Figure 1. Research Model

2.3.1 Effect of Data Quality on Information Processing Capability

The quality of data is an extremely important factor for any BI tool, as the level of data quality will affect the decision-making process of an organization either positively or negatively (Friedman & Smith, 2011; Hazen, Boone, Ezell, & Jones-Farmer, 2014). In other words, the results extracted from data are based on how and what is collected; improper data quality and data management ultimately results in costly decisions (Chae, Yang, Olson, & Sheu, 2014;

Warth, Kaiser, & Kügler, 2011). It is said that the cost of using poor data exceeds billions of dollars per year and can range from 8% - 12% of an organization's total revenue (Ghasemaghaei & Calic, 2019; Hazen et al., 2014). Furthermore, lack of trust in the data due to data quality issues could impede the development and use of BI; this could result in costly decision making without proper data foresight (Eckerson, 2002).

In contrast, the benefits of good data quality cannot be understated: It leads to great use of BI tools and cohesive trust between data and decision making (Watson & Wixom, 2007). An organization would be able to reap the benefits of investing in talent, technology, and business intelligence, which in turn could provide a host of valuable information for business strategy and sustainable competitive advantage (Shankaranarayanan & Cai, 2006). Also, good data quality allows an organization to be able to receive an accurate depiction of Key Performance Indicators (KPIs), that could mitigate detrimental use of resources and costly operational outcomes.

There are numerous challenges associated with data quality; one of such challenges is Big Data. The emergence of big data in various predefined formats/structure, has resulted in organizations becoming wary of data quality issues sabotaging their strategic plans (Eckerson, 2002; Friedman & Smith, 2011; Ghasemaghaei & Calic, 2019). According to Cai and Zhu (2015), the form, speed, and velocity that such data presents itself could pose as a problem for data quality. Now more than ever, there are multiple sources of data in high volume that could be hard to process and ensure proper quality in its entirety (Ghasemaghaei et al., 2018). Much more data is collected these days, that while valuable, could also become a hindrance to accuracy. For instance, data retrieved from external sources could be filled with a lot of errors and issues that would require proper cleaning and processing before being used for analysis. This could pose as a bigger problem if the quantity of this data is in high volume and velocity resulting in a possible bottleneck to automated reporting, delay of results, and usefulness of the data. Cai and Zhu (2015) further echoes this point as they state that insightful data can become invalid within a short span if organizations are slow to process the data collected. This could lead to an organization making decisions based on outdated information. The vast amount of available data makes it extremely difficult for organizations to verify its quality within a reasonable amount of time (Eckerson, 2002).

Based on the literature, data quality plays a crucial role in the use of analytics and decision-making (Ghasemaghaei & Calic, 2019; McAfee et al., 2012; Popovič et al., 2012). Even though analytical technology such as business intelligence tools have the potential to identify insightful data patterns to drive decision-making processes, the outcome derived from this tool will still be impacted by the quality of the data used (Ghasemaghaei et al., 2018). Hence, in order for an organization to obtain valuable insights to improve its decision quality, the data used needs to be of high quality (Davenport, 2009; Ghasemaghaei, 2018). In the context of information processing capability, which consists of analyzing data and using insights gained from the data to inform decision-making (Cao et al., 2015). If the data utilized is of low quality, then the information processing procedure will be gravely impacted. For instance, if the data captured is incomplete, then the outcome from processing the data will be negatively impacted as decisions will be made based on incomplete data. Data quality and information processing capability work hand in hand, as the absence of high-quality data could influence how information collected is processed within an organization; lack of quality data could affect how data is analyzed and synthesized. Hereby impacting the processing of data to fully maximize the use of analytics to improve decision quality. Thus:

H1a: Data quality positively influences information processing capability

2.3.2 Effects of Organizational Analytical Structure on Information Processing Capability

It is paramount to note that acquiring advanced analytic technology such as BI tools does not guarantee adequate decision-making without the expertise of personnel who are skilled in the art of data analysis and mining which includes but not limited to – extraction, transformation, loading, reporting and visualization (Ghasemaghaei et al., 2018). Nevertheless, the acquisition of these advance analytical tools is essential for any data-driven organization. These tools equip an organization with the ability to understand past events, analyse current situations and predict future happenings (Barton & Court, 2012; Davenport, 2013; Ghasemaghaei, 2019b). A number of these tools exist in the analytical landscape to serve multiple purposes to the organization as well as the analysts that generate them. For instance, Dashboard tools allow an organization to receive multiple visuals showing vital numbers that could leverage decision making. KPIs depict important areas of measurement that allow an organization to continually compare its performance in multiple dimensions (Popovič et al., 2012). Other tools such as, interactive reports allow the end-user to be able to interact with the information provided via visuals, filters etc. The vast knowledge of insightful data that can be potentially generated from these advanced analytical tools, can greatly enhance the decision-making process of decision-makers within an organization (Ghasemaghaei, 2019b).

The competence and knowledgeability of employees – usually referred to as analysts, are also very vital in the use of analytics for decision-making. Analysts need to be able to understand and interpret data, analytically extract data using technical tools and produce visualizations & analytics that tell stories with data to aid decision-making and corporate strategizing (Ghasemaghaei, 2019b; Wong, 2012). Furthermore, If analysts are unable or are incompetent to perform the aforementioned duties, then they may not be able to acquire insightful data from the analytical tools to aid decision-makers in the quality of their decision-making process (Ghasemaghaei, 2019b).

