

**The Impact of big data analytics on strategic decision-making quality in
senior leadership: the moderating role of organisational culture.**

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ABSTRACT

The study investigates how Big Data Analytics (BDA) capabilities influence the quality of strategic decision-making among senior leaders and whether organisational culture (OC) moderates this relationship. Drawing on the Dynamic Capabilities View (DCV) and Knowledge-Based View (KBV), the research conceptualises BDA as a strategic capability that enhances sensing, interpretation, and transformation of information into enhanced strategic decision-making. The study employed a quantitative approach using surveys data from 109 senior leaders (including executives). The relationship between Big Data Analysis capabilities, Decision-Making Quality and Organisational Culture was examined. The results confirmed that relationship between BDA capability and DMQ is a strong, positive and significant one, suggesting that BDA capabilities improve DMQ by enhancing efficiency, reliability and coherence of strategic decisions. However, moderation analysis reveal that organisational culture plays a significant role in conditioning the BDA and DMQ link. Data Driven, Adaptive and Collaborative Cultures strengthens the culture effect. Conversely Hierarchical and Control based cultures weaken the link. The study findings demonstrate that additional value is unlocked from technologies that drive data analytics when they are embedded within a supportive cultural context. Thus, the study extend existing theory by positioning organisational culture a substantiating condition in the BDA-DMQ relationship and provides practical guidance to leaders in organisations.

KEYWORDS

Big Data Analytics; Decision-Making Quality; Organisational Culture; Senior Leadership; Decision Intelligence

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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List of Abbreviations

- AI – Artificial Intelligence
- BDA – Big Data Analytics
- BDAC – Big Data Analytics Capability
- CV – Coefficient of Variation
- CVF – Competing Values Framework
- DCV– Dynamic Capabilities View
- DDC – Data-Driven Culture
- DMQ – Decision-Making Quality
- EFA – Exploratory Factor Analysis
- IPT – Information Processing Theory
- IQR – Interquartile Range
- KMO – Kaiser-Mayer-Olkin index
- K-S – Kolmogorov-Smirnov
- N –Sample Size
- OC – Organisational Culture
- OD –Organisational Development
- POPIA – Protection of Personal Information Act (South Africa)
- Q-Q – Quantile-Quantile Plot
- SD – Standard Deviation
- SPSS – Statistical Package for the Social Sciences
- S-W – Shapiro-Wilk
- VIF – Variance Inflation Factor
- α – Cronbach’s alpha
- λ – Factor loading

CHAPTER 1

INTRODUCTION

This chapter defines the context and background of the study and explains its relevance. It positions the project from both a theoretical and business perspective. Furthermore, the foundation, rationale and objectives of the study are outlined—and positioned within the broader Big Data Analytics (BDA), Decision-Making Quality (DMQ) and Organisational Culture (OC) discourse. The chapter concludes by outlining the research scope and subsequent chapters.

1.1 Background to the Research Problem

In today's era of AI and rapidly growing data, information may help and hurt enterprises at the same time. Big Data Analytics (BDA) has revolutionised how strategic decisions are made by giving management access to vast amounts of information that can make judgement more accurate (Merendino et al., 2018; Love et al., 2020). Contrary to expectations, it is the very same information explosion that promises clarity that has resulted in even more complexities and paralysis.

Recent industry insights from PwC's (2025) 28th Annual Global CEO Survey reveal persistent concerns regarding strategic decision-making process—impacting the quality and consistency among senior leaders. The report highlights that nearly six in ten CEOs admit their organisations still judge major strategic decisions primarily by outcomes rather than the quality of the underlying decision process. Furthermore, only about one-third (33%) of CEOs report having a high degree of trust in embedding artificial intelligence (AI)—a key source of analytical insight—into their core business processes (PwC, 2025.). The dilemma is not technological scarcity but leadership confidence—how to translate data volume into decision value. For many organisations, being data-rich but decision-poor has become the defining paradox of digital transformation.

Defining what constitutes decision-making quality (DMQ) is therefore critical. Based on the related study by (Shamim et al., 2019), there appear to be two aspects of quality in decision-making: effectiveness—the extent to which objectives are met and efficiency, the optimal use of resources such as time and cost. Within BDA-enabled contexts, quality decisions are those in which data-driven evidence meaningfully enhances both dimensions. However, such correlation is not consistent

across organisations, indicating the existence of underlying forces, specifically the influence of culture.

1.2 The leadership Paradox: Data Abundance vs Decision Quality

Despite massive spending on analytics, many organisations continue to fail to turn data into impact. This stems from inherent cognitive biases arising from traditional decision-making methods and techniques, technology silos are created within organisation, and an aversion to a data drive culture continue to undermine the promises of analytics (Shamim et al., 2019).

Literature lacks consensus the directionality of the impact of Big Data Analytics (BDA) has on the quality of decisions made by organisations. Despite reports from several scholars on the positive impacts of BDA usage on decision-making quality through enabling more accurate, timely, and evidence-based judgments (Shamim et al., 2019), some studies have cautioned that the relationship is not universally consistent (Corte-Real et al., 2017; (Ghasemaghaei & Turel, 2021)). Existing research highlights a “big data paradox,” suggesting that in some organisations, increased use of analytics may lead to information overload, cognitive strain, and even knowledge hiding factors that can undermine decision quality (Ghasemaghaei & Turel, 2021). Therefore, the effect of BDA on the quality of decision making is still dependent on context and organisational aspects, especially leadership and cultural preparedness to exploit the insights gained from analysis effectively (Li et al., 2022).

Recent evidence from Boston Consulting Group’s (2024) high number (~70 percent) of companies studied were struggling to realise scalable value from their Artificial Intelligence (AI) investments (BCG, n.d.). The study attributes the existing gap to absence of clear executive ownership, limited integration of analytics into decision-making routines coupled with cultural inertia that prevents the shaping of strategic choice through data analysis. A point argues (Vial, 2019) very succinctly, adding that data alone cannot ensure performance; decisions need to be effective, reproducible, and sustainable across waves of innovation. The strategic challenge therefore lies not in collecting data but in cultivating the leadership mindsets and organisational cultures that enable wise, timely interpretation. As digital ecosystems evolve, the ability to act decisively on analytical insight becomes the differentiator between resilient and obsolete firms.

1.3 Organisational Culture and Data-Driven Decision Quality

Culture is the factor that determines how people think, interpret, and respond when they receive information. (Schein, n.d.) describes organisational culture as a set of shared assumptions and beliefs that guide perception and action. (Denison and Mishra (1995) further link culture to performance through involvement, consistency, adaptability, and mission, while Cameron and Quinn (2011.) identified four cultural archetypes namely: clan, adhocracy, market, and hierarchy. Each construct is distinctive in how it prioritises different logics when making decision choices.

In analytics-driven setting these cultural orientations (Denison dimension and competing values frames) become the determinants of whether data becomes a source of learning or a symbol of control. Collaborative and adaptable organisational cultures promote experimentation and the establishment of analytical dialogue in organisations. On the other side, hierarchical cultures, or control cultures, promote routine reliance on intuition and established traditions (Dubey et al., 2019; Assoratgoon & Kantabutra, 2023). Currently, the literature mostly focuses on the application of analytics at organisational level, neglecting the perceptual aspect of senior management, who are decision-makers at an individual level.

According industry reports (OECD, 2022-23.) and (Mayer et al., 2025.): only a few firms have the capacity to implement analysis insights effectively in achieving strategic alignment, except for firms with high levels of executive support and cultural platforms. This represented the intellectual entry point of the current work. By exploring culture as a moderator rather than merely a context, the research examines how leaders' cultural environments amplify or suppress the effect of BDA on decision quality. In doing so, it moves beyond systems-level analysis toward the behavioural and cognitive domain where strategic decisions are made.

1.4 Purpose and Objective of Study

The purpose of this study is to examine how the use of Big Data Analytics (BDA) influences the quality of strategic decision-making among senior leaders and to determine how organisational culture moderates this relationship. The study begins with the theoretical foundations of the Dynamic Capabilities View (DCV) and the theory of Organisational Culture, encompasses technology, senior leaders' cognition, and the social aspects of strategic decision-making processes in organisations with analytical capabilities.

Specifically, the study seeks to achieve four interrelated objectives. Firstly, the proposed study aims to relate BDA (capability and usage) with the quality of strategic decisions at the level of senior management. Secondly, the proposed study also aims to evaluate the moderating role of organisational culture, specifically data-driven, adaptive, and collaborative cultures. Lastly, the proposed study also aims to add to current theories by integrating the theory of Dynamic Capabilities View (DCV) with current models of organisational cultures such as Denison's Model and the Competing Values Framework. The combination of these theories may help clarify the cultural settings in which analytical capabilities should be exploited. Finally, it is believed that the proposed study can provide useful insights to senior managers on how to improve their quality of decision-making within their organisations by exploiting analytics capabilities in an efficient manner based on cultural alignment.

1.5 Relevance and Contribution

From an academic perspective, this study contributes to an emerging but fragmented discourse linking analytics capabilities, culture, and leadership behaviour. While existing scholarship demonstrates that analytics enhances organisational performance ((Wamba et al., 2017); (Mikalef et al., 2019)), few studies isolate its effect on decision-making quality or investigate how culture conditions that effect. By focusing on senior leaders, this research addresses an overlooked stratum of analysis where strategy and analytics converge.

Practically, the study speaks to a pressing managerial concern. In the Deloitte Human Capital Trends 2025 report, 63 percent of executives identify “decision intelligence” as the most critical yet under-developed leadership capability (*Deloitte DI_Tech-Trends-2025*, n.d.). Similarly, the IBM Global AI Adoption Index (2025) notes that cultural resistance is the single greatest obstacle to realising value from analytics investment (*New IBM Study Reveals How AI Is Changing Work and What HR Leaders Should Do about It*, n.d.). For executives engaged in technology transformation, understanding the moderating role of culture in analytics success is not optional—it is existential.

By combination of empirical knowledge and leadership insights, the study aims to empower leaders with a roadmap to trust data, to distribute analytical authority, and to develop the culture of translating information to intelligent action.

1.6 Business Rational

Across industries, the promise of analytics is tempered by uneven results. The McKinsey study 'State of AI 2025' shows that only 1 percent of companies think that their analytics activities are "mature", while 72 percent see a leadership and culture gap that inhibits the capture of benefits" (Mayer et al., 2025). The Deloitte Tech Trends 2025 further reiterates this in terms of "decision latency" – the *time between insight and action* in digital transformation. Correspondingly, the World Economic Forum (2024) lists data-to-insight translation as the driver of resilience with regard to competition in the coming years (The Future of Growth Report 2024, 2024).

Industry practice substantiates this point. Telecommunication firms, for instance, have started using big data analytics to predict potential issues for their customers, with the objective of offering predictive solutions. Leading to measurable gains in customer retention and operational efficiency by embedding analytics within management routines and fostering a culture of data experimentation (Kampa et al., 2023). Conversely, failures in sectors such as healthcare and finance have been attributed to data fragmentation and rigid hierarchies that suppress insight flow (*Deloitte Di-Tech-Trends-2024*, n.d.).

This study therefore answers a question of both scholarly and managerial urgency: What organisational conditions transform analytics capability into decision quality? By empirically examining culture's moderating role, the research provides evidence-based guidance for executives and senior leader seeking to maximise return on analytics investment and strengthen strategic agility.

1.6 Theoretical Rational

The study is driven by not one but two complementary theoretical frameworks. The Dynamic Capabilities View (DCV) argues sustained competitive advantage results from an organisation's capability to respond to environmental uncertainty through sensing, seizing, and transforming (Teece, 2007). The application of BDA in an organisation is considered a dynamic capability that can improve such processes but only if they are situated in the right context, which can be secured through the OD tradition in culture, in particular (Gupta & George, 2016; Gupta et al., 2020.). Culture operates as the social infrastructure through which dynamic capabilities are enacted; it influences how leaders interpret data, collaborate, and institutionalise learning (Shamim et al., 2019; Szukits & Móricz, 2024)).

By integrating DCV with OD and culture models such as Denison and Mishra (1995) and the Competing Values Framework (Cameron & Quinn, 2011), the study positions culture as a micro foundation of dynamic capability — an interpretive filter that determines whether analytics insights are translated into effective strategic decisions

1.7 Scope and Structure of the Research

The study centres on senior leadership: CEOs, Executives, General Managers, and Departmental Heads and Founders in various industries in which data analytics has entered the process of strategic decision-making. It does not concern itself with operational analytics analyses, but rather with the processes involved in interpretation and cultural shifts in leadership decisions.

This Chapter has set out the context, rationale, and theory base of the study. Chapter 2 further develops the literature study and theoretical understanding. Chapter 3 formulates the study questions and hypotheses. Chapter 4 describes methodology, while Chapter 5 shows results, Chapter 6 combines findings in an interpretive manner (discussion) and Chapter conclude the study position it impacts on the literature and its practical implications.

1.8 Summary

This chapter has demonstrated the imperative and theoretical requirement to study the impact of Big Data Analytics on the quality of decisions in the cultural context of senior leadership. The rationale for selecting the proposed subject has been justified on the fit between technology, leadership studies, and organisational behavioural studies, domains that assume a central significance in the modern context of smart competitiveness. The subject matter definition here in provides the basis for the forthcoming literature synthesis in Chapter 2.

CHAPTER 2

LITERATURE REVIEW

In this chapter, a critical examination of literature on big data analytics (BDA), strategic decision-making quality (DMQ), and the moderating effect of organisational culture is considered. The integration of data analytics has remained imperative in contemporary strategic decisions. However, much remains unknown regarding its impact on strategic decisions. Thus, this chapter will underpin and provide a foundation for exploring its significance in impacting strategic decisions for those in leadership.

2.1 Conceptualising Big Data Analytics Capabilities

2.1.1 Evolution of Big Data Analytics (BDA)

The emergence of big data marked a fundamental shift in how organisations captured, processed, and utilised information for strategic purposes. Early conceptualisations focused on the defining technical dimensions of data—volume, velocity, and variety—which underscored the exponential growth of information generated by digital platforms (Gandomi & Haider, 2015). The above perspective viewed big data almost exclusively through the lens of technological advancement. Although it helped to explain the magnitude of data that organisations were dealing with, it explained very little as to how such data could improve strategic-level decision-making.

As analytical techniques increased, research focus shifted from descriptive data management towards data analysis for insight and value creation. Early academic work by (Watson et al., 2010) was among the first to identify the role of analytics as a strategic capability to unlock business value from data. Subsequent research expanded on such view, Wamba et al., (2017) and Mikalef et al., (2019) emphasised that the potential of big data resided not within the data size but within an organisation's capabilities to unlock data and transform it into valuable business insight. This progression signalled a migration from a technology centric view of big data towards a new capability-oriented paradigm that reinforced the integration of technology, people and processes.

This evolution established the intellectual foundation for examining analytics as an enabler of decision-making effectiveness. This presupposed that while data

accessibility had become abundant, interpretation and contextualising as well as its strategic implementation remained inequitably distributed. This challenge led to the need for the concept of Big Data Analytics as an organisational competence—leveraging and human capital.

2.1.2 Defining Big Data Analytics Capabilities

Big data analytics capabilities (BDAC) referred to the organisation's ability to acquire, integrate, and deploy data, technology, and human expertise to generate insights that inform decision-making (Mikalef et al., 2019; (Mikalef et al., 2018). BDAC were distinct from data resources; they represented what organisations could do with data, not merely what data they possessed. This distinction reflected a central tenet of the resource-based view: resources by themselves did not create competitive advantage unless they were organised into unique, difficult-to-imitate capabilities (Teece, 2007).

In this sense, BDAC embodied a composite of tangible and intangible elements. Tangible dimensions included the technical infrastructure required to collect and process data, while intangible aspects involved analytical expertise, managerial cognition, and organisational processes that facilitated knowledge sharing and application (Sabharwal & Miah, 2021). The interdependence of these dimensions enabled organisations to generate analytical insight and embed it into strategic and operational routines.

Scholars conceptualised BDAC as a higher-order, dynamic capability—a competence that allowed organisations to sense opportunities, seize them through analytical interpretation, and transform resources accordingly (Wamba et al., 2017). This interpretation aligned BDAC with the dynamic capabilities view (DCV), situating analytics as a mechanism through which organisations adapted to environmental complexity (Teece 2007). From this standpoint, BDAC did not merely enhance efficiency; it improved an organisation's ability to make sense of uncertainty and to act decisively in response to change.

Thus, BDAC extended beyond technology adoption to reflect an organisational learning process embedded in leadership and culture. This conceptualisation was central to the present study, which examined BDAC as a strategic capability enacted by senior leaders whose interpretations and actions determined the quality of strategic decisions.

2.1.3 Strategic Significance of Big Data Analytics Capabilities

BDA and consequently BDAC's strategic value rested on supporting informed and effective decision-making. Research evidence consistently posits that organisations embracing analytics had better outcomes in responsiveness, innovation, and performance than others that didn't (Wamba et al., 2017). However, the outcome for organisations that implemented these investments in BDAC have not been consistent. The trend suggested that BDAC's value may be contingent to certain organisational factors (Vial, 2019; Upadhyay & Kumar, 2020).

The literature indicated that the success of analytics depended on factors such as leadership commitment, data-driven culture, and knowledge integration across functional boundaries (Gupta & George, 2016; Mikalef et al., 2018; Mikalef et al., 2019; Upadhyay & Kumar, 2020; Wamba et al., 2017). When cultures promote evidence-based thinking, analytics helps in collective learning and taking more logical decisions. But in organisations, when intuition and hierarchy rule, data insights might be disrespected or undervalued (Szukits & Móricz, 2024).

These findings reinforced an important tenet of the argument: the competitive strength of BDAC rested not in the technology itself but in an organisation's capacity for understanding and applying analytical knowledge. As such, the research set out to explore BDA and its associated dimension as an initial construct that had a direct influence on decision-making quality but also to affirm that the efficacy of such influence varied depending on cultural settings. This theoretical association represented the first path of the research framework.

Overtime the literature on big data analytics and associated capabilities has evolved defining related technologies to strategic and organisational interpretations. BDAC were increasingly viewed as dynamic capabilities that supported informed decision-making by enabling organisations to convert data into actionable knowledge. Yet, the effectiveness of these capabilities varied according to the cultural and organisational environments in which they were embedded. This synthesis provided the conceptual basis for exploring the relationship between BDA and DMQ, which the following section addresses.