Organizational analytical structure is an important component of the use of analytics, as it is the required tools, skills and knowledge needed to perform advanced analytical tasks (Popovič et al., 2012). These tasks include – data mining, report building/automation, database management, visualizations, query building etc. These tasks and tools can bridge the gap between collecting/storing data and analyzing data by processing it; this is what inaugurates the pathway for information processing capability. As earlier stated, organizations with appropriate analytical structure that suits their objectives are able to adequately and efficiently mine insightful data to support end-user utilization for decision-making (Davenport, 2010; Ghasemaghaei et al., 2018; Popovič et al., 2012). An adequate organizational analytical structure that fosters the availability and use of tools/talent, allows for information processing that strengthens decision making (Ghasemaghaei, 2019a). In contrast, lack of appropriate analytical structure within an organization will impact the processing of information as this leaves room for data not to be captured and analyzed adequately, hereby impacting decision-making. Hence, to improve information processing capability, organizations need to implement appropriate analytical structure that support their objectives. Thus:

H1b: Organizational analytical structure positively influences information processing capability

2.3.3 Big Data and Information Processing Capability

As stated by Bughin (2016), big data is a new and exciting phenomenon in the business environment. It has the potential to revolutionize the field of business management by changing well established ideas about the value of experience, the nature of expertise, and the practice of management (McAfee et al., 2012). The large scale of data being generated from various sources such as, social media, online transactions, search engine/queries, browser cache etc. are all a result of our individual digital footprints. It is said that data creation will continue to grow at an astronomical rate of 40 – 60% per year (Bughin, 2016). This explosion of data allows organizations to know more about their business, and therefore utilize that newfound knowledge to make improved decisions.

Additionally, big data enhances prediction-making and improve traditional management areas dominated solely by intuition rather than by data (McAfee et al., 2012). This is possible by utilizing big data in conjunction with analytical tools such as business intelligence, machine learning, artificial intelligence, deep learning, and other advanced analytical tools (Hsinchun et al., 2012). For instance, in machine learning, we can teach the application how to perform classifications via supervised learning or allow the application to learn on its own using unsupervised learning to extract patterns or insights from big data (Al-Jarrah, Yoo, Muhaidat, Karagiannidis, & Taha, 2015). Organizations are leveraging these big data solutions to inform their strategic planning and decision-making, hence sustaining their competitive advantage over their competitors (McAfee et al., 2012).

As earlier discussed, bigness of data refers to the robustness of data in terms of volume, velocity, veracity and variety (Ghasemaghaei et al., 2018; McAfee et al., 2012). The advantages of big data in this digital era cannot be overstated, as access to large datasets affords organizations the luxury to appropriately reduce the risk of bias and errors from limited amount of data; hereby enhancing the identification of insightful patterns and trends about their business environment (Bughin, 2016; Fernández et al., 2014). Furthermore, this availability of enormous data improves an organizations ability to optimize business processes, which has the potential to positively impact decision quality (Ghasemaghaei, 2019a). Big data provides information in large expansive amounts that allows an organization to be able to optimally analyze information, that will provide a full picture of operational units, rather than basing decisions on limited information. This influences information processing capability in a way that provides analytical advantage, by supplying sufficient volume of information to synthesize for decision making. Hence, if data is not robust enough within an organization to support the scope of its operation, then end-users cannot fully maximize the use of analytics to inform decision-making. Thus:

H1c: Bigness of data positively influences Information processing capability

2.3.4 Mediating effect of Information Processing Capability

As discussed earlier, the enormous availability of data in different types and structure in this digital era has led to the big data evolution (Ghasemaghaei & Calic, 2019); where data is the engine that fuels BI tools, hence improving decision-making. Likewise, we are made aware of the challenges of big data – the ever-increasing volume and various structures of data are expanding data quality issues for organizations (Bughin, 2016). Consequently, it is equally important that an organization has the capability to process data/information effectively (McAfee et al., 2012). The theory of information processing addresses this as it emphasizes the fit between information processing needs and information processing capabilities being compatible to effectively perform a task (Galbraith, 1974). This is truer in this age of big data, as a lack of suitability between information processing needs and capabilities can lead to the processing of unnecessary volumes of data. Popovič, Hackney, Tassabehji, and Castelli (2018) suggests that the use of BI tools will have an impact on the processing capability of an organization, and the insights derived used to make high quality decisions.

Information processing theory proposes that organizations design their structure in such a way that it fosters the processing of information in an effective manner to ultimately improve decision-making (Galbraith, 1974). Cao et al. (2015) defined information processing capability as the ability to capture, integrate, and analyze data/information, and use the insights gained to inform decision-making. Cao et al. (2015) and other scholars Barton and Court (2012); Davenport (2006); LaValle et al. (2011) posits that for an organization to develop adequate information processing capability with the use of analytics, it needs to foster a culture that is data-driven along with acquiring competent talent, technological resources, and developing sound business processes that support analytic activities. It would be virtually impossible for an organization to implement proper information processing without having the right range of talent to be able to foster, process, analyze and use the information that has been gathered; therefore, investing in the right combination of talent and resources is paramount. The use of information processing capability is vast in the literature, for instance Premkumar et al. (2005) demonstrated the importance of information processing capability in an interorganizational supply chain context. Making the point that the fit between information processing capability and information processing needs further aids the integration of the supply chain process more effectively within that organization. Supply chain is very logistically driven; hence, optimal processing of current information will serve as the lifeline to aid future supply driven decisions. Fan, Cheng, Li, and Lee (2016) also argued that an organization's ability to process supply chain risk information can improve operational performance. Similarly, E. T. Wang, Tai, and Grover (2013) showed that there is a strong relationship between an organization's information processing capability and the performance of supply chain companies. These studies substantiate the importance of information processing capability to an organization's overall performance; the better the organization's information processing capabilities, the better the decision-making that leads to optimal performance.

Decision quality can be defined as the accuracy of decisions (Ghasemaghaei, 2019b). There are multiple moving parts that influence organizational decision quality: components such as data quality, bigness of data etc., explained earlier can provide some correlation or association to decision quality (Eckerson, 2002; McAfee et al., 2012). However, the link between data quality, organizational analytical structure, and bigness of data to decision quality is not as direct as it may seem. Prior studies have indicated that acquiring analytical technology does not necessarily guarantee reaping the benefits (Ghasemaghaei, 2018), and it is important to develop appropriate information processing capability to support decision-making. According to Cao et al. (2015), information processing capability is positively related to decision-making effectiveness. Additionally, other studies have echoed similar sentiments (Chen & Zhang, 2014; Davenport, 2013; Huber, 1990; Kiron & Shockley, 2011; LaValle et al., 2011) where they generally posit that organizations that are proficient in extracting and transforming data can identify and use insights to enhance business process, hereby making improved decisions. For instance, Huber (1990) suggests that the use of advanced IT with processing capability leads to increased accessibility to information hereby improving decision making.

Since information processing capability is defined as the capturing, integration, and analysis of data to be utilized in decision-making (Cao et al., 2015), then the fit between the component of analytics as described in this study and information processing capability can be argued to have a positive impact on decision quality. In addition to assuming a direct link between these components of analytics and decision quality, it is plausible to suggest that the components of analytics will impact information processing capability, which in turn enhances decision-making. Hence, it can be deduced that information processing capability will provide a mediating association between data quality, organizational analytical structure and robustness of data that will optimally influence decision quality. Thus:

H2a: Information processing capability improves decision quality

H2b: Information processing capability will fully mediate the relationship between the use of analytics and decision quality

2.3.5 Moderating effect of Analytical-based Culture

Even though a lot of organizations are implementing the use of analytics to guide decision-making, the anticipated benefits are not always realized (Sharma & Yetton, 2003). This is usually because organizations neglect environmental factors such as organizational culture that may impede how the insightful data gathered from the analytical tool is shared and used (Popovič et al., 2012). In order to fully realize the benefits associated with the use of analytics, an organization needs to foster an environment that is driven by data and in which decisions are made based on rationality i.e. hard facts, and not intuition (Davenport, 2006; Popovič et al., 2012). Decisions should not be made by forcing data to match an intuition; for example, trying to force data to show that a specific division is profitable based on a hunch that that division has made a lot of sales in the last quarter. Instead, organizations should adapt a culture where the data tells the story rather than the other way around; this is more indicative of an analytical based culture. Top management must do more than just sign-off or encourage the use of analytics, they should set strong examples such as putting in place policies that facilitate the use of data to inform decisions (Davenport, 2006, 2010).

Brynjolfsson et al. (2011) and Davenport (2009) argued that in order to integrate data-driven decision-making culture, it is paramount that the appropriate infrastructures are set in place and employees are encouraged to consistently use it. Also, LaValle et al. (2011) argued that a culture that encourages information sharing is necessary for the successful adoption of data-driven decision-making. Top management decision-making style can also be a factor that might hinder the adoption of a data driven culture as according to Khatri and Ng (2000), some senior management individuals surveyed said their strategic decision-making process is mostly based on intuition. Likewise, Pretz (2008) found that managers who are older and well experienced tend to also make decisions based on their intuition. Furthermore, Popovič et al. (2012) argued that employees that are analytical minded are more likely to adopt and use the analytical tools as well as its outcomes more than employees that are conceptually minded. The scholars concluded by stating that implementing an analytical based culture can help with getting over the familiar trade-off between reach and richness i.e., a greater number of employees using analytical tools and more insightful data to inform decisions. Additionally, Davenport (2010, 2013) argued that for an organization to enjoy the full benefits of using analytics and its outcome of insightful data, it may need to transform the culture into one that is mainly data driven.

When a strong organizational culture that promotes the use of analytics in decision-making process exists and is understood, employees are more likely to adapt the use of data to inform their decisions (Davenport, 2010; De Alwis & Higgins, 2002; Frishammar, 2003). Also, when employees notice that top management makes decisions based on data, it will also encourage and bolster the culture of analytics in all levels of the organization, i.e., leading by example. This type of culture will enable employees to always consider the use of readily available insightful data before embarking on a decision-making process (De Alwis & Higgins, 2002; Nutt, 1993; Seddon, Calvert, & Yang, 2010). Also, the implementation of data driven strategies has the potential to be an important source of competitive advantage for an organization (Barton & Court, 2012). Lastly, it is imperative to note that in an analytical culture there is sometimes tension between innovation and entrepreneurial desires as there is always a need for rationality before pushing ahead, and as such this makes creating a purely based analytical culture challenging (Davenport, 2009, 2010). It is essential to find the right balance that allows both sides to coexist in the realm of analytical culture.