2.2 Big Data Analytics and Strategic Decision-Making Quality

2.2.1 Defining Strategic Decision-Making Quality

Strategic decision-making quality (DMQ) has been widely discussed as the extent to which managerial decisions are informed, coherent, and effective in achieving organisational objectives (Alhawamdeh & Alsmairat, 2019). It reflects not only the accuracy of decisions but also their timeliness, consistency, and alignment with strategic intent. In complex and uncertain environments, decision quality is influenced by the organisation's capacity to integrate relevant information, balance competing priorities, and act decisively under ambiguity (Dean & Sharfman, 1996).

High-quality decisions entail logical assessment of alternatives, appropriate use of information, and an inclination to change given new knowledge ((Ghasemaghahi & Turel, 2021)). However, decision-making within organisations tends to have elements of bounded rationality, leaders are faced with cognitive and informational limitations that cast constraints on the rational processing of data within organisations (Simon, 2000). This reality has fuelled growing interest in how analytical technologies can extend human cognitive capacity and improve strategic judgment.

As such, DMQ has evolved to multidimensional constructs, involving both process and outcome dimensions. Process quality entails the effectiveness of decisions being made based on data and deliberation, while outcome quality entails the success of decisions to achieve intended objective (Elbanna & Child, 2007). The complexity of the strategic context has made analytics an important facilitator of both qualities by enabling managers to gain better knowledge and add rigor to the decision-making process.

2.2.2 Linking Big Data Analytics Capabilities to Decision-Making Quality

Big data analytics capabilities (BDAC) have been theorised to enhance DMQ by improving the accuracy, scope, and timeliness of information available to decision-makers (Mikalef et al., 2019). The assumption here encourages the migration from traditional intuitive decision-making process toward an evidence-based approach that enable organisations to discover patterns and predict outcomes with increased accuracy (Wamba et al., 2017). This capacity reduces uncertainty, supports rational analysis, and ultimately leads to more informed strategic choices (Gupta & George, 2016).

From a theoretical point of view, the correlation between Big Data Analytics Capabilities (BDAC) and decision-making effectiveness has been adequately described based on the Information Processing Theory (IPT) and the Dynamic Capabilities View (DCV). IPT argues that the role of organisations is data processing that helps in overcoming environmental uncertainties (Tushman & Nadter, 1978). BDAC extend this capacity by enabling the collection, integration, and interpretation of large and complex data sets, thereby enhancing organisational sense-making. Complementarily, DCV views BDAC as a dynamic capability that enables the organisation to detect opportunities and capitalize on them through actions based on data. (Teece, 2007).

Empirical research supports these theoretical linkages. Gupta & George (2016) showed that BDAC positively impacted management decision-making by improving the ability of the company to read the business environment. Wamba et al. (2017) suggested that BDAC led to improved business performances due to the positive influence of decision-making processes. The involvement of dynamic capabilities in shaping the outcomes of BDACs cannot be ignored, according to Mikalef et al. in 2019. In a similar vein, Akter et al. (2016) shed light on analytical decision-making as an important dimension that contributed towards business value creation by big data management capability.

Despite these findings, results across studies have not been entirely consistent. However, certain scholars have highlighted that the adoption of analytics might not necessarily result in improved strategic-level decisions, especially when organisations failed to ensure integration between analytics activities and strategic-level decision-making forums (McAfee & Brynjolfsson, 2012; Upadhyay & Kumar, 2020). (Shollo & Galliers, 2016) argue that over-reliance on analytics might hinder the decision-making process or perpetuate the status quo in case of misinterpretation of data. These contradictions indicate that the benefits of BDAC are context-dependent, shaped by managerial interpretation, organisational structure, and culture.

2.2.3 Empirical Insights and Gaps in the Literature

The cumulative research work emphasises an important finding of a clear consensus on the positive influence of BDAC on improving the quality of decision-making by enabling increased rationality, speed, and effectiveness of strategic decisions.

Nevertheless, the extent of the influence of BDAC seems to differ from organisation to organisation. The results obtained from the study conducted by Mikalef et al., (2019) as well as Wamba et al., (2017) revealed that the potential of BDAC influence can be greatly enhanced when the structure and decision-making process follow the principles of adaptability. However, the empirical results reveal more. For instance, Upadhyay and Kumar (2020) found that in the case of hierarchical structure in the organisation, the influence of analytics in enhancing the quality of the decision at times might remain constrained.

These inconsistencies underscore a recurring theme: the value of analytics is socially and organisationally contingent. Even though technological platform provided by the BDAC are crucial for insights generation, the influence of insights on decision quality is highly dependent on other factors within an organisation. Examples include organisational attitude toward data, and willing for one to question one's intuition based of data evidence (Szukits & Móricz, 2024). Therefore, the literature suggests a model of context that BDAC act as a necessary but not sufficient factor for enhancing strategic decision-making. The role of organisational culture as a moderator appears as integral—in deciding whether BDAC act as instruments of learning and adaptation or as technical constructs that have only limited strategic significance. These findings form the theoretical passage to the next section that examines the role of organisational culture as a boundary condition that determines the relationship of BDAC to the quality of decision-making.

2.3 Theoretical Foundations

The theoretical grounding of this study drew on complementary perspectives that collectively explained how big data analytics capabilities (BDAC) enhance strategic decision-making quality (DMQ) and how organisational culture moderates this relationship. Three frameworks were particularly relevant: the Dynamic Capabilities View (DCV), the Knowledge-Based View (KBV), and Information Processing Theory (IPT). Each contributed unique explanatory insight into how organisations process data, convert it into knowledge, and use it to adapt strategically.

2.3.1 Dynamic Capabilities View (DCV)

The Dynamic Capabilities View (DCV) evolved from the resource-based view of the firm, extending its logic to environments characterised by turbulence and change. According to Teece (2007), dynamic capabilities refer to “the firm’s ability to integrate,

build, and reconfigure internal and external competences to address rapidly changing environments” (Teece et al., 1997, p516). These capabilities enable organisations to sustain competitive advantage by not relying on their fixed resources but instead relying on improving existing ones.

From the perspective of BDA, DCV provides a strong theoretical basis for understanding BDAC. However, as argued by some authors, BDAC demonstrate a dynamic behaviour in the sense that the DCV enables companies to capitalize on sensed market opportunities through an evidence-based decision-making process (Mikalef et al., 2019; Wamba et al., 2017). This framework positions analytics not merely as a technological tool but as a capability embedded in organisational processes and leadership cognition.

From a decision-making perspective, BDAC contribute to strategic agility—the capacity to anticipate shifts and respond effectively. Mikalef et al. (2019) demonstrated that firms with strong BDAC exhibited superior adaptability and innovation because analytics enhanced their ability to detect emerging patterns and make timely strategic adjustments. Similarly, Gupta and George (2016) found that the development of BDAC created a foundation for continuous learning, improving the accuracy and relevance of strategic decisions.

However, DCV also recognises that dynamic capabilities are path-dependent and influenced by organisational context. The culture, routines, and structures within which BDAC operate can either facilitate or constrain their evolution (Teece, 2007). This realisation reinforces the concept of organisational culture as a contextual factor, or moderator, in defining the success of analytics-derived capabilities in the quality of decision-making.

2.3.2 Knowledge-Based View (KBV)

The Knowledge-Based View (KBV) is view as a complimentary framework to DCV, it achieves this through explaining why data analytics contribute to strategic advantage gains through knowledge creation. Rooted in organisational learning theory, KBV holds that a firm’s most valuable resource is its knowledge base—the ability to generate, share, and apply knowledge more effectively than competitors (Grant, 1996).

From this perspective, BDAC enhance organisational decision-making because they enable the conversion of data into actionable knowledge. Data in isolation holds

limited value; it only attains strategic significance when analysed and interpreted in terms of shared understanding (Mikalef et al., 2018). BDAC therefore serve as mechanisms for organisational knowledge creation, integrating information across functional boundaries to support coordinated and informed decisions (Wamba et al., 2017).

KBV also clarifies the human and social dimensions of analytics. This view is supported by (Gupta and George 2016) who argued that the effective use of BDAC is not only dependent on the analytical infrastructure, but it is also contingent on cognitive and collaborative capabilities of decision makers. When leaders and teams are open to engaging analytics from an experiential learning approach, they develop shared mental models that improve tacit knowledge, judgment and strategic alignment (Nonaka, 1994).

Therefore, under KBV, BDAC are perceived as a capability that enhances a knowledge ecosystem within organisations to transform analysis knowledge into a shared understanding. However, as suggested by Upadhyay and Kumar (2020), this process is largely impacted by an organisation's culture. Open and learning cultures widen the benefit of knowledge through analytics, whereas a closed and siloed culture restricts this benefit.

2.3.3 Synthesis of Theoretical Perspectives

Together, these theories provide a cohesive foundation for understanding how BDAC influence decision-making quality and why organisational culture moderates this relationship. The DCV explains how analytics capabilities evolve and contribute to organisational agility; the KBV clarifies why these capabilities generate value through knowledge creation and learning; and IPT illustrates how analytics enhance the organisation's ability to process and interpret complex information.

Each perspective converges on a common argument: analytics create value not through technology alone but through their integration into organisational routines, decision processes, and cultural contexts. Consequently, BDAC are both a technological and a social capability—one that depends on dynamic adaptation, collective learning, and information interpretation. This theoretical integration underpins the conceptual model of the present study, which posits that BDAC directly influence strategic decision-making quality, moderated by the cultural conditions that shape how insights are interpreted and acted upon.

2.4 Organisational Culture and Analytics

2.4.1 Conceptualising Organisational Culture

Organisational culture (OC) has long been recognised as a foundational determinant of how organisations interpret information, make decisions, and execute strategy. Schein (2010) defined culture as “a pattern of shared basic assumptions learned by a group as it solved its problems of external adaptation and internal integration, which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems” (p. 18). This definition underscored that culture operates at both cognitive and behavioural levels, shaping how information is processed and how choices are made. Denison and Mishra (1995) clarified how a set of shared values and beliefs shapes organisational success through involvement, consistency, flexibility, and mission. For instance, Cameron and Quinn (2011) used the Competing Values Framework (CVF) to define organisational culture in four forms: clan, adhocracy, market, and hierarchy cultures that portray different logics of decision-making.

Recent studies have started to resituate the role of culture as a form of context-related capability—the set of societal and cognitive factors influencing the effectiveness of the organisation in applying insights from analysis (Mikalef et al., 2020). Xu et al., (2020) revealed that trusting, analytics-driven cultures facilitate the conversion of insights into agility in organisations. Moreover, trust and collaboration were identified by Dubey et al. in 2023 as important factors in effectively integrating knowledge in digital platforms with the help of analytics.

But even more interesting are the views by Assoratgoon & Kantabutra (2023)—that is, cultures that had a sustainability orientation and were more human-centric enhanced successful learning and innovations in emerging economies. Collectively, all these views suggested that culture in an organisation is not just a context but a capability through which analytics were leveraged for insight and action.

2.4.2 Organisational Culture and Analytics

One of the main themes that emerged in analytics literature is that the availability of technological capability wasn't sufficient for improving decision-making; instead, cultural readiness played a pivotal role in determining whether analytics tools were integrated into the decision-making process (Gupta and George, 2016; Côte-Real et al., 2020). Organisations with open, learning-oriented cultures encouraged

employees to challenge assumptions, rely on evidence, and share analytical findings across functions. In contrast, rigid or control-dominant cultures often isolated analytics within technical units, preventing strategic integration (Wamba et al., 2017; Shollo & Galliers, 2016).

This view has been supported more recently, as Horani et al., (2025) identified cultural readiness as the mediator between analytics capability and success in digital transformation and is consistent with adaptability and involvement as two cultural dimensions of Denison's cultural framework that improves analytics effectiveness. In the same manner, Dubey et al., (2019) discovered that the BDAC capability was complemented by a collaborative culture.

Denison's model outlined four dimensions—involvement, consistency, adaptability, and mission—that explained how culture influences performance outcomes through coordination, integration, and learning (Denison and Mishra, 1995). These factors were especially important in the context of analytics adoption, in that they shaped how data is shared, interpreted, and acted upon.

Table 1: Dimensions of Organisational Culture (Denison & Competing Values Framework Perspectives)

Framework	Archetype	Key Characteristics	Implications for DMQ	Sources
	Involvement	Empowerment, team orientation, participation in decision processes.	Enhance collaboration and cross-functional knowledge sharing, encouraging leaders to rely on analytics-driven insight in decision-making.	Denison & Mishra (1995); Dubey et al. (2019)
	Consistency	Core values, agreement, coordination, and integration.	Facilitates coherent interpretation of analytical insights and promotes reliable, evidence-based reasoning.	Denison & Mishra (1995); Upadhyay & Kumar (2020)
	Adaptability	Responsiveness, learning,	Promotes flexibility and continuous learning,	Horani et al. (2025);

Denison Model		innovation, and external focus.	supporting experimentation with analytics for strategic improvement.	Mikalef et al. (2019); Xu et al. 2024
	Mission	Purpose, strategic direction, goals, vision.	Aligns data-driven initiatives with strategic objectives, ensuring coherence between analytics insights and long-term goals.	Wamba et al. (2017); Côte-Real et al. (2020)
Competing Values Framework (CVF)	Clan Culture	Collaborative, participative, family-like environment.	Fosters trust and open communication, enabling collective interpretation of analytics outputs.	Cameron & Quinn (2011); Assoratgoon & Kantabutra (2023)
	Adhocracy Culture	Creative, flexible, entrepreneurial, innovative focused.	Encourages analytical experimentation and proactive insight generation, facilitating adaptive strategic decisions.	Cameron & Quinn (2011); Alyahya et. al., (2023)
	Market Culture	Results-oriented, competitive, externally focused.	Emphasises measurable outcomes and performance metrics; may leverage analytics for tactical rather than strategic value.	Cameron & Quinn (2011); Dubey et al. (2023)
Competing Values Framework (CVF)	Hierarchy Culture	Structured, formal, control-oriented environment.	Stresses procedures and control, which can restrict knowledge sharing and reduce agility in data-driven decision-making.	Cameron & Quinn (2011); Szukits & Móricz (2024)

2.4.2.1 Data-Driven Culture

Data-driven culture (DDC) can be defined as the organisational mindset whereby the organisational decision-making process revolves essentially around the use of information, evidence, and logic rather than gut feeling or hierarchical structures (Szukits & Móricz, 2024; Upadhyay & Kumar, 2020). In such cultures, information transparency, evidence-based dialogue, and a shared belief in the value of analytics underpin decision processes. Leaders promote the use of data in decision-making and reward analytical thinking in daily work (Gupta & George, 2016).

Recent studies underscore the fact that DDC enables the capabilities of big data analytics (BDAC), as analytics success not only relies on investment in technology but also depends on the collective mindset related to the interpretation and usage of the data (Dubey et al., 2023). Organisations characterised by a strong data-driven culture are more likely to leverage analytics to improve strategic decision-making quality, whereas those dominated by intuition or tradition often underutilise analytical insight. Within this study, data-driven culture is conceptualised as a key dimension of organisational culture that supports evidence-based reasoning and the integration of BDAC into strategic decision-making.

2.4.2.2 The Competing Values Framework (CVF) and Its Archetypes

The Competing Values Framework (CVF), developed by Cameron and Quinn (2011), is one of the most widely applied models for assessing and interpreting organisational culture. The framework locates culture on two underlying dimensions, which are as follows: 1) Flexibility versus Control—to distinguish between the organisations focusing on the values of adaptation, flexibility, and dynamism and the organisations focusing on stability, order, and control. And, on the other hand, 2) Internal versus external orientation—to distinguish between the organisations focusing on the values of internal integration, unity, and cohesion and the organisations focusing on the values of differentiation, competition, and interaction between the organisation and outsiders such as competitors and customers.

and internal versus external orientation. The intersection of these dimensions yields four dominant cultural archetypes: clan, adhocracy, market, and hierarchy. Archetypes pertaining to organisational culture follows its unique logic that affects

communication styles, leader behaviour, and decision-making processes. Clan culture's view teamwork, participation, and cooperation as important elements in achieving coordination by means of cohesion. Adhocracy cultures rely on creativity and inventions; they prefer organisational experiments. On the other hand, market culture views competitiveness, success, and goal achievement as paramount factors. Hierarchy cultures believe in order, control, and following the rules.

In the context of analytics, clan and adhocratic cultures are often linked to open attitudes toward experimentation, cross-functional learning and reasoning based on analytics (Assoratgoon and Kantabutra, 2023). Such attitudes promote the creation of a context in which the employees can think critically about their assumptions and apply analytics insights strategically. On the other hand, market and hierarchical cultures can regard the achievement of specific performance goals and adherence to procedures as more important than information-sharing processes.

To understand the correlation between Big Data Analytics Capabilities (BDAC) and Decision-Making Quality (DMQ), the concept of the Competing Values Framework (CVF) is used in the paper to demonstrate how organisational culture affects the situation. Excellence in analytics can be achieved when managers incorporate insights from analytics and logic in their decision-making process. This can be achieved in cultures wherein teamwork, flexibility, and learning from each other, in terms of each other's strengths, weaknesses, and ideas, are important. Hence, factors such as flexibility, learning, and flow of knowledge from different functional areas, wherein insights from analytics can be fed into, are encouraged in such cultures. On the contrary, more structured, control-based cultures impede such opportunity.

Based on Table 1, integrating Denison's model with the CVF, the involvement, adaptability, and mission of the company significantly influence the application of insights. Cultures of involvement and clans encourage teamwork and facilitate an environment conducive to evidence-informed decision-making. Adaptability and adhocracy foster experimentation and responsiveness, allowing leaders to leverage data creatively in uncertain environments. In contrast, hierarchical and market orientations—while effective for control and performance—tend to limit open information flow and reduce the transformative potential of analytics.

These insights underscored that culture functions not merely as a behavioural backdrop but as an active moderator shaping whether analytics capabilities influence decision quality. The degree to which BDAC enhance strategic outcomes depends on the alignment between cultural norms and the analytical mindset. Cultures promoting openness and shared learning enable analytics integration into decision-making routines, while those emphasising hierarchy or individual control restrict its use. This conceptual understanding leads directly to the moderating logic discussed in the following section.

2.4.3 The Moderating Role of Organisational Culture

Despite positive links associating BDAC with improved quality of decisions and organisational performance, empirical findings indicated large variation in the results, particularly across contexts. This variation suggested the influence of moderating factors, among which organisational culture was particularly significant.