To create an environment where analytics is used to improve the decision quality of an organization, employees need to feel accustomed to using data to drive decision-making. One of the main factors that contributes to using data to drive decision-making is an organization's culture (Popovič et al., 2012). As discussed earlier, the culture of an organization drives what is acceptable or not, and also influences the decision-making process in an organization (Hofstede, 1980). An analytical-based culture is one in which data is used to inform decisions that are based on rationality and not mere intuition (Popovič et al., 2012). If the culture of an organization is not strong enough to support the utilization of insights generated from analyzing data to inform decisions, then the anticipated benefits of analytics may not always be realized. For example, decision-makers who prefer to rely on their intuition to make decisions may reject fact-based outputs generated from analytical tools in favour of their gut feeling (Davenport, 2009). Another variation of this example are decision-makers who initially refer to analytical fact-based outputs, but do not fully accept the results; rather, such decision-makers prefer to slice and dice information in multiple ways to achieve a much more favourable outcome than initially produced; this is still a gut feeling approach, and not indicative of an analytical-based culture. An organization with an analytical-based culture will simply allow data tell the story to inform their decision-making, and not the reverse. Therefore, analytical-based culture plays a role in the decision quality of an organization who employ the use of analytics. Hence,

H3: Analytical-based culture will moderate the relationship between information processing capability and decision quality, such that the effect will be stronger with a strong analytical culture

CHAPTER 3: METHODOLOGY

This study will use a quantitative approach to investigate the relationships in the proposed research model. Survey measures will be used to investigate the mediating role of information processing capability on the impact of analytics on the decision quality of an organization. Also, the moderating role of analytical-based culture on improving decision quality will be explored. The measures that will be used to evaluate the relationships between these variables will be previously validated questionnaire-based surveys.

3.1 Research Model Constructs

To develop and test the research model, a few constructs are identified and presented in **Table I**. All constructs were previously validated measurement items in the literature – DQ from R. Y. Wang and Strong (1996); OAS from Popovič et al. (2012); BD from Ghasemaghaei et al. (2018); IPC from Cao et al. (2015); AC from Popovič et al. (2012); and QD from Olson, Parayitam, and Bao (2007). The data of all variables of the postulated hypotheses are collected through a survey questionnaire using 7-point Likert scales with “1” indicating “strongly disagree” and “7” indicated “strongly agree”.

Table i. Measurement items

DQ	Data used for analysis is Reliable	1	2	3	4	5	6	7
	Data used for analysis is Appropriate	1	2	3	4	5	6	7
	Data used for analysis is Secure	1	2	3	4	5	6	7
	Data used for analysis is Timely	1	2	3	4	5	6	7
	Data used for analysis is Relevant	1	2	3	4	5	6	7
	Data used for analysis is Accurate	1	2	3	4	5	6	7
OAS	Paper reports are used extensively	1	2	3	4	5	6	7
	Interactive reports (Ad-hoc) are used extensively	1	2	3	4	5	6	7
	Online analytical processing (OLAP) are used extensively	1	2	3	4	5	6	7
	Analytical applications including trend analysis and what-if scenarios are used extensively	1	2	3	4	5	6	7
	Data mining techniques are used extensively	1	2	3	4	5	6	7
	Dashboards, including metrics, key performance indicators (KPI), alerts are used extensively	1	2	3	4	5	6	7
BD	High volumes of data	1	2	3	4	5	6	7
	Real time data	1	2	3	4	5	6	7
	Different types of data	1	2	3	4	5	6	7
IPC	Capturing data/information	1	2	3	4	5	6	7
	Integrating data/information	1	2	3	4	5	6	7
	Analyzing data/information	1	2	3	4	5	6	7
	Using insights gained from data/information	1	2	3	4	5	6	7
AC	The decision-making process is well established and known to its stakeholders	1	2	3	4	5	6	7
	It is our policy to incorporate available information within any decision-making process	1	2	3	4	5	6	7
	We consider the information provided regardless of the type of decision to be taken	1	2	3	4	5	6	7
QD	The effect the decision had was good	1	2	3	4	5	6	7
	Relative to what we expected, the results of the decisions have been good	1	2	3	4	5	6	7
	Overall, I believe that the decisions were good	1	2	3	4	5	6	7

3.2 Data Collection

To empirically test the hypotheses, data was collected from industry professionals in the field of analytics within Canada. A questionnaire survey was generated using seven-point Likert scale measurements for all constructs with “1” indicating “strongly disagree” and “7” indicating “strongly agree”. All constructs used in this study are validated constructs from existing studies. The survey was created and delivered electronically through Microsoft forms. Participants were contacted through LinkedIn, by searching for profiles with “analyst”, “data analyst”, “information analyst”, etc., in their job title. Messages were directly sent to profiles that suits the search criteria; messages included an introduction to the study, participation request and a web link to the survey questionnaire. There were no unique identifiers such as name or signature in the survey, as confidentiality and anonymity were emphasized to encourage accurate participation. Although demographic information such as age, gender, job title, firm size and industry characteristics were collected for analysis purposes. Of the 140 messages sent to various potential participants, 54 completed the survey questionnaire (i.e., a response rate of 38.6%)

3.3 Respondent’s Profile

Table II summarizes the respondent’s characteristics in terms of industry characteristics, company size, gender and age. The respondents are from a varying number of industries, for example, 24% from manufacturing sector, 22% from retail/wholesale/distribution, 11% from banking/finance/accounting, and 7% from healthcare/medical. Overall, the sample of respondents represents various industries. The reported age range of the respondents suggest that 33% of them are between the ages of 20 – 30, and 67% are between 31 – 50. Based on company size, most of the respondents are from a medium sized organization (67%). Additionally, most of the respondents are female (55%).

Table ii. Summary of respondent's characteristics

Industry	**%**
Manufacturing	24
Banking/Finance/Accounting	11
Healthcare/Medical	7
Transportation/Utilities	6
Information Services/Data Processing	2
Retail/Wholesale/Distribution	22
Education	4
Marketing/Advertising/Entertainment	22
Other	2

Company Size	**%**
Small	9
Medium	63
Large	28

Gender	**%**
Woman	56
Man	44
Non-binary	0

Age	**%**
20 - 30	33
31 - 50	67
51 +	0

CHAPTER 4: HYPOTHESIS TESTING AND RESULTS

The reliability of constructs is measured through Cronbach's alpha. To establish reliability, the Cronbach alpha of the constructs were tested against the value of 0.7 (D. George, 2011). In the initial model, not all reliability of the measures was satisfactory. The constructs OAS and BD had Cronbach alpha values of 0.39 and 0.64 respectively, which are lower than the suggested 0.7 value. OAS had a mixture of positively (OAS2 – OAS6) and negatively (OAS1) worded questions, which caused alpha to be low; so, the item OAS1 was removed which increased alpha to 0.71. Since BD had just 3 items (BD1, BD2 & BD3), the construct was tested against the value of 0.5, as it is difficult to get a high alpha value on a scale with less than 10 items (Tavakol & Dennick, 2011). Overall, all Cronbach Alpha's met the expected threshold (0.5 for BD, and 0.7 for the other constructs), showing internal consistency of items measuring each construct, hereby confirming construct reliability. After analyzing reliability, a correlation assessment was performed to assess relationship between variables. The correlation matrix shows some high correlation between variables such as, AC & QD (0.717), IPC & QD (0.586), OAS & QD (0.677). This result raised some concerns, as variables could affect each other via multicollinearity and consequently, affect the validity of the model. To mitigate those concerns, Variance Inflation Factor (VIF) was used to determine the presence of multicollinearity and to examine whether the variables are high correlated. The VIF values of all the constructs were below the threshold value of 3 (Petter, Straub, & Rai, 2007). Hence, our constructs do not have a multicollinearity issue.

Table iii. Construct Reliability

Reliability	
Variable	**Cronbach's Alpha**
Data Quality (DQ)	0.82
Organizational Analytical Structure (OAS)	0.71
Bigness of Data (BD)	0.64
Information Processing Capability (IPC)	0.73
Analytical-based Culture (AC)	0.75
Decision Quality (QD)	0.88

Table iv. Correlation Matrix

Construct Correlation Matrix					
	DQ	**OAS**	**BD**	**IPC**	**AC**
OAS	0.41				
BD	0.53	0.30			
IPC	0.5	0.58	0.47		
AC	0.39	0.59	0.36	0.49	
QD	0.55	0.68	0.42	0.59	0.72

Table v. Collinearity Assessment

Collinearity Assessment: Decision Quality (QD)	
Indicators	**VIF**
Data Quality (DQ)	1.617
Organizational Analytical Structure (OAS)	1.910
Bigness of Data (BD)	1.531
Information Processing Capability (IPC)	1.882
Analytical-based Culture (AC)	1.692

4.1 Hypothesis Testing

Ordinal logistic regression modelling was employed for hypothesis testing, with SPSS and R used as statistical applications for analysis. Testing began with checking for a direct relationship between DQ, BD and OAS with IPC. H1a suggests that data quality has a direct and positive effect on information processing capability, which is supported as results indicates that DQ is significantly and positively related with IPC ($B = 1.269$, $p < .05$). H1b suggests that organizational analytical structure has a positive and direct effect on information processing capability, which is also supported as it is significantly and positively related with information processing capability (B = 0.840, $p < .05$). For H1c, it assumes that bigness of data will have a positive and direct effect on information processing capability. This was also the case as BD is significantly related with IPC (B = 0.788, $p <= .05$); thus, this finding supports H1c, and it is accepted. Table VI below shows summary of findings.

Table vi. Regression analysis

Summary of Findings				
Variables	**Beta Coefficient**	**Pseudo R2**	**t-values**	**p-values**
Dependent variable: QD = DQ+OAS+BD				
DQ	1.269	0.464	2.654	0.008
OAS	0.840		2.465	0.014
BD	0.788		1.958	0.05

H2a suggests that information processing capability will have a positive and direct impact on decision quality. This is supported as results show that it is significantly and positively related to QD (B = 1.851, $p < .001$). H2b argues that information processing capability will fully mediate the relationship between data quality, organizational analytical structure & bigness of data and decision quality. Following Baron and Kenny (1986) method to test for mediation, three regression iterations were performed. First, the direct relationship between DQ, OAS, and BD with QD were tested. The results indicate that while DQ (B = 1.460, $p < .01$) and OAS (B = 1.801, $p < .001$) has a positive and direct relationship with QD, BD (B = 0.228, $p > .05$) did not. Second, as previously performed for H1a, H1b and H1c: all independent variables (DQ, OAS and BD) significantly predicted the mediator (IPC). Lastly, the independent variables and mediator were tested against the dependent variable. The results show that DQ (B = 1.396, $p < .001$), and OAS (B = 1.649, $p < .001$) both have positive and significant relationship with QD.

BD (B = 0.140, p > .05) and IPC (B = 0.467, p > .05) on the other hand, did not have a significant relationship with QD. Baron and Kenny's approach requires all conditions are met to support mediation; this was not met on all regression iterations as BD did not show significance. Table VII below shows summary of findings.