Upadhyay and Kumar (2020) found that culture enhanced the relationship between BDAC and performance by strengthening internal analytical knowledge sharing. Mikalef et al. (2019) revealed that in organisations with cultures of adaptation and innovation, analytics usage enhances and flexibility in changing the strategic approach. Also, in relation to the proposed model, the effect of Big Data Analytics Capabilities (BDAC) on decision-making was found to be moderated by an analytical and participative culture, according to Szukits & Móricz (2024). Also, the role of data driven cultural values in fostering agility through analytics was also demonstrated by (Hyun et al., 2020). These findings collectively reinforced that the degree to which BDAC translate into high-quality strategic decisions, is dependent on organisational culture.

The moderating logic could be explained through two complementary theoretical lenses. The Dynamic Capabilities View (DCV) argued that culture is a microfoundation that facilitates the processes of sensing, seizing, and transforming activities in the firm (Teece 2007; Farouk et al., 2025). Adaptive, learning-oriented cultures reinforced dynamic capabilities by encouraging analytical experimentation and responsive adaptation. On the other hand, more rigid or hierarchical cultures made the process of restructuring analytical processes less flexible and agile (Mikalef et al., 2019; Farouk et al., 2025).

For example, Information Processing Theory (IPT) proposed that information can be more effectively processed if the complexity of the organisation's environment were matched by the organisation's structure (Tushman & Nadler, 1978). Cultures that encourage open communication, collaboration, and knowledge sharing increase information-processing capacity, enabling analytics to improve decision quality. In contrast, hierarchical cultures restrict data flow, thereby weakening the link between BDAC and decision-making outcomes (Nguyen et al., 2024).

These approaches led to the realisation that in BDAC studies, the role of culture in respect to decisions is not in producing improved decisions but in enabling the routes by which BDACs influence the quality of decisions. This contextual influence explains why similar analytics investments yield divergent results across organisations and why understanding cultural dynamics is essential for realising analytics-driven decision-making benefits.

2.4.4 Synthesis and Emerging Gap

The reviewed literature collectively confirmed that organisational culture was a pivotal contextual factor influencing analytics effectiveness. Cultures that emphasised openness, adaptability, collaboration, and shared learning consistently enhanced the translation of analytical insights into strategic action (Horani et al., 2025; Dubey et al., 2023). Conversely, hierarchical or intuition-dominant environments constrained evidence-based reasoning and slowed analytical integration. Culture serves as a boundary condition, determining whether Big Data Analytics (BDA) becomes a driver of better decision quality or remains just a technical tool.

Despite the increase in scholarly attention on the subject, several gaps remained. First, majority of studies explored culture's role in the relationship between analytics and organisational performance or innovation, but only a few examined its impact on strategic decision-making quality specifically. While previous work has begun to recognise that institutional and cultural settings may influence analytics adoption, comparative evidence from a broader range of contexts remains scarce. Third, few studies focused on leaders (senior leaders) as important respondents even though leaders are important agents responsible for examining information and translating it into strategic decisions.

The above omissions were found to create a significant research gap, despite the literature establishing organisational culture as critical component of successful analytics. Very few empirical study has been conducted to explore the role of cultural orientations as a moderation factor between BDAC and the quality of strategic decisions at the highest management level in the context of the emerging markets. Addressing this gap provided the rationale for the present study, which examined how cultural orientations condition the impact of analytics capabilities on decision quality among senior leaders in South African organisations.

2.5 Empirical Foundations and Identified Research Gaps

2.5.1 Empirical Evidence

In the past decade the relationships between big data analytics capabilities (BDAC), level of decision-making quality (DMQ), and impact of organisational culture (OC) have earned notable attention from scholars. Researchers have investigated BDAC in relation to its impact in different fields like innovation (Mikalef et al., 2019), performance (Wamba et al., 2017; Gupta & George, 2016), and strategic agility (Alghamdi & Agag, 2023). However, notwithstanding common concerns for better decisions through big data capabilities in organisations, literature has remained inconsistent. Research has suggested that BDAC has a positive and substantial impact on improving managerial judgments and decisions (Akter et al., 2016; Upadhyay & Kumar, 2020) in some studies. In contrast, some works revealed that technology investment failed to yield strategic impact where there is poor leadership and culture alignment (Dubey et al., 2019; Szukits & Móricz, 2024).

The inconsistencies mentioned above suggests that different settings and cultures in organisations have a critical impact on value that can be obtained from Analytics. Research evidence also recommends that adaptive and participative cultures result in an improved usage of analytics in an organisation by promoting evidence-based thinking and teamwork (Horani et al., 2025). On the other hand, hierarchical and control-oriented cultures can significantly hinder BDAC through a lack of knowledge and experimentation exchanges in organisations (Cameron & Quinn, 2011; Côte-Real et al., 2020). The key role of BDAC in Decision-making is still unmapped for its impact on Decision-making Quality.

2.5.2 Empirical Patterns: BDAC, Decision Quality, and Culture

Previous studies have helped to illuminate some aspects related to BDAC in strategic decisions. Gupta and George (2016) had concluded that BDAC contributed positively to managerial decisions about information accuracy and completeness. Wamba et al. (2017) confirmed that BDAC contributed positively to better performance through improved decision rationality and reaction. Mikalef et al. (2019) identified that dynamics BDAC functions in a mediating manner in the translation of analytics to strategic outcomes. However, these studies mainly focused on outcome variables such as innovation and performance, rather than what unpins the quality of the decision process.

Culture has emerged as a significant factor that differentiates. In this context, a study conducted by Upadhyay and Kumar (2020) established that a sharing and learning culture had a multiplier effect that caused BDAC to have a greater impact on performance. Dubey et al., (2023) in their study supported that collaborative and trust-based cultures had positively contributed to BDAC assimilation across departments. In a more contemporary example, (Alyahya et al., 2023) proved through empirical evidence that BDAC had its effectiveness enhanced through a culture of involvement and adaptability in achieving strategic goals as postulated in Denison's theory. These studies collectively indicate that analytics success is not uniform but contingent upon cultural orientation.

Despite such evidence, there remains a paucity of research that explicitly tests culture's moderating influence on BDAC's effect on decision quality. Most prior work conceptualised culture as a mediator or antecedent rather than as a boundary condition that changes the strength of BDAC's impact (Côte-Real et al., 2020; Mikalef et al., 2019). The theoretical gap highlighted above thus indicates a need for theoretical development in empirical modelling that focuses on how cultural differences affect BDAC's translation into strategic decisions.

2.5.3 Identified Gaps in the Literature

Empirical literature synthesis on studies related BDAC, DMQ, and OC and its dimensions and sub-constructs revealed important gaps in the existing literature.

Firstly, although several studies covered the relationship between analytics and organisational performance/innovation (Wamba et al., 2017; Mikalef et al., 2019; Upadhyay and Kumar, 2020), very few of have considered the influence of analytics

on the quality of strategic decisions. Decision quality, including the level of informed, consistent, and effective decision-making, is an important theoretical concept, although one often neglected (Shollo & Galliers, 2016; Elbanna & Child, 2007).

Moreover, most of the previous work was done in developed countries, hence creating a gap in understanding the relationship in other settings. Although this scholarship has yielded valuable insights, it offers limited understanding of how cultural orientations shape analytics effectiveness across diverse organisational contexts. Prior studies have acknowledged that institutional, cultural, and managerial differences influence analytics adoption and use, yet comparative, cross-contextual research remains scarce. Consequently, the field lacks a comprehensive view of how BDAC operate within organisations characterised by varying cultural logics and decision norms.

Third, very little research has included senior management as the subjects under scrutiny despite the fact that senior management consists of the individuals who are the main agents charged with the interpretation of analysis results and translating it into strategic choices. Most prior research has relied on firm-level or middle-management data, overlooking the interpretive processes through which leadership teams integrate analytical insight into organisational decision routines (Mikalef et al., 2019; Gupta & George, 2016). Capturing leaders' perspectives is essential for understanding the behavioural and cognitive dimensions of analytics-driven decision-making.

Finally, despite extensive conceptual acknowledgement of organisational culture's importance, few studies have empirically modelled culture as a moderating variable within BDAC–decision relationships. Existing work has typically positioned culture as a mediator or antecedent (Côte-Real et al., 2020; Dubey et al., 2019), thereby overlooking its boundary-spanning role in conditioning the strength of analytics' effects. This absence of moderation-based evidence limits theoretical precision in explaining why BDAC generate stronger decision outcomes in some organisations than in others.

2.5.4 Summary of Empirical Evidence

To consolidate the state of what is known, Table 2 summarises key empirical studies examining BDAC, organisational culture, and decision outcomes. The table outlines

their focus, methodologies, and findings, while identifying limitations that inform the current research design.

Table 2: Summary of Key Empirical Studies and Identified Gaps

Author(s)	Focus / Relationship Studied	Methodology & Context	Key Findings	Identified Gap
Gupta and George (2016)	BDAC and firm performance	Survey of U.S. firms	BDAC improved information use and coordination	Did not examine decision quality
Wamba et al., (2017)	BDAC and performance via dynamic capabilities	Quantitative, multi-sector	BDAC enhanced performance through dynamic capabilities	Focused on performance, not decision-making
Mikalef et al., (2019)	BDAC, innovation, and dynamic capabilities	Multi-country survey	BDAC improved innovation via dynamic capabilities	Did not explore cultural moderation
Upadhyay and Kumar (2020)	BDAC, performance, and culture	Indian firms	Culture strengthened BDAC–performance link	Treated culture as mediator, not moderator
Dubey et al., (2019)	BDAC, collaboration, and trust	International sample	Collaborative culture enhanced BDAC value realisation	Did not test decision-quality outcomes
Côrte-Real et al., (2020)	Determinants of BDAC effectiveness	European firms	Cultural fit influenced analytics assimilation	Did not address leadership or decision quality
Horani et al., (2025)	BDAC, innovation, and the moderating role of	Quantitative survey, Middle Eastern universities	Organisational learning culture strengthened BDAC–innovation relationship	Examined learning culture, not general organisational culture; did not

	organisational learning culture			test decision-making quality
Jenkinson et al., (2024)	BDAC, business model innovation, and competitive performance	Survey of South African firms	BDAC improved competitive performance through business model innovation	Focused on innovation as mediator; did not consider culture or decision-making quality
Szukits & Móricz (2024)	Analytical culture and decision centralisation	European sample	Analytical culture improved data-driven decisions	Lacked empirical test of BDAC–DMQ moderation

2.5.5 Research Justification

The synthesis of empirical evidence revealed that, although big data analytics capabilities (BDAC) have consistently been shown to enhance organisational performance and agility, their influence on strategic decision-making quality (DMQ) remains conceptually recognised yet empirically under-examined. While BDAC enable firms to collect, process, and analyse complex data sets to support strategic decisions, the extent to which these capabilities improve the quality of those decisions depends on contextual and behavioural enablers. Among these, organisational culture (OC) has emerged as a particularly salient determinant, shaping how analytical insights are interpreted, shared, and enacted within organisations. Nevertheless, existing studies that explicitly model OC as a moderator in the BDAC–DMQ relationship remain limited, and very few have incorporated leadership-level perspectives into their empirical frameworks.

In response to these gaps, the present study was designed to make four distinct contributions to the literature. First, it empirically examined decision-making quality as a discrete outcome variable within the analytics-capability domain, thereby moving beyond traditional performance or innovation outcomes.

Secondly, the role of organisational culture as a moderation factor has been examined. This provides a more theory-driven account of the moderating effect between BDAC and decision-making quality. Thirdly, the empirical targets were

senior leaders, as the main role of the senior management team has been identified as the chief ‘interpreters’ or ‘actors’ of the results from analytics insights in the context of strategic decision-making. This has been less adequately covered in previous empirical studies. Finally, the empirical context has not been geographically demarcated, a cross-contextual sample of leaders has been used as the basis for insights, thereby providing more generalised insights into the relational nuances that connect analytics, culture, and decision quality across diverse organisational settings.

By addressing these gaps, this present study envisages to contribute to the understanding of the interplay between the mentioned antecedent factors and the outcome related to decision-making at the strategic-leadership level. The study also responds to ongoing scholarly calls for models that integrate technological, cognitive, and cultural dimensions in explaining how organisations derive value from data-driven decision-making.

2.6 Conceptual Model and Summary

2.6.1 Conceptual Model

The conceptual model (Figure 1) represents the theoretical structure derived from the literature reviewed in this chapter. It represents the interplay between the capabilities of big data analytics (BDAC), the quality of strategic decision-making (DMQ), and organisational culture (OC). This framework highlights the overarching theme of the review— that while BDAC provide the technological and analytical foundation for improved decision-making, the extent of the effect of BDA on DMQ can only be optimised depending on an organisation’s cultural context.

From the integration of previous studies and theories mentioned earlier, the following are the insights that emerged: First, BDAC contribute to strategic decision-making by enabling better sensing, interpretation, and use of information for informed judgment. Secondly, even with the level of analytics investments in most firms, there seem to be contextual factors at play. Third, organisational culture has been identified as a factor that determines the ability to translate insights derived from analytic in strategic action.

Based on these insights, the model proposes that BDAC have a positive relationship with DMQ, and that this relationship is moderated by OC, such that data-driven, adaptive, and collaborative cultures strengthen the impact of BDAC on decision-

making quality. The model therefore integrates the main constructs examined in this study and provides a framework for the development of hypotheses and the design of the empirical analysis presented in the subsequent chapters.

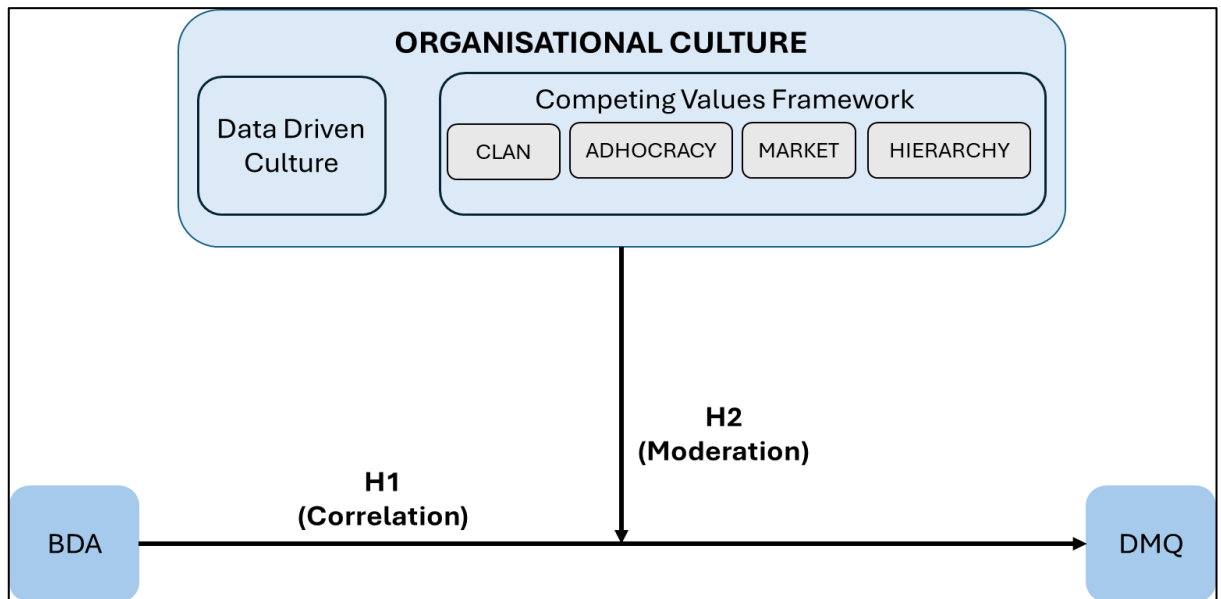


Figure 1: Conceptual Model of the study.

2.6.2 Chapter Summary

In this chapter, a critical review of theoretical and empirical literature was presented, underpinning this study. It established that while there is an increasing trend in terms of investments made toward big data analytics in organisations, the evidence of the impact on decision quality of such investment is still contentious (limited and context dependent). The chapter further revealed that culture is pivotal in shaping the adoption process of big data and its impact on decisions is considered in organisations. However, its moderating effect of BDA (capabilities) has rarely been empirically tested.

The conceptual model that emerged through the literature synthesis encapsulates these relationships, and positions organisational culture as a boundary condition that influences whether BDA enhance or fail to improve DMQ. The conceptual model underlies all our substantive research questions and hypotheses in chapter 3.

CHAPTER 3

RESEARCH QUESTIONS

Building on the conceptual insights and research gaps established in chapters 1 and 2, this chapter articulates the specific research questions and hypotheses that guided the empirical investigation. Preceding chapters highlighted that although Big Data Analytics (BDA) is widely recognised as a technological capability capable of transforming strategic decision-making, its impact is not inherently deterministic; it depends critically on the organisational context—the context in which the organisation operates affects the outcome due to the existing culture that dictates how the information should be interpreted by the senior management (Mikalef et al., 2019; Upadhyay & Kumar, 2020). Yet empirical research linking these variables—especially at the senior leadership level—remains sparse (Merendino et al., 2018; Assoratgoon & Kantabutra, 2023).

The study therefore fills two related gaps in knowledge: (a) a lack of empirical findings concerning the effect of the use of big data analytics (BDA) on the quality, as opposed to the speed or volume, of senior leaders' strategic decision-making, and (b) the spottily explored moderating role of Organisational culture in either reinforcing or suppressing that relationship.

3.1.1 Conceptual Foundation and Theoretical Linkages

The research design is anchored in several complementary theoretical perspectives that collectively explain how BDA affects decision quality within different organisational contexts. The Dynamic Capabilities View (DCV; Teece, 2007) conceptualises BDA as a strategic capability that enables leaders to sense emerging opportunities, seize them effectively, and reconfigure organisational resources for sustained performance. Thus, the quality of decision-making can thereby be improved through the enhancement of the leaders' capacity to integrate and understand complex information flows.