Table vii. Mediation Analysis Method 1a

Summary of Findings: Mediation Analysis				
Variables	**Beta Coefficient**	**Pseudo R2**	**t-values**	**p-values**
Iteration 1 – Dependent variable: QD = DQ+OAS+BD				
DQ	1.460	0.559	2.912	0.004
OAS	1.801		4.497	0.000
BD	0.228		0.556	0.578
Iteration 2 – Dependent variable: IPC = DQ+OAS+BD				
DQ	1.269	0.464	2.654	0.008
OAS	0.840		2.465	0.014
BD	0.788		1.958	0.05
Iteration 3 – Dependent variable: QD = DQ+OAS+BD+IPC				
DQ	1.396	0.567	2.736	0.006
OAS	1.649		3.838	0.000
BD	0.140		0.329	0.742
IPC	0.467		0.966	0.334

The presence of BD within the regression models produced inconclusive results that affects the hypothesis. A decision was made to attempt the regression iterations without BD present. The findings indicate there is a positive and direct relationship between the independent: DQ (B = 1.550, p < .01) & OAS (B = 1.807, p < .001) and dependent variables: QD. Also, DQ (B = 1.631, p < .001) and OAS (B = .936, p < .01) significantly predicts the mediator IPC. Lastly, DQ (B = 1.438, p < .01), OAS (B = 1.643, p < .001) and IPC (B = .511, p < .05) are all significantly associated to QD. Since DQ, OAS and IPC are significantly related to QD in the third regression iteration, then we can surmise that IPC accounts for some of the relationship between DQ and OAS with QD. Also, that there is some direct relationship between the independent (DQ and OAS) and dependent (QD) variables. Ultimately, without BD present in the model, it can be said that IPC might explain some mediation effect between the variables. Table VIII below shows summary of findings.

Table viii. Mediation Analysis Method 1b

Summary of Findings: Mediation Analysis				
Variables	**Beta Coefficient**	**Pseudo R2**	**t-values**	**p-values**
Iteration 1 – Dependent variable: QD = DQ+OAS				
DQ	1.550	0.556	3.354	0.001
OAS	1.807		4.52	0.000
Iteration 2 – Dependent variable: IPC = DQ+OAS				
DQ	1.631	0.421	3.66	0.000
OAS	0.936		2.743	0.006
Iteration 3 – Dependent variable QD = DQ+OAS+IPC				
DQ	1.438	0.565	2.978	0.003
OAS	1.643		3.829	0.000
IPC	0.511		1.088	0.027

A second approach was taken to test for mediation, using R. This approach involved the use of discretization to convert the mean of IPC, into integer form to depict high or low mediation (Liu, Hussain, Tan, & Dash, 2002). Initially, high vs. low mediation was separated with an average split of 3.5 to the 7-point Likert scale, but it was discovered that the distribution was highly skewed towards high values; therefore, the mean of the IPC distribution was used instead (5.8). High mediation was depicted with the value of 1 while low mediation in comparison was flagged as 0. The value for high IPC mediation was used as an interaction variable to each independent variable within a linear regression model. Two linear regression model iterations were performed. In the first case, the model showed only significance in the interaction between high mediation and OAS ($p < 0.01$). However, due to the inconclusive results that had been initially present with BD inside the model, a decision was made to attempt another iteration of the model without BD present. This second iteration still showed significance in the interaction between OAS and high IPC mediation ($p < 0.05$), however, DQ started to show significance in this 2nd iteration ($p < 0.05$), without BD present.

Overall, IPC seems to provide some mediation with OAS and DQ in relation to decision quality within the model. In contrast, BD produced fundamentally inconclusive results, as it seems to affect the significance of DQ within the linear regression model. Table IX below shows summary of findings.

Table ix. Mediation Analysis Method 2

Summary of Findings			
Variables	**Estimate**	**t-value**	**p-value**
QD = DQ+OAS+BD+IPC+(DQ x IPC)+(OAS x IPC)+(BD x IPC)			
DQ	0.38737	1.53	0.13279
OAS	0.01152	0.062	0.95066
BD	0.32856	1.371	0.17702
IPC	0.24308	0.14	0.88916
DQ x IPC	-0.17803	-0.593	0.55615
OAS x IPC	0.68873	2.76	0.00827
BD x IPC	-0.39516	-1.44	0.15662
QD = DQ+OAS+IPC+(DQ x IPC)+(OAS x IPC)			
DQ	0.62769	3.432	0.00124
OAS	0.05917	0.325	0.74658
IPC	-0.47358	-0.298	0.76673
DQ x IPC	-0.43208	-1.781	0.08118
OAS x IPC	0.63593	2.573	0.01324

H3 assumes that analytical-based culture moderates the path between information processing capability and decision quality. To test this hypothesis, Hayes (2017) process model 14 in SPSS was used to conduct the analysis. QD was entered as the dependent variable, IPC as mediator variable, AC as moderator variable, DQ as independent variable, and OAS & BD as covariates. Confidence interval set at 95 percent, and number of bootstrap samples set at 5000. The first regression output from the model shows the regression of IPC on DQ, OAS and BD. DQ ($p < .05$) and OAS ($p < .05$) are statistically significant as well as positive predictor of IPC, while BD (p > .05) was not significant. The second regression output shows the regression of QD on DQ, OAS, BD, IPC, AC, and the interaction between IPC & AC. The results show that only DQ (p < .05) and AC (p < .001) are positive and significant predictors of QD. OAS (p > .05), BD (p > .05), IPC (p > .05), interaction between IPC & AC (p > .05), were not. Table X below shows summary of findings.

Table x. Moderation Analysis Method 1

Summary of Findings: Moderation Analysis

Variables	Beta Coefficient	t-values	p-values	LLCI	ULCI
Dependent variable: IPC = DQ+OAS+BD					
DQ	0.2935	2.0322	0.0475	0.0034	0.5836
OAS	0.3001	2.1861	0.0335	0.0244	0.5758
BD	0.2121	1.6692	0.1013	-0.0431	0.4673
Dependent variable: QD = DQ+IPC+AC+(IPC x AC)+OAS+BD					
DQ	0.2533	2.1252	0.0389	0.0135	0.4932
IPC	0.1869	1.6224	0.1114	-0.0449	0.4187
AC	0.4383	4.2133	0.0001	0.229	0.6476
IPC x AC	0.0528	0.4588	0.6485	-0.1787	0.2843
OAS	0.184	1.5122	0.1372	-0.0608	0.4289
BD	0.0054	0.0504	0.96	-0.2117	0.2226

To check for moderated mediation in the model, the index of moderated mediation is examined. The index, which is the coefficient value (.0155) is tested for significance to determine whether there is evidence of moderated mediation. The test is performed by using the bootstrap confidence intervals that are derived from the model. If zero (0) which is the null hypothesis falls outside of the lower and upper band of the confidence interval, then it can be determined that the coefficient value is statistically significant. From our results, 0 falls within the lower (-.0832) and upper (.0888) band of the confidence interval, so it can be derived from the results that there is no evidence of a statistically significant moderated mediation effect. Hence, H3 is not supported.

Table xi. Index of Moderated Mediation

	Index of moderated mediation			
	Index	**BootSE**	**BootLLCI**	**BootULCI**
AC	0.0155	0.0402	-0.0832	0.0888

Another Moderation approach using R was performed (Cohen, 2008), with Analytical-based Culture (AC) as the moderator. This approach involved the use of AC as an interaction variable to each independent variable within the model. Also, QD remained the dependent variable, with the rest of the variables serving as independent variables within the linear regression model. The first iteration of the linear model with the moderator interaction variable present showed no significance to any of the independent variables ($p > 0.05$); only IPC showed significance on its own ($p < 0.05$). Hence, no moderator effect was present within this 1st model iteration, as we are looking for a significance in the interaction of AC to the independent variables. Afterwards, a second iteration of the linear model was attempted without BD present, due to the insignificance it has shown in previous models. In this iteration, the moderator showed some significance in its interaction with DQ within the model ($p < 0.05$), while IPC continued to show significance on its own as it did in the previous iteration ($p < 0.05$). Despite these findings, the same conclusion can be stipulated here: no moderation effect is present in the model. Table XII below shows summary of findings.

Table xii. Moderation Analysis Method 2

Summary of Findings

Variables	Estimate	t-value	p-value
QD = DQ+OAS+BD+IPC+(DQ x AC)+(OAS x AC)+(BD x AC)+(IPC x AC)			
DQ	-2.30452	-1.7	0.0961
OAS	0.33442	0.291	0.7723
BD	-0.45801	-0.549	0.5857
IPC	3.0133	2.093	0.0421
AC	0.42995	0.669	0.5069
DQ x AC	0.47091	1.901	0.0639
OAS x AC	-0.0216	-0.103	0.9184
BD x AC	0.08134	0.556	0.5813
IPC x AC	-0.51931	-1.973	0.0548
QD = DQ+OAS+IPC+(DQ x AC)+(OAS x AC)+(IPC x AC)			
DQ	-2.47062	-1.904	0.0632
OAS	0.13068	0.123	0.9029
IPC	2.8772	2.095	0.0417
AC	0.41336	0.696	0.4898
DQ x AC	0.49937	2.1	0.0412
OAS x AC	0.01492	0.077	0.9393
IPC x AC	-0.49459	-1.964	0.0556

Table xiii. Summary of Hypothesis Testing

Summary Results of Hypothesis Testing

	Hypothesized Path	Beta Coefficient	R2	p-values	No. of Observation	Hypothesis Test
H1a	DQ -> IPC	1.269	0.464	0.008	54	Supported
H1b	OAS -> IPC	0.840	0.464	0.014	54	Supported
H1c	BD -> IPC	0.788	0.464	0.050	54	Supported
H2a	IPC -> QD	1.851	0.304	0.000	54	Supported
H2b	IPC mediates the proposed path				54	Rejected
H3	AC moderates the proposed path				54	Rejected

CHAPTER 5: DISCUSSIONS AND CONCLUSION

This study examines the impact of information processing capability and analytical-based culture on decision quality through data quality, organizational analytical structure, and bigness of data. Analyzing these components together within a model or otherwise, allows us to better understand their varying impacts to decision quality. Different approaches and methodologies were performed to understand the sample in multiple ways, with the conclusion ultimately reaching similar results. The findings suggest that data quality, organizational analytical structure and bigness of data are significantly and positively related to information processing capability. This means that companies with high level of data quality and analytical structure, as well as robust access to data are in a better position to appropriately capture, integrate and analyze data, as well as utilize insights gained from the process to inform their decision-making. Furthermore, the results of the findings derived from this study shows that information processing capability is significantly and positively related to decision quality. This indicates that an organization with the ability to process information adequately will be in a better position to make accurate and timely decisions. Also, the results suggest that data quality and organizational analytical structure are positively related with decision quality and the indirect effect through information processing capability is also significant. This means that information processing capability might explain some mediation between the variables. However, when bigness of data is included in the model, the findings derived from the study does not support the postulation that information processing capability will fully mediate the relationship between the independent variables and decision quality as hypothetically aforementioned. Hence, the hypothesis was rejected. Similarly, the results do not support the notion that an analytical-based culture moderates the relationship between information processing capability and decision quality. Although analytical-based culture is positively related with decision quality, it is not moderating the relationship of information processing capability and decision quality. Based on this finding, it can be suggested that there might not be enough data points due to the small sample size to capture a relationship or an effect between the variables.