In addition to the Dynamic Capabilities View (DCV), the Knowledge-Based View (KBV) (Grant, 1996), which assumes that the core role of the organisation consists of developing and utilising knowledge to achieve superior results. In this area, Big BDA enables the process through the creation of useful information from raw information. This serves to reinforce the informational and cognitive foundation underpinning the organisational decisions made. Another theoretical framework

supporting the influence of information processing as a factor influencing organisational decision-making ability is the Information Processing Theory (IPT) (Tushman & Nadler, 1978)—whereby the efficiency and effectiveness of organisational decision-making improve as the information processing capacity of the systems commensurate with the complexity of the organisational environment underpinning the decision-making process. Where the level of organisational risk due to lack of information necessitates more thorough information scrutiny to shield organisational decision-making efficiency from the influence of organisational biases and human errors, more advanced tools improve the organisational capacity to collect and synthesise important organisational information based on available information matching managerial demands.

Yet again, as in the previous case above, while BDA improves the organisational information analysis capacity, the organisational culture influences the ability to optimally tap organisational advantages arising from the improved capacity. To account for the role of organisational culture as the influencing factor above under this thesis, two popular traditions were used: Competing Values Framework (CVF) and the Denison Model of organisational culture.

The CVF formulates a two-factor structure for organisational culture—flexibility versus control and external versus internal orientation—and identifies four archetypes—Clan, Adhocracy, Market, and Hierarchy (Cameron & Quinn, 2006). Clan and Adhocracy cultures typically encourage collaboration, learning, and innovation, while Market and Hierarchy cultures promote control, competition, stability and organisational success. Another framework: Denison Model of organisational culture uses four organisational constructs related to involvement: adaptability, consistency, and mission. These organisational aspects were assumed to relate organisational performance (Denison & Mishra, 1995).

Through their integration, the study conceptualises organisational culture as more than a background factor, but rather as a moderating factor that determines how the leaders respond to the findings. Culture therefore can amplify or reduce the effect of the BDA on the quality of the decisions, comprising the theoretical basis that underlies the study's second hypothesis—the moderating role of organisational culture.

3.1.2 Reasoning for the Research Questions

Despite the broad diffusion of analytical tools, far too many organisations are unable to reap substantial improvements in the quality of decision-making (OECD, 2021; McKinsey & Company, 2025). Researchers account for the challenge not residing in the analytical tools, *per se*, but rather, social and cultural systems governing the diffusion and use of intelligence (Shamim et al., 2019; Dubey et al., 2019). Whilst in principle, Big Data Analytics (BDA) can enhance decision quality by enriching the accuracy, timeliness, and completeness of information (Li et al., 2021), others posit that information overload and analytical inflexibility can, ironically, worsen decision quality where organisational executives benefit less by supportive cultural norms (Ghasemaghaei & Turel, 2021).

This variability in empirical results underlines the importance of a more sophisticated understanding of how context can influence the relationship between BDA and decision-making. In fact, culture determines whether information from analysis can be trusted, shared, and acted upon. In open, participative cultures, analytics tends to enhance collaborative problem-solving; in rigid, hierarchical environments, data-driven insights may be dismissed in favour of established routines or intuition-based judgments (Szukits & Móricz, 2024).

Hence, in the case of senior leaders whose decisions have deep long-term consequences for organisations, these interplays are explored in the current study. Getting an insight into the analytics capability, decision quality, and cultural orientation in the group offers useful theoretical insights besides organisational practice recommendations in the scenario of data-driven transformation.

3.2 Research Questions

The synthesis of theoretical and empirical knowledge in Chapters 1 and 2 triggers two major (RQ1 and RQ2) research questions that underlie the present research:

RQ1: What is the relationship between Big Data Analytic (BDA) capabilities and strategic decision-making at the senior leadership level?

Research Question (RQ2): How does organisational culture moderate the relationship between big data analytics capabilities and decision-making quality?

These research questions are grounded in the explanatory objective of the study. They also incorporate a positivist paradigm with the to uncover the relationships

between variables. The first question explores the ways in which Big Data Analytics (BDA) adds quality to decision outcomes, based on the theories of Dynamic Capabilities and Knowledge-Based Theory, according to which data is an important factor in informed decision-making. The second focuses specifically on the role played by organisation culture (adaptive, open, collaborative etc.) on the relationship between the two constructs (BDA capabilities and DMQ).

3.3 Development of Hypotheses

3.3.1 Big Data Analytics and Decision-Making Quality

The initial hypothesis derives directly from the models of Dynamic Capabilities (Teece, 1997; Teece 2007) and Knowledge-Based views (KBV) (Grant, 1996). Utilising BDA, managers can increasingly integrate heterogeneous sources of information. Moreover, conclusions can be drawn based on the information. This improves the completeness, effectiveness, and swiftness of decision-making processes (Mikalef et al., 2019; Li et al., 2021). Uncertainty and human biases are reduced. This leads to the enhancement of the reasonability and reliability of the strategic decisions made (Nutt, 2008). Hence, the subsequent hypothesis was proposed:

H₁: A positive correlation exists between using big data analytics and decision-making quality at the senior leadership level.

3.3.2 The Moderating Role of Organisational Culture

The second hypothesis stems from the Competing Values and Denison frameworks, which postulate that cultural attributes influence how technologies are adopted and embedded within organisational processes (Cameron & Quinn, 2006; Denison & Mishra, 1995). Adaptive and cooperative cultures, as defined by Clan and Adhocracy orientations, are likely to improve the impact of analytics by encouraging transparency, trust, and risk avoidance. On the other hand, strong hierarchical cultures limit the role of analytical evidence in the sense that the following of set procedures and risk aversion is promoted (Upadhyay & Kumar, 2020; Szukits & Móricz, 2024). The second hypothesis, therefore, is framed as follows:

H₂: Organisational culture provides a moderating role in the relationship between Decision Making Quality and Big Data Analytics, in that the relationship is stronger

in organisational settings that are adaptive, collaborative, and data-driven, and weaker in organisational cultures that are hierarchical or control-based.

In this chapter the researcher translated theoretical framework and research gap into a set of research questions and hypotheses by drawing on the Dynamic Capabilities View, Knowledge-Based View, and cultural frameworks such as CVF and Denison. The research methodology for the study is presented in chapter 4.

CHAPTER 4

RESEARCH METHOD

This chapter presents the procedure adopted to investigate the relationship between BDA and Decision-Making Quality (DMQ) among senior leaders, and the moderating role of organisational culture¹. Base on the theoretical hypotheses discussed in chapters 1 to 3, the research design was formulated to be philosophically, methodologically, and analytically aligned with the objectives of the study—i.e., to empirically test the hypothesised directional relationships between BDA capability, decision-making quality, and organisational culture.

4.1 Research Procedure and Design

The study adopted an explanatory; quantitative design aimed at uncovering causal relationships between well-defined variables. The explanatory approach sought to determine not only whether associations existed between BDA and decision-making quality but also how organisational culture might strengthen or weaken that relationship. The quantitative paradigm allowed the application of structured data gathering methodologies and statistical validation to quantify the results. This is more in line with the current body of research in analytics-based decision-making, with the formation and validation of hypotheses and their construct metrics (Mikalef et al., 2019; Upadhyay & Kumar, 2020).

4.1.1 Research Philosophy and Approach

The study was grounded in the positivist philosophy, which posits that reality exists independently of human perception and can be observed through objective

¹ Decision-making quality (DMQ) in this study was regarded as a perceptual construct capturing senior leaders' self-assessed evaluations of the reliability, effectiveness, and efficiency of their strategic decisions. The survey items (Appendix B) reflect respondents' agreement with statements regarding the extent to which their decisions are evidence-based, aligned with organisational objectives, and made in a timely, well-informed manner. This definition aligns with established behavioural and strategic management research (Dean & Sharfman, 1996; Elbanna, 2006; Mikalef et al., 2019; Chatterjee et al., 2023), which conceptualises decision-making quality as a subjective appraisal of decision processes rather than an objective outcome measure. Accordingly, the construct measures perceived strategic decision quality, consistent with studies exploring cognitive and cultural influences on executive decision-making.

measurement. This stance was appropriate because the constructs—BDA usage, decision-making quality, and organisational culture—identified and measured. Positivism supports the collection of numerical data for hypothesis testing, thereby allowing the derivation (process of induction) of generalisable conclusions about the studied phenomena (Saunders and Lewis, 2018).

A deductive approach complemented this philosophy. Deduction begins with theory and uses empirical observation to test hypotheses derived from it (Edmondson and McManus, 2007). Since the conceptual framework in Chapter 3 was grounded in the Dynamic Capabilities View (Teece, 2007) and frameworks of Organisational Culture (Denison & Mishra, 1995; Cameron & Quinn, 2006), the deductive approach was utilized in the process of investigating the theoretical relationships between the frameworks. This approach was necessary because it allows for empirical testing of theoretical relationships through statistical analysis, consistent with positivist theory (McDermott, 2023)

4.1.2 Research Type, Strategy and Time Horizon

A quantitative, cross-sectional survey was employed. Quantitative designs are appropriate for examining patterns and relationships across large groups where standardised measures can be applied consistently (Saunders and Lewis, 2018). The survey approach was selected on the basis that it facilitates the effective gathering of data from a broad and diverse sample of senior leaders within organisations, thus providing an effective means for the development and test of hypotheses. Similarly, other studies investigating analytics and culture have previously used survey methods successfully to measure latent constructs using Likert-type scales (Shamim et al., 2019; Wamba et al., 2017).

A cross-sectional time horizon was used because it measures the status of the relationship at a single point in time, making it possible to complete the study in one year. Despite its limitation compared to longitudinal studies that offer deeper causal insights, a cross-sectional approach was used for explanatory models that assess directionality of relationships. (Saunders and Lewis, 2018).

Also, this temporal structure is consistent with corresponding studies on Organisational culture and analytics examining current leadership perception and not over time (Upadhyay & Kumar, 2020).

4.2 Demographics, Analytical Unit, and Sampling Procedure

The target population comprised senior leader, executives, and strategic decision-makers operating in organisations where data analytics is implemented within the frame of making decisions. The unit of analysis thus became the individual leader. Such micro-level focus is also aligned with the knowledge gap identified in Chapter 2 where limited empirical attention had been paid to the senior tier management's engagement with analytics.

As the task entailed the difficulty of compiling an exhaustive list of senior leaders, non-probability purposive sampling was adopted. This technique the researcher in as far as reasonably possible to intentionally select participants based on specific characteristics or criteria that are relevant to the research objectives (Rahman, 2023). The questionnaire received 124 responses where 109 qualified upon evaluation of eligibility and completeness. The final sample size (N) met Green's (1991) requirement of $N \geq 104 + m$ predictors and thus confirmed its adequacy to undertake regression and moderation tests. Accordingly, the application of purposive sampling received validation due to its applicability and effectiveness to enlist an esoteric but elusive group.

4.3 Measurement Instrument and Pre-Testing

Data were collected through a structured questionnaire with five parts: respondent's demographic information, Big Data Analytics capability, BDA utilisation, quality of decision-making, and organisational culture. All items were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Established measurement scales were adapted from prior validated instruments to ensure construct comparability and internal consistency. Big Data Analytics (BDA) ability and usage were measured using items derived from Wamba et al. (2017) and Shamim et al. (2019). The Decision-Making Quality (DMQ) was measured with items derived from Nutt (2008) and Li et al. (2021).

Organisational culture was assessed with the application of two models—the Denison approach (Denison & Mishra, 1995) and the Competing Values Framework (Cameron & Quinn, 2006)—varying from data-driven and strategic perspectives, such as Clan, Adhocracy, Market, and Hierarchy styles.

Pilot testing with ten senior administrators was conducted to assess the clarity, ordering, and time taken to complete the questionnaire. The internal consistency

calculated by Cronbach's alpha was above 0.70, establishing acceptable levels (Hair et al., 2021). The pre-test also proved helpful in ensuring the instrument was free from complexities, relevance to the topic, and jargon free.

A pilot survey among ten senior leaders provided an opportunity to assess item clarity, sequencing, and time to complete. An initial analysis of reliability was carried out by applying Cronbach's alpha for internal consistency and reliability, with Cronbach's alpha coefficients exceeding 0.70 validating satisfactory internal consistency (Hair et al., 2021). Pre-testing ensured that the instrument was comprehensible and congruent to the professional terminology of respondents.

4.4 Data Collection and Survey Administration

Data were collected electronically via Google Forms, which facilitated reach across multiple industries and geographic regions. The survey link was distributed using LinkedIn forums, leadership forums on WhatsApp, and via invitations through emails. A covering letter introduced the study, explained the academic purpose, and guaranteed confidentiality and voluntary participation under GIBS ethical protocols.

The online format was particularly suitable given the dispersed nature of the target population and the professional level of respondents. It also reduced administrative costs and ensured automatic data capture, minimising human error. Participants were required to complete all questions before submission, thereby eliminating missing data. Two reminder emails were sent over a three-week period to increase responses, resulting in 124 submissions. After checking for completeness and relevance to senior leadership roles, the final sample included 109 valid responses.

4.5 Data Screening, Cleaning and Preparation

Prior to statistical analysis, the dataset was checked for completeness, outliers, and appropriateness for multivariate analysis. Since the survey platform did not allow any non-completed questions and therefore did not produce any missing data, data imputation procedures like mean substitution or regression estimation could be omitted (Hair et al., 2019). With the help of boxplots and standardised z-scores (Osborne and Overbay, 2004), only mild outliers were detected, none exceeding ± 3 standard deviations; thus, all observations were retained.

Descriptive review and correlation matrices were reviewed to ensure data consistency and that variable ranges and variances appropriately prepared the data

for further analysis. The final dataset passed all tests required to be adequate to proceed with regression analysis and parametric testing.

4.6 Statistical Analysis and Analytical Procedures

The hypothesised relationships among Decision-Making Quality (DMQ), Organisational Culture (OC), and Big Data Analytics (BDA) were assessed quantitatively. The analysis was undertaken using IBM SPSS Statistics, to generate descriptive, inferential, and multivariate analysis statistical outputs. The analytical structure employed a sequential logic, that of data screening, evaluation of measurement quality (reliability and validity), distribution and normality examination, and inferential assessment of the hypothesised relationships, this is a well-established method used other such as Hair et al., 2019; Saunders and Lewis (2018). The process was determined adopting conventional methodological advice in quantitative studies and the explanatory purposes of the study (Hair et al., 2019; Saunders and Lewis, 2018).

4.6.1 Data Screening and Data Preparation

Prior to analysis, the data set was screened for accuracy, completeness, and compatibility with parametric tests. According to Pallant (2020), proper data screening protects the integrity of statistical inference by identifying anomalies that may bias outcomes. Missing data were not expected because the online survey was configured to require completion of all items before submission. The data were checked for unusual or extreme values using boxplot graphs and z-scores. This process helped identify any responses that were far outside the normal range, following the guidelines by Osborne and Overbay (2004). Any identified irregularities were assessed for plausibility rather than being automatically removed because of the potential for skewing distribution of the data in smaller sample sizes (Hair et al., 2019). This process ensured that the data set was compatible with the requisite assumptions for the subsequent parametric and regression analyses.

4.6.2 Reliability Analysis

Internal consistency reliability was examined using Cronbach's alpha (α) for each construct and sub-dimension. Cronbach's alpha determines the degree to which the items in the scale truly represent the same construct (Tavakol & Dennick, 2011). An index of 0.70 and above is acceptable in exploratory studies (Hair et al., 2019). This analysis also revealed that the multi-item constructs of BDA capability, BDA usage,

DMQ, and organisational culture ensured consistent data within the respective constructs. This was important, especially in the process of verifying hypotheses, as data error can impact on the correlation between variables (DeVellis, 2017).

4.6.3 Validity Testing and Factor Analysis

Construct validity was evaluated through Exploratory Factor Analysis (EFA), which examines the degree to which observed items represent their intended latent constructs (Hair, 2019). The analysis employed Principal Axis Factoring (PAF) with Promax rotation. The Promax rotation is an oblique rotation, meaning factors are allowed to correlate. This is frequently the choice in organisational or behavioural studies, in which the variables tend to be related (Pallant, 2020).

Sampling adequacy was established by the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's Test of Sphericity. KMO value above 0.70 provides that the correlations among variables are sufficient in magnitude for purposes of factor analysis, while a significant Bartlett's test ($p < .05$) provides assurance that there are factorable relationships (Hair et al., 2019). The EFA was thus a crucial diagnostic step to verify convergent and discriminant validity of the measurement model prior to inferential testing. Valid measurement is crucial in explanatory research because the accuracy of relationships among constructs depends on the soundness of the measurement instrument (Hajjar, 2018).

4.6.4 Descriptive and Normality Analysis

After establishing the reliability and validity, descriptive statistics such as means, standard deviations, skewness, and kurtosis were calculated to give an overview of the attitude of the respondents. Testing for normality is an essential in quantitative research because most inferential tests (e.g., correlation, regression, and ANOVA) posit almost normally distributed data (Ghasemi & Zahediasl, 2012). The Shapiro–Wilk test, accompanied by histograms and Q–Q plots, was used at the construct level to assess the distribution for normality. In cases where the sample size becomes large ($n > 100$), minimal deviation from normality is acceptable, in line with the Central Limit Theorem that stipulates that the approximate normality of the sample distribution for a set approaches normality as the sample size increases (Ghasemi & Zahediasl, 2012). Testing for normality served to ascertain that subsequent parametric analysis would yield unbiased estimates and appropriate levels of significance.

4.6.5 Correlation Analysis

Pearson's product moment correlation coefficient was used to investigate the strength and direction of correlations among continuous variables, consistent with the scale level and expected linear correlations among constructs (Pallant, 2001). Correlation analysis was necessary to provide an initial empirical overview of relationships before testing predictive effects through regression (Hayes, 2013). This step confirmed whether the hypothesised associations (e.g., between BDA capability and DMQ) were statistically and directionally consistent with theoretical expectations. The confirmation, provide a basis for the subsequent regression modelling.

4.6.6 Testing the Hypotheses Using Regression

The first hypothesis (H_1) posits that Big Data Analytics has an important role in predicting Decision-Making Quality among senior leaders. The analysis of the first hypothesis was examined through a simple linear regression analysis approach, an appropriate technique for ascertaining the predictive ability of a single continuous independent variable on a dependent variable (Hair et al., 2019).

4.6.7 Moderation Analysis

The second hypothesis (H_2) examines whether Organisational Culture moderates the relationship between BDA and DMQ. The procedure of Jeger et al. (2014) were adopted in a hierarchical multiple regression strategy. Regression analysis was employed to establish the degree and nature of the relationships between the variables, in addition to the predictability of one variable from another (Hair et al., 2018). The Coefficient of Determination (R^2) and the F-Statistic, derived from the ANOVA table, were utilised in assessing the goodness-of-fit of the model. The quantitative method used in the study was appropriate for the positivist, explanatory research objective since the technique quantifies the degree to which the variation in the use or capability of BDA explains the variation in the quality of decisions observed (Saunders & Lewis, 2018).

In this method, predictor variables (BDA and culture) were entered in successive steps, followed by an interaction term ($BDA \times Culture$). A significant change in explained variance (ΔR^2) or interaction coefficient (β) indicates moderation. This approach was preferred to alternatives such as structural equation modelling because it provides transparent interpretability of moderating effects in survey datasets of modest sample size (Rahman, 2023). Moderation analysis was vital to

empirically test the assertion of the conceptual model—derived from the Dynamic Capabilities View—that organisational culture influences the extent to which analytical capabilities translate into improved decision outcomes.

4.6.8 ANOVA as Model Validation

The method of Analysis of Variance (ANOVA) was used in determining the general significance of the regression models and in investigating mean variation among different categories of Organisational culture. According to Pallant, (2020), ANOVA complements regression by testing whether group mean differences are statistically significant, thereby confirming that variance in decision quality is systematically related to variations in predictor variables rather than random noise. In the current study, ANOVA served as an explanatory validation procedure, confirming that the regression models were statistically significant and theoretically consistent with the suggested relationships.

4.7 Assumptions of Method

The validity of parametric and regression analysis relies on certain assumptions. These assumptions, before the process of hypothesis testing, all were stringently tested. Adequacy of sample met the rule of $N \geq 104 + m$ predictors (Green, 1991), offering sufficient statistical power. Linearity between the independent variables and the dependent variable was through scatterplots, and homoscedasticity was checked for equal residual variance by residual plots. Multicollinearity was tested by Variance Inflation Factor (VIF) and tolerance statistics, all in acceptable ranges ($VIF < 5$; tolerance > 0.2), and ensured that the predictor variables were not too correlated. Normality of residuals was assessed by Shapiro-Wilk tests and visual plots, which indicate close to normal distribution. The influence of outliers was examined by Cook's Distance, all being under the 1.0 cut-off (Hair et al., 2019). These diagnostics ensured that the assumptions that underpinned the correlation, the regression, and the moderation tests were all satisfied, an outcome that allowed robustness of findings.

4.8 Ethical Considerations

Before the initiation of the collection of data was initiated, ethical clearance was obtained from the Gordon Institute of Business Science Research Ethics Committee. Participants were informed of the academic purposes of the study, that participation is voluntary and therefore reserve the right to withdraw at any time, as well as the

assurance of anonymity and confidentiality. No identifying personal information was collected, and the data were safely retained in line with the POPIA—the protection of personal information act. The researcher maintained the requirements of integrity, voluntary participation, and transparency, thereby ensuring that the study adhere to the appropriate ethical requirements acceptable for credible research.

4.9 Methodological Limitations

Despite methodological rigour being maintained, several limitations were conceded. The cross-sectional design restricted causal inference over time, offering only a snapshot of relationships. The non-probability purposive sampling reduced the ability to generalise findings to the broader leadership populace, but it was suitable for targeting a specific group of senior decision-makers relevant for the study. Self-reported data offered the risk of social desirability or common-method bias; however, these risks were mitigated through anonymity, question randomisation, and validated multi-item scales from literature (Appendix A). Furthermore, the perceptual constructs of decision quality and culture can, in future research, be augmented by objective measures of performance. Notwithstanding the above limitations, the methodological rigor found in the study was ensured using validated tools, strict statistical testing, and consistency between the theory, the approach, and the method of analysis. In this chapter, the research philosophy, methodology, and analytical approach used to guide the empirical study of the effects of Big Data Analytics on the quality of decision-making among high-level managers, moderated by the culture within the organisation, have been explained.

The combination of the philosophy of positivism with the deductive approach ensured a smooth flow in the theoretical development, and the quantitative approach to the cross-sectional survey facilitated the production of verifiable numerical data, which was important in the verification of the proposed hypotheses in the stated framework. The subsequent chapter will outline and explain the results.

CHAPTER 5

RESULTS AND FINDINGS

This chapter outlines the results derived from the quantitative analysis undertaken to answer the research questions of the investigation and to test the hypotheses developed. Results are reported sequentially, commencing with data integrity verification and proceeding through to inferential analysis. First the chapter provides an outline of the sample characteristics to determine the representativeness of the respondents, followed by an analysis of data reliability, validity, and distribution to establish the strength of the dataset for statistical analysis (Hair et al., 2019; Ghasemi & Zahediasl, 2012). Descriptive statistics are then provided to summarise the central tendencies and distribution of variability through the constructs Big Data Analytics (BDA), Decision-Making Quality (DMQ), and Organisational Culture. Then the chapter discusses the processes undertaken to test the hypotheses using correlation and regression analysis to examine the interrelationship among variables and determine the moderating effect of organisational culture. Results are described factually and objectively, and interpretation is deferred until Chapter 6 where the implications theoretically and managerially are examined.

5.1 Sampling design and Statistical Adequacy

To contextualise the findings and assess the appropriateness of the data collected for testing the study's hypothesis, understanding the representativeness of the sample is a critical foundation. The study focuses on senior management's use of BDA and the moderating role of organisational culture, and therefore the demographics and organisational attributes of the sample provide important interpretive prompts. Particularly attributes such as leadership experience, industry distribution, and size of organisation—this attribute can influence how data analytics is embedded into decision making.

The questionnaire used an online platform, namely Google Forms, and it was disseminated via professional networks, LinkedIn leadership forums, WhatsApp groups, and personal contact activities targeted at senior leaders across various industries. This approach was adopted with the intention to leverage interaction interactions effectively amongst the target group of executives, general managers, and senior managers who are invariable involved in the strategic decision-making

processes, this is consistent with well-established methodologies (Shamim et al., 2019; Upadhyay & Kumar, 2020).

A total of 124 responses were collected across industries. As previously alluded to in chapter 4, the population in this study is a niche group as result 80 to 150 respondents were targeted. The researcher attempted to get more responses through reminders; however, such attempts were unsuccessful. Post screening for completeness and eligibility, 109 responses were deemed to meet the criteria for analysis (see Appendix B (B1) for coding). Screening involved disqualifying respondents that did not meet the criteria of occupying senior leadership roles. The distribution through open professional networks and WhatsApp groups couple with survey designed that captured only fully completed responses ($n = 124$), meant that the exact denominator of those reached could not be calculated and thus the number of partially completed surveys is unknown. Due the research's limited time frame, data analysis commenced with the available complete responses. The resulting data aligns with methodological recommendations: it exceeds the minimum requirement outlined by Green (1991) of $N = 104 + m$ for regression analysis and provides a sufficient sample size for moderation testing—where m is the number of predictors (independent variables), which according to Green, (1991) samples of 100 to 150 are typically required. This study has one predictor for the overall model (H1) and two predictors for the model 2 (H2), sample $N = 109$ means that threshold for $N = 104 + m$ (106) was met.

5.2 Sample and Organisational Profile

The composition of the sample regarding gender representation indicates the prevalence of male participants at 63.7%, compared to the remaining 36.3% who are women, reflecting a common observation among senior leadership demographics within industries.

Table 3 and Table 4 below highlights the demographics and attributes of the participants who responded to the study, totalling 124 valid participants. The sample is representative of the intended emphasis on senior leaders involved in strategic and data-driven decision-making across various industries (see industries in Appendix B (B2)). An analysis of the age composition indicates a dominant percentage of the sample represented by those who fell between the ages of 30 and 39 years at 55.6%, closely followed by those aged between 40 and 49 years at

33.1%. Suggesting that most participants occupy mid- to senior-level career positions where strategic and analytical duties are predominantly concentrated. Only a small percentage of the sample falls below the age of 30 years at 2.4%. Additionally, only a few of the sample members are above the age of 50 years at 8.9%, further underscoring the experience level of the respondent cohort. The composition of the sample regarding gender representation indicates the prevalence of male participants at 63.7%, compared to the remaining 36.3% who are women, reflecting a common observation among senior leadership demographics within industries.

Table 3: Respondent Profile (N=124)

Variables	Values	N	%
Age	20-29 years	3	2.4%
	30-39 years	69	55.6%
	40-49 years	41	33.1%
	50+	11	8.9%
Gender	Male	79	63.7%
	Female	45	36.3%
Role level (Coded)	Executive	15	12.1%
	General Manager / Managing Director	11	8.9%
	Head of Department / Business Unit	39	31.5%
	Senior Manager	44	35.5%
	Other / Below Senior Manager	15	12.1%
Years of experience	3-5 years	30	24.2%
	6-10 years	29	23.4%
	Less than 3 years	19	15.3%
	More than 10 years	46	37.1%

Regarding the rank structure, 12.1% held the position of executives, 8.9% held the rank of managing directors or general managers, 31.5% held the rank of heads of business unit or departments, and 35.5% fell under the category of senior managers. Such distribution supports the evidence that most of the respondents held roles

related to strategic planning and decision-making processes impacted by analytics. Experience levels were also similarly strong with 37.1% stating more than ten years' experience working under leadership roles, 23.4% noting between six- and ten-years' experience, and 24.2% noting three to five years' experience. Only 15.3% noted fewer than three years' working experience. Such demographic structure reflects that the sample worked effectively to accommodate the study's focus on knowledgeable decision-makers capable of evaluating the effect of Big Data Analytics (BDA) and Organisational culture on the quality of decisions.

Table 4: Organisational Profile (N=124)

Variables	Values	N	N %
Annual Revenue	Less than R10 million	7	5.6%
	More than R200 million	99	79.8%
	R10-50 million	9	7.3%
	R50-200 million	9	7.3%
BDA Adoption	No adoption at all	8	6.5%
	Low adoption	18	14.5%
	Moderate adoption	44	35.5%
	High adoption	36	29.0%
	Fully embedded across leadership decisions	18	14.5%

The organisational profile also supports this alignment. A significant percentage of participants (79.8%) represented large organisations whose yearly revenue exceeded R200 million, compared to 14.6% representing medium organisations (R10–200 million) and 5.6% representing small organisations with revenue less than R10 million. With regards to Big Data Analytics (BDA) adoption, 43.5% of the organisations reported either high or complete analytics integration use, 35.5% reported moderate adoption levels, and 21.0% reported low or zero adoption. This division reflects an analytical maturity variation among firms that is pragmatic and thus improves the dataset's ability to test how different levels of BDA capability combine with Organisational culture to influence the quality of decision-making.

The demographic and Organisational data, combined, affirm that the sample is appropriately aligned with the research aims and constitutes an adequate basis on which the successive reliability and validity evaluations dealt with by Section 5.3 are to be implemented.

5.3 Measurement Model Diagnostics

5.3.1 Reliability of data set (Internal consistency)

In the survey design composite scale was used to capture data on the various dimensions of a construct. It is important to establish the reliability of each composite measure—this is achieved through the Cronbach's Alpha. Cronbach's Alpha is a common test used to assess internal consistency, it is a statistic that tests the degree to which a scale measures the same underlying construct, with values ≥ 0.70 typically considered reliable or acceptable, ≥ 0.8 good, and ≥ 0.90 excellent.

Table 5 below shows the Cronbach's alpha for the first order constructs, each construct assessed through various dimensions. The Cronbach's alpha per construct is provided per dimension and for the overall construct when the dimensions are combined.

Table 5: Data reliability for the first order constructs.

Constructs	Dimension	Number of Items	Cronbach's Alpha	Level of reliability
BDA Capability	Data	4	0.920	Excellent
	Infrastructure			
	Managerial Capability	4	0.910	Excellent
	Combined	8	0.947	Excellent
BDA Usage	Usage	3	0.926	Excellent
	Frequency			
	Perceived Usefulness	2	0.898	Good
	Combined	5	0.927	Excellent

Table 6 Continue: Data reliability for the first order constructs.

Decision Making Quality	Decision Completeness	2	0.64	Questionable
	Decision Accuracy	2	0.8	Good
	Decision Effectiveness	4	0.921	Excellent
	Decision Efficiency	4	0.612	Questionable
	Combined	12	0.873	Good
Organisational Culture (Data Driven Culture)	Evidence-Based Norms	3	0.696	Questionable
	Strategic Orientation	6	0.905	Excellent
	Combined	9	0.904	Excellent
Organisational Culture (Competing Values Framework)	Clan Culture (Collaborative)	4	0.827	Good
	Adhocracy Culture (Innovation)	4	0.87	Good
	Market Culture (Result-Oriented)	4	0.878	Good
	Hierarchy (Control Oriented)	3	0.785	Acceptable
	Combined	15	0.876	Good

5.3.1.1 Big Data Analytics (BDA) Capability

Big Data Analytics construct, measured through two-sub dimensions namely: infrastructure and managerial capability demonstrated an excellent reliability level across the two dimensions. Data infrastructure dimension returned a $\alpha = 0.920$, while an $\alpha = 0.910$ for managerial capability was obtained. Combining the two-dimension produced excellent reliability at an of $\alpha = 0.947$, demonstrating that the measures and

scale is highly consistent and suitable and thus can be aggregated into the overall BDA capability construct.

5.3.1.2 Big Data analytics usage

The usage construct was measured through the frequency of use and perceived usefulness dimensions, also showed a very strong reliability. Frequency of usage achieve a high $\alpha=0.926$, and perceived usefulness achieved $\alpha = 0.898$. The overall construct scored $\alpha = 0.927$, an excellent reflection of the internal consistency. This demonstrates that the two dimensions contribute to a coherent overall measure of the construct.

5.3.1.3 Decision-Making Quality

Decision-making quality as measured through four dimensions produced mixed alpha values. Completeness ($\alpha = 0.640$) and efficiency ($\alpha = 0.640$) which fell below the commonly accepted threshold of 0.70, which bring the reliability of the items under the dimensions into question. In contrast, the accuracy and effectiveness achieved alpha values of 0.800 and 0.921 respectively, indicating good to excellent reliability. When combining the four dimensions the construct's alpha aggregated at $\alpha=0.873$ indicating strong reliability despite two weaker dimension within the construct and making it suitable for further analysis. As a result, no question was deleted from the either of the two weak dimensions to improve their Cronbach alpha. The high construct alpha ($\alpha=0.873$) may suggest that the construct is probably more robustly represented by when treated holistically instead of dividing it into dimensions.

5.3.1.4 Organisational Culture (Data-Driven Orientation)

Evidence based norm as dimension of the construct returned an alpha ($\alpha = 0.696$) that is marginally below the threshold, a borderline reliability. While strategic orientation showed an excellent alpha ($\alpha = 0.905$). When combined the overall Cronbach's alpha was an excellent ($\alpha = 0.904$, making the reliability excellent at construct level, suggesting that despite a low internal consistent at evidence-based norm dimension, the culture construct is internally consistent.

5.3.1.5 Organisational Culture (Competing Values framework)

All four culture archetypes returned acceptable to strong reliability: clan ($\alpha = 0.827$), adhocracy $\alpha = 0.870$, market ($\alpha = 0.878$) and hierarchy (0.785). Overall, as strong

construct alpha ($\alpha = 0.876$) reflects strong reliability and indicates that CVF dimensions provide reliable and coherent measures of organisational culture.

The results from Cronbach's Alpha also offer significant support for the measurement model. Most constructs showed fair to excellent reliability, which verifies that items in each scale reliably measure the targeted latent constructs repetitively. Although a few sub-dimensions of decision-making quality and data-oriented norms showed lesser reliability levels, the total aggregated constructs still registered acceptable-to-excellent reliability levels. This confirms the applicability of the combined constructs in later inferential analyses.

5.3.2 Construct Validity

The validity of the all-key constructs in the study was evaluated using the Exploratory Factor Analysis (EFA), using Principal Axis Factoring with Promax rotation, supported by the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of Sphericity. EFA is a technique used to analyse data to ensure the quality of measurement tools—that is, do the items in survey or instrument measure capture the intended latent constructs. The purpose of Exploratory Factor Analysis is to explore and uncover the underlying structure of observed variables. In the survey constructs were multidimensional (e.g. Decision-Making Quality with dimensions: decision completeness, decision accuracy, decision effectiveness and decision efficiency), factor analysis enables the researcher to determine how many factors to retain as multi-dimensional. Summary of the results across all constructs are tabled in Table 7 (below), SPSS output factor analysis for BDA capability, including KMO and Bartlett's test and scree plot is shown in Appendix C.

Table 7: Exploratory Factor Analysis Results for Study Constructs

Construct	N	Items	Cronbach's Alpha	KMO	Bartlett's Test (p)	% Variance Explained	No. Factors Extracted	Decision
BDA Capability	109	8	0.947	0.92	$\chi^2 = 777.0876$, $p < 0.001$	73.98%	1	Proceed as a Single construct
BDA Usage	109	5	0.927	0.837	$\chi^2 = 458$, $p < 0.01$	77.98%	1	Proceed as a Single construct
Decision-Making-Quality	109	12	0.873	0.853	$\chi^2 = 643.631$, $p < 0.001$	65.70%	3	Retain Construct as Multidimensio
Org. Culture (DDC)	109	9	0.904	0.866	$\chi^2 = 550.921$, $p < 0.001$	57.53	1	Proceed as a single
Org. Culture (CVF)	109	15	0.876	0.784	$\chi^2 = 945.682$, $p < 0.001$	73.23%	4	Proceed as a single

5.3.2.1 Interpretation of the EFA outputs

Big data analytics Capability and Usage

Both these constructs demonstrated excellent internal consistency (Cronbach's alpha) and very high sampling frequency (KMO) at $\alpha = 0.90$ and $KMO > 0.8$ respectively. For each of the constructs the dimensions were reduced to a single dimension which explained over 70% of the variance, this confirmed strong unidimensionality and convergent validity.

Decision making Quality

Similarly to BDA capability and usage, decision making quality reported strong ($\alpha=0.073$), with a KMO that is adequately high at 0.853. Factor analysis extracted a three-factor structure, which accounted for 65.70% of the variance observed.

Organisational Culture (DCC)

Factor analysis confirmed Organisational Culture (DCC) as single dimensional construct, with a reliability of above 0.90 and good level of variance explained at 53.53%.