This study contributes to literature by highlighting the importance of analytics in this digital era for organizations. The findings help to develop an understanding of the components through which analytics improves decision quality. Although there have been prior studies that show the importance of various aspects of analytics to organizational performance and decision-making (Brynjolfsson et al., 2011; Ghasemaghaei et al., 2018; McAfee et al., 2012; Popovič et al., 2012), there have been little empirical evidence to validate the combined effect of components discussed in this study. This study helps to contribute more knowledge by developing theoretical understanding through applicable theories and providing some empirical evidence. By theorizing the association between analytics and decision quality, the study explores the correlations between different factors that impacts the use of analytics to improve decision quality.

The study also adds evidential explications to the buzz surrounding the use of analytics and data to inform decision-making. It shows how multiple components of quality decision making can be explained by certain components such as proper analytical structure. Various industries and organizations have profited from the valuable insights and strategies that analytics provides. Evidence from the study suggest that proper analytical structure – tools, implementation, integration, etc. will help organizations reap advantages of analytics to make discerning decisions and improve as a whole.

Another implication for organizations is analytical culture in relation to how analytics is perceived within the organization. The importance of having a culture where the results from analytics are taken as the gold standard is also cohesive to quality decision making. Advocating a culture where data is allowed to tell the story rather than the reverse correlates with how decision are made. Even though the study did not find a moderating effect of analytical culture, it still showed significance in correlation to decision quality. Hence, an organization's analytical culture still plays a contributing role in its superior decision making. Therefore, a data driven organization needs to focus on building or developing analytical culture to improve decision quality.

The study has some limitations. First, the sample size of the study is 54, which can be considered as too small to identify significant relationships from the survey data. Second, the Cronbach Alpha threshold used for the variable BD (0.64) was 0.5 because of the number of questions (3). Even at that, the threshold is still really low, thus rendering the measurement questionable. Third, there is limited accessibility to more data due to time constraint as this is a thesis-based research. Lastly, the study is limited to industry professionals within Canada. Despite these limitations, there is room for further future research. First, a more in-depth exploration to understand other factors that influence the use of analytics to improve decision quality. Second, a more expanded study of the research since the advancement of the use of analytics will vary from region to region depending on their exposure to the technology. In other words, time should also be considered: as more changes and technological advancements occur in the realm of analytics and data science, more factors/components to quality decision making will become present, and will add more footing to future research. Third, understanding how the use of analytics varies depending on the size of an organization, as it is not one size fits all.

Overall, there is still more to explore with research pertaining to the organizational use of analytics, as there are factors beyond the limitations stated in this paper to observe; nonetheless, this is still an interesting realm of study for understanding the use of analytics in decision making as a whole.

CHAPTER 6: REFLECTION FOR FUTURE RESEARCH

Reflecting on the research study, there are a few areas that would require improvements for future research prospect. This reflection will discuss the shortcomings of the research designs and results, and will aim to provide some realistic plans to address aspects of those limitations.

One of the biggest limitations of the paper was the sample size. The inferences that can be produced from a small sample size, corners a research study into more limited views than can be accessed by an adequate sample size. An example of this was issues identifying significant relationships from data points. Determining factors such as mediation and moderation effects proved difficult to conclude, as the sample size might have limited the relationship inferences between variables; perhaps a more robust sample size might have allowed for more precise statistical insights from the data.

For future research it is paramount to have a suitable sample size. A possible remedy for sample size limitations is to determine the sufficient sample size that might be representative of the research before analysis begins. It could prove useful to continue to gather the data points until the appropriate sample size needed for the research is reached. This could also help to enhance the accuracy and reliability of results.

Another limitation of the research is the survey administration. The data was collected based on individual responses, and not on an organizational level. The problem with this is that the study attempts to understand the use of analytics on an organizational level, and this in itself might restrict the research. In order to address this, a more suitable approach might be to conduct a case study research across multiple organizations and sample employees across teams/departments to analyze from an organizational perspective.

Another component that could be improved for future research is the research design. The study uses variables that might be too abstract or generic for analysis. For example, the decision quality variable could be interpreted in multiple ways and might be subjective depending on the context. This could be improved by refining the variables to be more precise or specific by conducting a qualitative research for a more profound investigation on the subject.

The discussion on the cultural aspect within the study is lean and could be further elaborated upon. Future research can further expand on the cultural aspect of the research. Organization culture is a robust topic that could differ across organizations, perhaps expanding on different levels or variations of organizational culture and its impact on the use of analytics could improve future research.

The statistical findings did not support the main research question, which could be as a result of the small sample size. Future research can further investigate the research questions with an adequate sample size to either substantiate or refute the findings. Additionally, a different research design such as case study can be used to address the research question.

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