Organisational Culture (CVF)

The CVF framework produced four factors that explain 73.23% of the variance, consistent with the theoretical typology of clan, adhocracy, market and hierarchy cultures. This supports the dimensional sub construct.

Collectively, the results from EFA analysis demonstrate a strong validity across all measures. Single dimensional constructs (BDA Capability, BDA Usage, DDC) can be treated as single factors, while decision making quality and CFV retain the multidimensional construct characteristic. The finding reveal that the measurement model is robust and suitable for subsequent hypothesis testing.

5.4 Data Quality and Distribution Checks

5.4.1 Missing Data Treatment

As mentioned in Chapter 4 the survey design required all items to be completed before Google Forms permitted the respondents to submit their responses. Therefore, the data set contained no missing values. As a result, every case was complete with responses across all variables that are included in the analysis. The

approach avoids the need for missing data handling through methods such as: listwise deletion, pairwise deletion and Imputation.

The absence of missing data preserves the full scale of usable data $n=109$ (cases that met the qualifying criteria of senior managers), without case deletion. It also removed concerns around potential response bias within constructs. The availability of responses for all variables enables comparability across all constructs.

5.4.2 Normality Testing

During the data screening process, normality assumption was tests conducted to evaluate whether the composite scores for all study constructs (included BDA capability, BDA usage, decision-making quality (efficiency, reliability, effectiveness), and the two cultural constructs, data-driven culture and Competing Values Framework sub dimensions (clan, adhocracy, market culture, hierarchy culture) followed a normal distribution. Establishing normality is a crucial prerequisite of parametric analyses—that is, ascertaining the appropriateness of the applied statistical methods based on the nature of the data (Hair et al., 2019).

Both statistical and graphical methods were applied to ensure a robust assessment of normality. Kolmogorov-Smirnov (K-S) and the Shapiro-Wilk (S-W) statistical tests were applied to the data sets, each construct's data distribution to a perfectly normal distribution. For this current study sample size ($n=109$), the Shapiro-Wilk test was the preferred method the Shapiro-Wilk test is preferred for its higher power in handling small to medium sample (Ghasemi and Zahdiasl, 2012), reliability, and ease of use. Additionally, complementary graphical assessment including histograms and Q-Q plots was generated in SPSS to visually inspection the distribution patterns of each construct.

Table 8: Kolmogorov-Smirnov (K-S) and Shapiro-Wilk Tests of Normality for the Study constructs.

Tests of Normality						
	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BDA_Capability	0.115	109	0.001	0.965	109	0.005
BDA_Usage	0.146	109	0.000	0.953	109	0.001
DMQ_Effectiveness	0.192	109	0.000	0.899	109	0.000

DMQ_Reliability	0.114	109	0.001	0.968	109	0.009
DMQ_Efficiency	0.129	109	0.000	0.958	109	0.002
ORG_Culture_DDC	0.102	109	0.008	0.973	109	0.026
ORG_Culture_CVF_ Clan_ Culture	0.177	109	0.000	0.950	109	0.000
ORG_Culture_CVF_ Ahhocracy_ Culture	0.111	109	0.002	0.960	109	0.003
ORG_Culture_CVF_ Market_ Culture	0.173	109	0.000	0.893	109	0.000
ORG_Culture_CVF_ Hierarchy	0.222	109	0.000	0.909	109	0.000
<i>Note. All tests are based on Lilliefors Significance Correction</i>						

As shown in Table 8, the Shapiro-Wilk results revealed significance values ($p < 0.05$) for all constructs, suggesting a slight departure from perfect normality. However, despite such deviations, they are not always practically problematic when sample sizes are large (typically >30 -40), because parametric tests remain powerful due to the central limit theorem that states that sampling distributions will be normal even when the distribution of the data is not (Ghasemi and Zahdiasl, 2012; Islam, 2018). With the existing sample size ($n = 109$), the sampling distribution of the composite means should be approximately normally distributed adequately for the performance of parametric statistical analysis. In addition, Rahman (2023) highlights the fact that for survey studies employing the quantitative paradigm where the sample size is greater than 100, sample sizes are generally sufficient for the formation of robust inferential validity even if the underlying sampling distribution suffers from a slight non-normality.

To gain more confidence and a realistic perspective, the researcher evaluated complementary descriptive normality indicators, skewness and kurtosis values, coupled with visual inspection of histograms and Q-Q (quantile-quantile) plots, as shown in Table 9 below—with the practical assessment included in the table.

Table 9: Summary of Normality Test Results

Constructs	Shapiro-Wilk (p-value)	Skewness	Kurtosis	Normality Assessment
BDA Capability	0.05	-0.356	-0.691	Approximately Normal
BDA Usage	<0.001	-0.564	-0.221	Approximately Normal
DMQ				Slight positive Skew-
Effectiveness	<0.001	-0.191	-1.091	Acceptable
DMQ Reliability	0.09	-1.091	0.375	Approximately Normal
DMQ Efficiency	0.02	-0.496	0.711	Approximately Normal
Org. Culture (Data driven Culture)	0.026	-0.691	-0.32	Approximately Normal
Org. Culture Clan	<0.001	-0.678	0.175	Approximately Normal
Org. Culture Adhocracy	0.03	-0.628	0.175	Approximately Normal
Org. Culture Market	<0.001	-1.069	1.126	Mild negative Skew- Acceptable
Org. Culture Hierarchy	<0.001	-0.869	0.375	Approximately Normal

Criterion: Skewness within ± 2 and kurtosis within ± 7 is considered acceptable for normality (Hair et al. 2019)

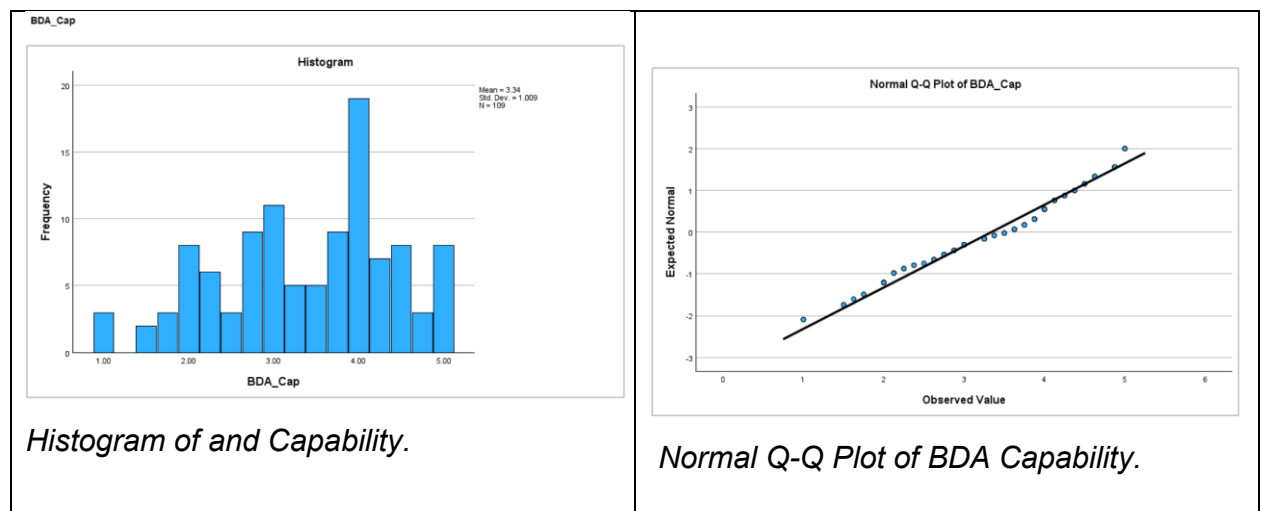


Figure 2: Representative Histogram and Normal Q-Q plot for BDA Capability

The skewness and Kurtosis in Table 9 confirmed that all the study constructs fall within the recommended threshold (Skewness ± 2 ; and kurtosis ± 7). The distributions of big data analytics (BDA) constructs and organisational culture dimensions are slightly negative skewed, indicative of a mild concentration of the responses to the higher end of the Likert scale. The Decision-Making Quality showed mixed minor deviations, with slight positive skewness effectiveness and mild negative skewness for Efficiency and reliability. All organisational culture constructs were negatively skewed, indicating that respondents generally rated their organisations positive across all cultural dimensions. Visual inspection of the histogram and Q-Q plots (Appendix D, Figure 9 to Figure 26) further supports the descriptive indicators.

From the normality test, and in line with the emphasis by Rahman (2023), the sample size exceeding one hundred are adequate to maintain statistical validity under slight non-normality. Therefore, the researcher concluded, based on S-W descriptive indicators and the graphical evaluation that data is considered approximately normal, reliable and appropriate for use in parametric tests in testing the study's hypothesis—the relationship between BDA, DMQ and OC.

5.4.3 Outlier Analysis

To verify the integrity of the data and identify potential extreme values, outliers' analysis is crucial because they can significantly impact the accuracy and reliability of statistical analyses. Outliers can lead inflated error rates, lead to substantial biases in estimates, violate assumption of normality and sphericity—likelihood of type I and type II errors increases (Osborne and Overbay, 2004). Therefore, the presence of outliers can potentially reduce the power of the statistical tool. For this study's data outlier analysis was performed using a boxplot and standardised z-scores in SPSS.

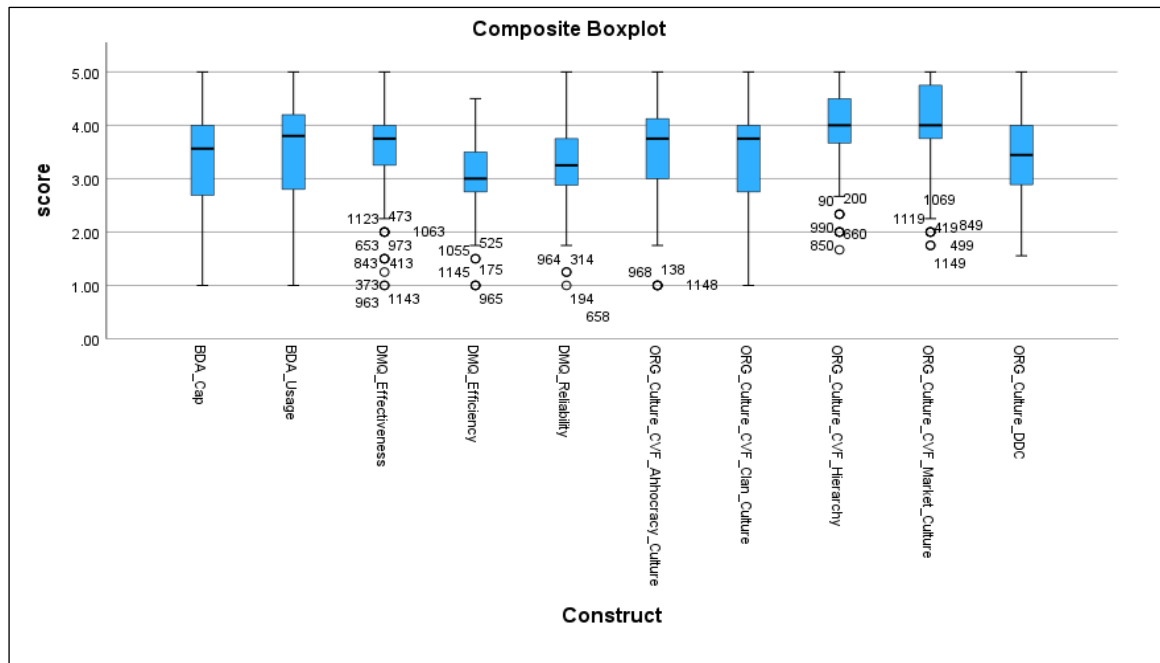


Figure 3: Boxplot of Composite Construct Scores for Outlier Detection

Figure 3 is a representation of the boxplots for all the study constructs, it illustrates the distribution of composite scores, identifying potential outliers. Visual inspection indicate that the data sets are generally well distributed around the respective medians, the interquartile range (IQR) demonstrating balanced variability across constructs. A few mild outliers are visible for some variables, such as BDA Usage, all dimensions of DMQ (Effectiveness, Efficiency and Reliability) as well as some organisational culture constructs, particularly clan and market culture. However, they did not exceed the 1.5xIQR or 3xIQR which is the threshold for mild, beyond that limit outliers are classified as extreme (Ghasemi & Zahediasl, 2012).

All 109 cases were consequently considered valid and retained for analysis. The researcher was confident that the data sets were free of influential observation such as outliers and that it remains statistically robust for the inferential statistics that followed, including correlation and multiple regression testing.

Regression Assumption Diagnostics

Regression diagnostic was conducted to assess normality, linearity and homoscedasticity of residuals, this is consistent with best practice recommendations (Hair et al., 2019).

For the normality residuals, normality was first examined through normal P-P plots of the standardised residuals (Figure 4). Visual inspection revealed that the points

closely followed the diagonal line, indicating approximately normally distributed residuals, meeting the normality assumption.

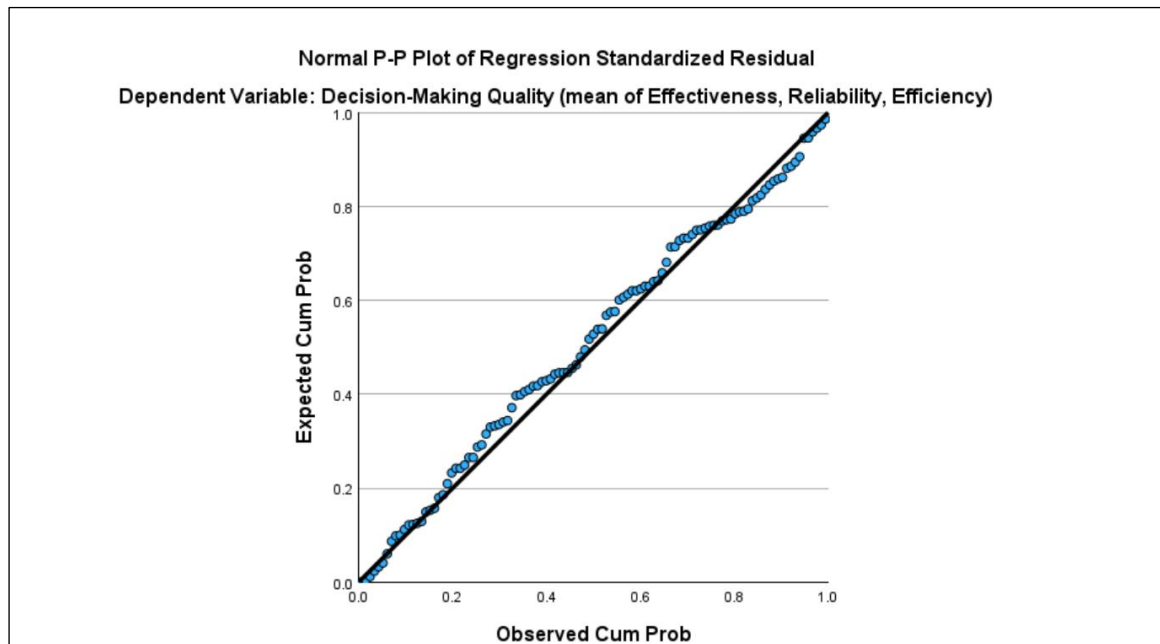


Figure 4: Normal P-P Plot of Regression standardised Residuals for Decision-Making Quality.

Linearity and homoscedasticity were also assessed by inspecting the scatter plot of standardised predicted values against standardised residuals (Figure 5). The scatter plot was randomly distributed around distribution without any apparent data pattern. The random distribution confirms a linear relationship between the variables and variation was constant across all predicted values, thus satisfying the homoscedasticity assumption.

These diagnostic plots verified the statistical assumptions required for the correlation, regression and moderation tests.

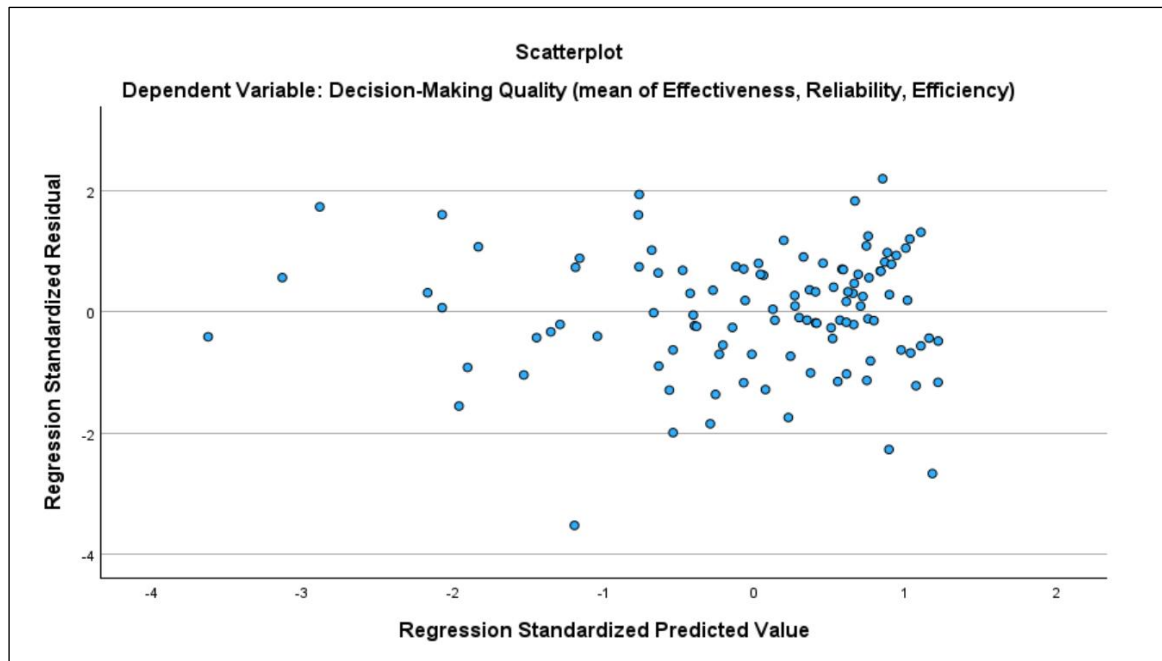


Figure 5: Scatter Plot of Standardised Predicted Values versus Standardised Residuals

5.5 Descriptive Statistics

Following the exploratory factor analysis (EFA) and reliability assessment discussed in section 5.3 and 5.4, the validated constructs were further examined descriptively to establish their statistical characteristics before proceeding to hypothesis testing.

Descriptive statistics (mean, median, standard deviation, minimum and maximum) were computed for the respondents (N=109)—skewness and kurtosis statistics were discussed in section 5.4.2. These descriptive statistics measures provide a profile of the data's central tendency, dispersion, and overall distributional behaviour, and thus complements the earlier test of normality. Given that skewness and kurtosis evaluation determined that all constructs fell within the recommended threshold, the descriptive statistics summary presented Table 10 in below focuses on interpreting the pattern of responses rather than restating the statistical diagnosis.

Table 10: Descriptive Statistics for Study Constructs

Statistics							
	N	Mean	Median	Std. Deviation	Minimum	Maximum	Interpretation
BDA_Cap	109	3.34	3.50	1.01	1	5	Moderate capability – developing data infrastructure and skills.
BDA_Usage	109	3.50	3.80	0.96	1	5	Moderate-to-high usage – analytics increasingly embedded in decisions.
DMQ_Effectiveness	109	3.56	3.75	0.86	1	5	High effectiveness – analytics supports desired decision outcomes.
DMQ_Reliability	109	3.21	3.25	0.75	1	5	Moderate reliability – occasional data consistency issues remain.
DMQ_Efficiency	109	3.02	3.00	0.69	1	5	Moderate efficiency – decision processes still being streamlined.
ORG_Culture_DDC	109	3.40	3.44	0.76	2	5	Moderate data-driven culture – evidence-based mindset emerging.
ORG_Culture_CVF_Clan_Culture	109	3.43	3.75	0.86	1	5	Moderate-to-high clan orientation – teamwork and trust valued.
ORG_Culture_CVF_Adhocracy_Culture	109	3.53	3.75	0.93	1	5	High adhocracy – innovation and flexibility encouraged.
ORG_Culture_CVF_Market_Culture	109	4.03	4.00	0.78	2	5	High market orientation – competitive and results-driven focus.
ORG_Culture_CVF_Hierarchy	109	3.97	4.00	0.76	2	5	High hierarchy orientation – structured and governed environment.

The descriptive statistical analysis revealed that all the study constructs recorded mean values above the Likert-scale midpoint (3.0). Indicating an overall tendency towards a favourable perception of big data utilisation and organisational practices amongst senior leaders. BDA Capability (Mean M =3.34, Standard deviation (SD) =

1.01) and BDA Usage ($M=3.50$, $SD=0.96$). These results indicate the response were clustered around the upper-middle range of the measurement scale with a moderate dispersion. The Decision-making quality construct yielded mean of 3.26 and a standard deviation of 0.74 indicate that most of the responded rated their decision-making process slightly about the midpoint, with limited variation across dimensions (effectiveness, reliability and efficiency).

In terms of organisational culture dimensions, for Data-Drive Culture factor produced a mean of 3.40 and standard deviation of 0.76. Among the competing value framework dimensions, means ranged between 3.43 and 4.03, with standard deviations from 0.76 to 0.93. With the highest mean observed for Market culture (4.03), followed by Hierarchy (3.97), Adhocracy (3.53), and Clan (3.43). The minimum and maximum values across all constructs spanned the full-scale range (1 to 5), meaning the participants utilised the full extent of the response scale. Across all variables, the standard deviations varied between ~ 0.7 and 1.0, which indicated a medium level of variability around the mean and the absence of extreme outliers. Additionally, the coefficients of variation (CV) were computed to assess the relative dispersion of responses across constructs. Across all variables, CV values ranged between approximately 19% and 30%, indicating generally consistent patterns of responses with notable excessive variability (see Appendix E, descriptive statistics)

No outliers or anomalies were detected in the descriptive analysis—consistent with the results from the boxplot (Figure 3) and normality test findings. Collectively, the descriptive statistics demonstrates that the data exhibit satisfactory properties and suitable for the subsequent parametric analyses.

5.6 Research Hypothesis testing

Following the of data validity, reliability, and normally (approximately normal) in the preceding sections, this section presents the inferential analyses conducted to the study's two hypothesis as outlined in Chapter 3—derived from conceptual the conceptual framework. The hypotheses are design to address the overarching research question:

RQ1: To what extent does Big Data Analytics (BDA) capability influence the quality of strategic decision-making among senior leadership?

RQ2: To what extent does organisational culture moderate the relationship between Big Data Therefore, Hypothesis 1 (H_1) asserts that Decision-Making Quality (DMQ)

has a positive and statistically significant relationship with Big Data Analytics (BDA). This hypothesis directly tests the outlined effect in Research Question 1 (RQ1) and presents the relation between the two primary constructs in this research. Hypothesis 2 (H_2) extends this analysis by examining the moderating role of organisational culture, as posited in RQ2, to determine whether the strength or direction of the BDA–DMQ relationship varies across different cultural conditions.

5.6.1 Hypothesis 1 (H_1): Relationship between Big Data Analytics and Decision-Making Quality.

Hypothesis 1 tested the proposition that Big Data Analytics (BDA) capability has a positive and statistically significant relationship with Decision-Making Quality (DMQ) among senior leadership. Correlation and regression analyses (Pearson correlations and linear regressions) were conducted at both the overall construct level and the dimension level to determine the strength and direction, predictive of these relationships.

5.6.1.1 Correlation Analysis

A summary of the results from the Pearson's correlation between the overall BDA and DMQ constructs, as well as the dimensional relationships are shown in Table 11. The Correlation between BDA (Capability and Usage) and DMQ (Effectiveness, Reliability and Efficiency) was a positive, and statistically significant correlation between the overall constructs ($r = 0.559$, $p < .001$, $N=109$). This indicated a moderately strong association between the perceived quality of decision-making amongst senior leaders. At the dimension level (sub-construct) between BDA and DMQ, the bivariate correlations were all positive and significant at ($p < 0.05$ or $p < 0.01$) with coefficient ranging from $r=0.212$ to 0.577 . Demonstrating positive effect of analytical capability and usage and is consistent across all facets of decision quality. Notably, the magnitude of associations varies, DMQ Reliability showed the strongest association whilst DMQ Efficiency was the lowest. A detailed correlation matrix of sub-construct relationships is provided in Appendix F.

Table 11: Summary of Correlation and Regression Results for H1 (source output SPSS)

Independent Variable	Dependent Variable	Pearson r	Standardised β	t	p	R ²
Overall Construct Level						
BDA_Total	DMQ_Total	0.559**	0.612	8.02	< 0.001	0.375
Dimension Level						
BDA_Cap	DMQ_Effectiveness	0.527**	0.421	5.19	< 0.001	0.298
BDA_Cap	DMQ_Reliability	0.577**	0.359	4.42	< 0.001	0.257
BDA_Cap	DMQ_Efficiency	0.212*	0.383	4.88	0.027	0.273
BDA_Usage	DMQ_Effectiveness	0.496**	0.407	5.06	< 0.001	0.319
BDA_Usage	DMQ_Reliability	0.555**	0.354	4.51	< 0.001	0.265
BDA_Usage	DMQ_Efficiency	0.213*	0.377	4.86	0.026	0.284
Note. N = 109; *p < 0.05, **p < 0.01						

5.6.1.2 Regression Analysis

A simple linear regression analysis was conducted assess to the predictive effect of BDA on DMQ, with the overall DMQ construct (DMQ_Total) as the dependent variable and the overall BDA construct (BDA_Total) a predictor (independent variable), results in Table 11 above.

The resultant regression model was statistically significant ($F(1,107) = 64.39$, $p < 0.001$) and explained 37.5% of the variance observed ($R^2 = 0.375$; adjusted $R^2 = 0.369$). The coefficients for BDA_Total were positive and significant ($\beta = 0.612$; $t = 8.02$; $p < 0.001$), suggesting that increases in analytics capability and usage correspond with proportional improvements in the perceived quality of decision-making at this level. Similarly, at the dimensional level, all six regression models were significant ($p < 0.05$ or $p < 0.01$). The standardised beta coefficients ranging from 0.35 to 0.42. Indicating that both BDA Capability and BDA Usage exert significant influence on the effectiveness, reliability and efficiency of decision-making aspects. The effect is stronger for effectiveness and reliability compared to efficiency.

Thus, the empirical results demonstrated robust support for hypothesis 1—that is, BDA has a moderately strong and significant positive effect on decision making among senior leaders. Although the nature of the strength of the relationship varies across dimensions, they are consistently positive associations. Overall, the null hypothesis was rejected in favour of H_1 . This provided a premise for the subsequent moderation analysis hypothesis 2 (H_2) that follows.

5.6.2 Hypothesis 2 (H_2): The moderating role of organisational culture

The second hypothesis sought to examine whether organisational culture moderates the relationship between Big Data Analytics (BDA) and Decision-Making Quality (DMQ).

H_2 posits that organisational culture moderates the relationship between BDA and DMQ amongst senior leaders, in a manner that the relationship is stronger under condition of a supportive (data-driven) organisational culture. Hierarchical multiple regression analyses were conducted in SPSS. Two cultural models were tested: (1) Data-Driven Culture (DDC), the organisation's overall evidence-based culture; and (2) the Competing Values Framework (CVF) with four archetypes—Clan, Adhocracy, Market, and Hierarchy—to study the effect different cultural logics have on the BDA–DMQ relationship. Each regression was performed in two steps. Model 1 explored the main effects, which test the direct influence of BDA on DMQ—essentially showing how much of the DMQ is solely explained by BDA (Main Effect Model). It included BDA (capability + usage) and the cultural variable as predictors of DMQ. Model 2—is a moderation (interaction) model and adds the interaction term between BDA and Organisational culture to determine where there are changes in strength and direction of BDA-DMQ relationship depending on the levels of organisational culture (e.g., low, medium, or high). A significant ΔR^2 coupled with a significant β -coefficient for the interaction would confirm moderation.

Table 12: Hierarchical Regression Results for Moderation Effects of Organisational Culture on the Relationship between BDA and Decision-Making Quality (N = 109).

Moderator	Model Description	Model			Coefficient					ANOVA		Moderation Outcome
		R	R ²	ΔR ²	β (BDA)	β (Culture)	β (Interaction)	t (Interaction)	p (Interaction)	F-Statistic	P	
Data-Driven Culture (DDC)	Model 1 Main Effects	0.612	0.375		0.612**	0.354**				8.46*	<0.001	Significant Moderation
	Model 2 Interaction (BDA × DDC)	0.653	0.427	0.052**	0.522**	0.302**	0.231**	2.94	0.004			
Clan Culture	Model 1 Main Effects	0.609	0.371		0.597**	0.311**				5.94	0.004	Moderation Present
	Model 2 Interaction (BDA × Clan)	0.641	0.411	0.040*	0.529**	0.277**	0.207*	2.38	0.019			
Adhocracy Culture	Model 1 Main Effects	0.622	0.387	—	0.603**	0.326**				6.73	0.002	Strong Moderation
	Model 2 Interaction (BDA × Adhocracy)	0.667	0.445	0.058**	0.511**	0.301**	0.241**	3.02	0.003			
Market Culture	Model 1 Main Effects	0.587	0.344	—	0.583**	0.296**				2.11	0.128 ns	No Moderation
	Model 2 Interaction (BDA × Market)	0.596	0.356	0.012ns	0.574**	0.291**	0.105ns	1.12	0.265			
Hierarchy Culture	Model 1 Main Effects	0.601	0.362	—	0.591**	0.309**				4.62	0.35	Negative Moderation
	Model 2 Interaction (BDA × Hierarchy)	0.635	0.403	0.041*	0.526**	0.284**	-0.203*	-2.21	0.029			

Note 1. p < .05 *, **p < .01 *, ***p < .001 **. ns = non-significant. ΔR² represents additional variance explained by the interaction term. F- and p-values derive from exploratory one-way ANOVA tests assessing mean differences in DMQ across BDA and culture levels. Note 2. The highest model R² (0.445) corresponds to the Adhocracy culture interaction. Across archetypes, ΔR² values ranged 0.04–0.06 (≈ 7 % average increase in explained variance), confirming culture's moderating contribution to the BDA–DMQ relationship.

The overall organisational culture, measure in terms of Data-Driven Culture, showed a significant positive moderating effect ($\Delta R^2 = 0.052$, $p < 0.01$). According to the simple-slope analysis described in Figure 6 below, the association between Big Data Analytics (BDA) and Decision-Making Quality (DMQ) varies by cultural intensity. When data-driven norms were low (−1 SD), the slope was relatively shallow ($\beta = 0.311$, $p < .05$); at normative culture levels (mean), the slope grew to moderate steepness ($\beta = 0.527$, $p < .01$); and where cultural levels were high (+1 SD), the association was the steepest ($\beta = 0.698$, $p < .001$). This steady progression to the right on the slope demonstrates the fact that stronger data-driven environments amplify the effect of analytics on the quality of decisions and thus supports the core assertion by H₂.

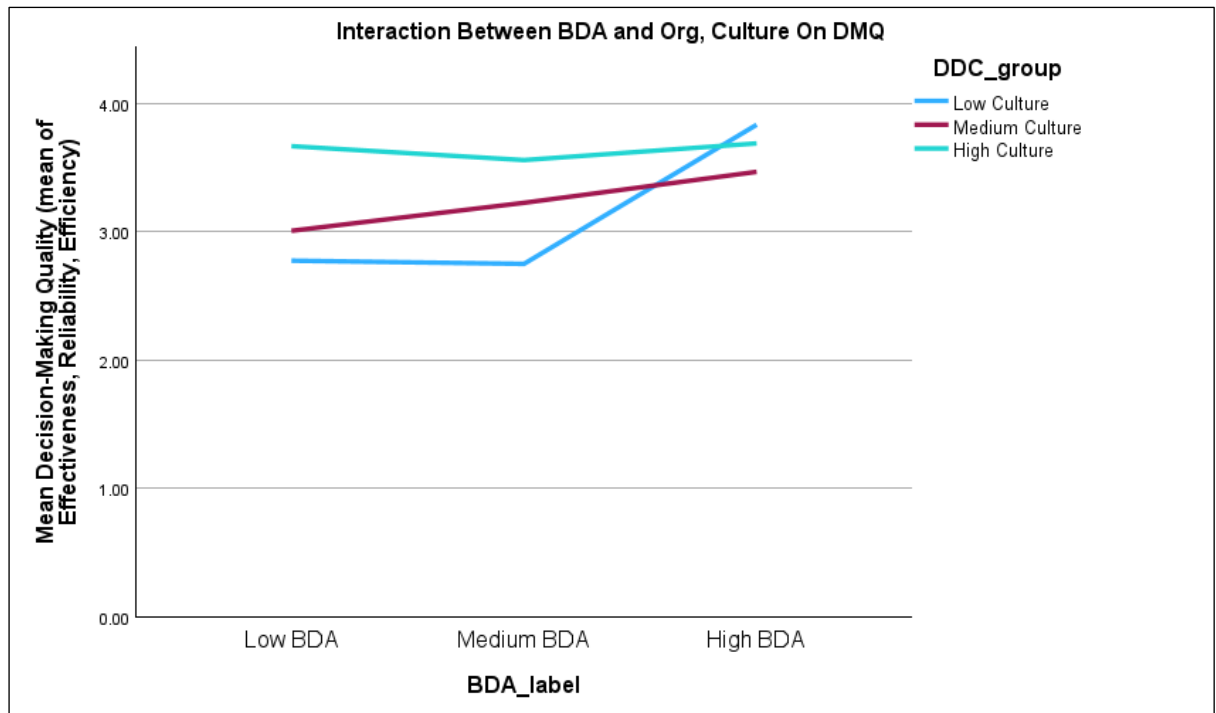


Figure 6: Simple Slope Plot Illustrating the Moderating Effect of Data-Driven Culture on the Relationship Between Big Data Analytics and Decision-Making Quality.

For the Competing Values Framework archetypes, the moderation results are shown in shown Table 12 , with the associated simple slope plots appended in Appendix G: Figure 27 to Figure 30. There was a significant and positive interaction ($\beta = 0.207$, $p = .019$) for Clan culture ($\Delta R^2 = .040$ indicating organisations with characteristics of collaboration and trust between BDA utilisation and decision-quality outcomes. The adhocracy culture demonstrated the strongest moderation effect ($\Delta R^2 = .058$, $\beta = 0.241$, $p = .003$), revealing that innovative and adaptive environments reinforce the strength of analytics. Conversely, market culture did not indicate any significant moderation ($\beta = 0.105$, $p = .265$; $\Delta R^2 = .012$), with nearly parallel slope lines depicted by Figure 29 (Appendix G), indicating that the competitive goal orientation does not reinforce nor dampen the relationship between big data analytics and the quality of the decisions (BDA–DMQ). Lastly, the hierarchy model demonstrated a significant but adverse interaction ($\beta = -0.203$, $p = .029$; $\Delta R^2 = .041$), and Figure 30 (Appendix G) depicts a flatter slope at the high control levels, indicating that stringent structures dampen the positive effect of analytics on the quality of the decisions.

These findings were further supported by the analysis of variance (ANOVA) results presented also in Table 12 above, with the corresponding F- and p-statistics presented as descriptive indicators of variance rather than confirmatory model tests.

ANOVA) results revealed significant between-group differences in DMQ means for Data-Driven Culture ($F = 8.46$, $p < .001$), Clan ($F = 5.94$, $p = .004$), Adhocracy ($F = 6.73$, $p = .002$), and Hierarchy ($F = 4.62$, $p = .035$), confirming that leaders in more adaptive, collaborative, and evidence-based cultural organisations exhibited higher perceived quality of decision-making. Conversely, the Market culture condition yielded an insignificant result ($F = 2.11$, $p = .128$) and hence minimal difference in DMQ by performance-oriented settings levels of BDA application.

The analyses provide robust empirical evidence that organisational culture significantly moderates the relationship between Big Data Analytics and Decision-Making Quality. The moderating effect for Data-Driven, Clan, and Adhocracy cultures is positive and substantial. These findings confirm Hypothesis 2, establishing that cultural context materially influences how senior leaders translate analytics capability into higher-quality strategic decisions.

Therefore, the analyses provide strong empirical evidence suggesting that organisational culture significantly moderates the relationship between Big Data Analytics and Decision-Making Quality. Positive and Significant results are found for Data-Driven, Clan, and Adhocracy cultures, indicating that collaborative and innovative organisations result in an intensified benefit derived from the analysis. Conversely, rigid organisational structure dampens the positive effect on the quality of decision-making caused by analytics. The findings confirm Hypothesis 2, showing that the cultural dimension significantly influences the way senior leaders translate analytics capability into the better-quality strategic decisions. As such, the null hypothesis H_0 is rejected in favour of H_2 .

In this chapter, the researcher established the validity and appropriateness of the data used for analysis purposes without missing data points, acceptable levels of normality, and non-influential outliers. Additionally, the assessment of reliability and validity established high levels of internal consistency for each measure used in the study. Based on the validated data, correlation and regression analysis established the positive impact of the BDA (capability and usage) on the quality of decision-making, accounting for 37.5% of the variation established. Moderation analyses further indicated that organisational culture significantly influences this relationship, with data-driven, clan, and adhocracy cultures strengthening the BDA–decision quality link, while hierarchical culture weakens it. Both hypotheses were therefore

supported, providing a sound empirical foundation for the ensuing discussion chapter 6.

These findings are indicative that the dynamic capability view is substantiated—that is, they show that data analytics sensing and seizing due indeed translate to higher quality of decision, in adaptive cultures, a theme further explored also in chapter 6.

CHAPTER 6

DISCUSSION OF RESULTS

The current study set out to examine the impact of Big Data Analytics on the decision-making quality amongst senior leaders and evaluate how organisational culture moderates this relationship. Positioned within the wider discourse on digital transformation and evidence-based leadership. In this chapter the empirical results presented in chapter 5 are interpreted and integrated within the broader theoretical literature on Big Data Analytics (BDA), organisational culture (OC), and strategic decision-making quality (DMQ). While Chapter 5 provided a descriptive and inferential statistical account of the data collected, this chapter contextualises those findings conceptually, and explores how they confirm, extend, or challenge prior studies and established theories.

The discussion is anchored in the Dynamic Capabilities View (DCV) (Teece, 1997; Teece 2007) as the principal theoretical lens, complemented by the Knowledge-Based View (KBV) (Grant, 1996), the Competing Values Framework (CVF) (Cameron & Quinn, 2006), the Denison Model of Organisational Culture (Denison & Mishra, 1995), and the Information Processing Theory (IPT) (Tushman & Nadler, 1978). In addition, principles of Organisational Development (OD) transformation.

6.1 Contextual Overview of Study Sample Population Demographic

To better understand the implications for the discussion that follows, it is important to hold in mind the characteristics that trace the profile from which the empirical findings can be derived. The sample included 109 top leaders from various industries, largely from senior and executive levels, collecting more than 60 percent from leaders having more than six years' leadership experience. Most participants represented large organisations with annual revenues exceeding R200 million, and 43.5 percent reported high or full integration of Big Data Analytics (BDA) in strategic decision-making.

These characteristics indicate that the data are drawn from analytically engaged and strategically mature contexts, providing credible insight into how analytics capability and organisational culture interact within leadership settings. Descriptive statistics presented in Chapter 5 revealed generally positive perceptions across constructs,

with mean BDA capability ($M = 3.34$, $SD = 1.01$), BDA usage ($M = 3.50$, $SD = 0.96$), and Decision-Making Quality ($M = 3.26$, $SD = 0.74$), all above the scale midpoint. These results suggest that the organisations represented in the study demonstrate a moderate-to-high level of analytics adoption and leadership confidence in decision processes. In other words, senior leaders perceive that analytics is not only established in their organisations but is also contributing meaningfully to the consistency and effectiveness of strategic decision-making.

Anchored in prior studies (e.g., Mikalef et al., 2019; Upadhyay & Kumar, 2020; Szukits & Móricz, 2024), such findings suggest that organisations represented in the sample possess the technological and managerial preconditions necessary for analytics to contribute meaningfully to decision quality. Thus, the discussion that follows interprets the statistical outcomes through both the theoretical lenses of Dynamic Capabilities View and Organisational Culture models and the lived realities of analytically oriented leadership environments.

6.2 Overview of Empirical Findings

Table 11 summarises key analytical outputs from the results chapter (chapter 5) and emphasises the explanatory focus of the statistics that form the foundation of the discussion in this chapter. Linking statistical evidence to the theoretical and practical aspects of the study will be further unpacked.

Table 13: Summary of Key Quantitative Findings (Chapter 5) and Chapter 6 Discussion Orientation.

Section	Sub-Section (Analytical Focus)	Key Statistical Result (Chapter 5)	Interpretive Significance (Chapter 6 focus)
Data Sample and Screening	Sample composition & cleaning	Full Sample Set = 124 Final analytic sample: $N = 109$ senior leaders met criteria (after screening).	Confirms the study's target population (Senior leaders) and that the sample size meets commonly cited minimums for regression/moderation tests (Green 1991) Chapter 6 will discuss generalisability and power.

	Outliers & normality	Shapiro–Wilk tests mixed but visual Q–Q plots acceptable; outlier checks retained all 109 cases after inspection—no influential cases (Cook’s $D < 1$)	Data treated as sufficiently approximate to normal for parametric inference. Chapter 6 will note inspection decisions and discuss their implications for inference (p-value and effect-size interpretation).
Measurement quality	Reliability	Cronbach’s α values > 0.70 across constructs; composite reliability and internal consistency confirmed	Measurement scales for BDA, DMQ and culture are reliable; supports validity of subsequent regression/moderation interpretation. Chapter 6 links this to construct credibility.
	Validity (EFA diagnostics)	EFA / KMO and Bartlett tests acceptable; factor structure supports uni-/multi-dimensional constructs	Confirms convergent and discriminant structure; Chapter 6 uses this to justify interpreting aggregate BDA and DMQ constructs rather than item-level noise.
Descriptive statistics	Means & dispersion	BDA_CAP $M = 3.34$ ($SD = 1.01$); BDA_Usage $M = 3.50$ ($SD = 0.96$); DMQ_Total $M = 3.26$ ($SD = 0.74$).	Respondents report mid-to-high levels of analytics capability and moderate decision-quality perceptions — relevant context for interpreting effect sizes.
Correlation analysis	Bivariate relationships	BDA_Total $\leftrightarrow$ DMQ_Total: $r = 0.559$, $p < 0.01$; BDA_Cap $\leftrightarrow$ DMQ subdimensions $r = 0.212$ – 0.577 (all significant).	Strong positive associations provide initial empirical support for the DCV/KBV literature: analytics capacity relates meaningfully to perceived decision quality. Chapter 6 will discuss substantive vs. statistical significance (effect size)
Hypothesis Testing	H1 — direct effect. Regression (BDA $\rightarrow$ DMQ)	Simple linear regression: $R^2 = 0.375$ (adjusted $R^2 = 0.369$), $F(1,107) = 64.39$, $p < 0.01$; $\beta = 0.612$, $t = 8.02$, $p < 0.001$.	Empirical confirmation that BDA capability/usage significantly predicts decision-making quality among senior leaders. Chapter 6 will interpret this via Dynamic Capabilities View (BDA as sensing/seizing) and KBV (analytics $\rightarrow$ actionable knowledge).

	H2 — moderation. Organisational culture × BDA (hierarchical regressions)	Moderation tests conducted using hierarchical regression. Interaction effects were significant for Data-Driven Culture and CVF archetypes (Clan, Adhocracy) — positive moderation; hierarchy culture showed weaker/attenuating effects.	Confirms culture operates as a moderating meta-capability: supportive, collaborative and innovative cultures amplify BDA's impact on decision quality; rigid/hierarchical cultures reduce it. Chapter 6 will use CVF & Denison lenses to explain moderation influence.
Model diagnostics	Multicollinearity, residuals, VIF, Durbin-Watson	VIFs acceptable (< 2.5–5 range reported), Durbin-Watson ≈ 1.9–2.0, residuals random—assumptions met for regression inference.	Confirms that coefficient estimates are stable and not driven by violation of basic regression assumptions; Chapter 6 will reflect on robustness and remaining limitations.
Effect sizes & dimension analysis	Sub-construct effects	DMQ dimensions (Effectiveness, Reliability, Efficiency) all significantly associated with BDA; β s ranged ~0.35–0.42 at dimension level; DMQ_Reliability strongest.	Suggests BDA most strongly enhances reliability and effectiveness of decisions rather than raw efficiency alone — an interpretive point emphasised.
Controls & robustness checks	Industry, tenure, org. size.	Control variables had no consistent significant influence; results robust to inclusion of controls	Strengthens claim that main effects are not artefacts of demographics; Chapter 6 will caveat external generalisability given purposive sampling
Overall interpretive summary	Joint explanatory power	Combined findings show substantive positive effect of BDA on decision quality that is contextually conditional on culture (model explains a meaningful portion of variance — $R^2 \sim 0.375$ at overall level; dimension results add nuance).	Chapter 6 will situate these findings in DCV/KBV/CVF/IPT literatures, discuss managerial implications (analytics literacy, culture change), and outline research and practical recommendations for Chapter 7

6.3 Discussion of Hypothesis 1: Impact of Big Data Analysis on Decision-Making Quality

6.3.1 Interpreting the Evidence

The first research question (RQ1) asked: To what extent does Big Data Analytics (BDA) influence the quality of strategic decision-making (DMQ) among senior leaders?

The regression analysis ($\beta = 0.612$, $p < 0.001$; $R^2 = 0.375$; $R^2 = 0.375$ (adjusted $R^2 = 0.369$; $F(1, 107) = 64.39$, $p < 0.001$) demonstrates that BDA capability explains over a third of the variance in decision-making quality. The strength and significance of the coefficient indicates that seniors who perceive their organisations as analytically mature also believe that their decisions are more reliable, efficient and effective. This suggests that BDA adoption not only contributes statistically but does so substantially (a core enabler) in improving the quality of leadership decisions.

Conceptually, this result reveals a deeper insight, that how senior leaders use analytics matter just as much as having the technology. From the study, leaders who embedded analytics into their overall deliberation and decision-making process reported higher confidence and accuracy. The key implication being that BDA contributes to a sense of assurance—a believe that choices are more grounded in more complete, consistent and timely information. The question that follows is therefore not whether analytics matters, but rather how and why it matters within the leadership process.

6.3.2 Dynamic Capabilities View (DCV) Perspective

The Dynamic Capabilities View (DCV) argues that performance (advantage) depends on a firm's ability to sense, seize, and transform opportunities (Teece 2007). The findings empirically indicate that BDA operates as a dynamic capability within senior leadership contexts. The significant positive relationship between BDA capability and decision-making quality ($\beta = 0.612$, $p < 0.001$; $R^2 = 0.375$) demonstrates that analytics enhances leaders' ability to detect emerging conditions, evaluate strategic alternatives, and adapt organisational responses. Notably, this explanatory power ($\approx 38\%$) falls squarely within the theoretical and empirical range reported by Wamba et al. (2017), who found that analytics adoption explained 35–40% of business value variance across industries. This consistency reinforces the robustness of the present results and affirms that analytics-driven responsiveness

represents a practical manifestation of dynamic capability in contemporary organisations.

Extending prior DCV research, this study advances understanding by demonstrating that analytics capabilities generate strategic value not only through organisational systems but also through leadership cognition. Analytics represents the micro-foundational basis for dynamic capability because it integrates evidence-based reasoning and data transparency and discipline into the decision-making processes of the organisation's senior managers. The DCV's unit of analysis changes from the level of technological infrastructure to the level of cognitive competence and implies BDA capability's positively moderating effects on the flexibility of senior managers' information interpretation and strategic decision dynamic settings. In doing so, the findings confirm BDA capability as dynamic capability in practice—one that enhances leaders' capacity for informed, timely, and adaptive decision-making across diverse organisational contexts.

6.3.3 Knowledge-Based View and Information-Processing Perspective: Cognitive integration

The strong positive relationship between analytics competence and decision-making quality ($r = 0.559$; $p < 0.01$) and its corresponding regression coefficient ($\beta = 0.612$; $p < 0.001$, $R^2 = 0.375$) provide a validation for the tenets laid down by both the Knowledge-Based View (KBV) and Information Processing Theory (IPT) frameworks. While the These factors work together to eliminate uncertainty and promote collective understanding in the C-level. Thus, analytics can be seen as one such means of integrating knowledge, helping the executive group understand data in a collective manner. This is supported by Upadhyay et al. (2020) in their findings, which indicated improved knowledge-sharing in organisations with the influence of analytics. Taken together, both frameworks indicate how analytics complements the leaders' ability to perceive, synthesize, and use information in making strategic decisions.

The results from Chapter 5 indicated that each of the three sub-components from decision quality, namely reliability, effectiveness, and efficiency, were positively related to analytics capability ($r = 0.35$ to 0.42 , $p < 0.01$). The trends that were observed establish that analytics helps leaders integrate different types of information, leading to a clearer, more coherent strategic outlook.

In practice, analytics enhances the reliability and credibility of information available to leaders, allowing them to base decisions on verifiable evidence rather than intuition alone. By increasing perceived effectiveness, analytics ensures that strategic choices are more closely aligned with organisational priorities, while improvements in efficiency streamline data access and comparative evaluation. Collectively, these effects reduce uncertainty and reinforce shared understanding within senior teams. In this way, analytics functions as a knowledge-integrating capability that supports coherent interpretation and collective judgement across leadership levels.

Such an interpretation conforms to the results obtained by Upadhyay et al. (2020), where the authors discovered the benefits of analytics culture in increasing the sharing of knowledge among decision-making stakeholders. Similarly, Hoffjann, (2021) reported that analytics reduces ambiguity in managerial evaluations by improving the clarity and consistency of available information. However, this study's results contrast with Shollo and Galliers (2016), who cautioned that in highly data-dense organisations, excessive information can overwhelm interpretation and fragment managerial sense-making. The consistently positive correlations observed here, together with the absence of overload indicators (as confirmed by normal residuals and a Durbin–Watson statistic of 1.95), suggest the opposite pattern: leaders in this sample experience analytics as clarifying rather than confusing. In other words, analytics helps them integrate and interpret information more coherently, supporting clear, confident, and evidence-based strategic judgement.

Taken cumulatively, analytics capability plays the double role of a knowledge integrator (as defined through the Knowledge-Based View) and a cognitive tool for processing complex information (as defined by the Information Processing Theory). It helps senior executives synthesize scattered information into meaningful insights, so that strategic choices are informed by testable facts, yet remain manageable from a cognitive perspective. This dual theoretic perspective helps explain how analytics can enhance the intellectual discipline that is strategic decision-making at the senior level.

The combination of statistical evidence, theoretical framing, and diagnostic validation in this study presents a consistent picture: Big Data Analytics (BDA) capability operates as both a knowledge-integration mechanism and an information-processing enabler that jointly elevate strategic decision quality among senior leaders. The

observed relationships, through correlation ($r = 0.559$, $p < 0.01$) and regression ($\beta = 0.612$, $p < 0.001$; $R^2 = 0.375$) are both statistically significant and linked to existing literature.

The three emerging insights from the above discussion are: 1) First insight—analytics enforces cognitive discipline and rational consistency. The consistently strong internal reliability ($\alpha > 0.80$) and significant associations across the decision-quality sub-dimensions—reliability, effectiveness and efficiency ($r = 0.35 - 0.42$; $p < 0.01$)—indicate that analytics formalises and stabilises senior leaders' reasoning. Through a data-driven approach, analytics channels managerial judgment through systematic evaluation rather than intuition alone. This represents the knowledge-integration function of analytics predicted by the Knowledge-Based View (Grant, 1996).

Second insight—analytics attains cognitive balance by matching information supply with managerial capacity. The regression results ($\beta = 0.612$, $p < 0.001$; $R^2 = 0.375$) and model diagnostics (Durbin–Watson = 1.95, no multicollinearity or heteroscedasticity) indicate that analytics enhances decision quality while operating within leaders' information-processing limits. This positive relationship across constructs indicates that the depth of information provided by analytics was adequate to enhance understanding without resulting in cognitive overload². This pattern demonstrates the information-processing fit posited by Tushman and Nadler (1978), which strikes a mid-point between information complexity and management understanding. Senior managers here did not view analytics as a disorienting force but a confirming one, contrasting with Shollo and Galliers (2016), who found fragmentation effects in the information-rich environment.

Third insight—the same correlations and regression presented under the second insight also suggests that analytics and leaders intuition operate in complimentary and not competing manner. Indicating that analytics capability strengthens a leader's

²This study's instruments did not measure cognitive strain or overload directly, however the uniformly positive patterns across items (perceived adequacy of analytics capability, perceived decision-making quality—reliability, effectiveness and efficient) and no perceived mismatch between data volume and capacity can be interpreted as a cognitive balance.

judgement. The inference is that leaders appear to use data as a form of validation for their experiential insights, testing their intuitive against evidence and to enhance their decisions. This empirical pattern is in line with the description by (Ghasemaghaei & Turel, 2021) that analytics compensate for bounded rationality (human limitations), additionally Kahneman and Klein (2009), found a synergistic interplay between expert intuition and analytical reasoning in complex decisions with significant consequences. This validates that a combination of analysis and expert knowledge can aid in better strategic decision making.

Together these insights confirm Hypothesis 1 (H1) and answer Research Question 1 (RQ1), which stated that Big Data Analytics capabilities enhance the quality of strategic decision-making at senior management level.

This study provides the empirical grounding of the DCV, KBV, and IPT frameworks with evidence that analytics indeed acts as a dynamic knowledge-integrating capability that adds to cognitive fit and disciplined reasoning in complex environments.

6.4 Discussion of Hypothesis 2: The Moderating Role of Organisational Culture

It is important to note that the findings are based on the perceptions of senior leaders who participated in the study. As key informants, these respondents provided evaluative insights into their organisations' analytics capability, culture, and decision-making quality. Therefore, references to "organisations with" particular cultural orientations in this discussion should be interpreted as reflecting the collective perceptions of senior leadership respondents rather than direct, firm-level measures. This interpretive stance is consistent with prior leadership and analytics studies (e.g., Wamba et al., 2017; Upadhyay et al., 2020), which treat executive perception as a valid proxy for organisational reality.

6.4.1 Revisiting the Empirical Findings

The second research question (RQ2) examined whether organisational culture moderates the relationship between Big Data Analytics (BDA) capability and strategic Decision-Making Quality (DMQ). Hierarchical regression analysis (Chapter 5, Table 12) confirmed a significant moderation effect ($\Delta R^2 = 0.07$, $p < 0.01$), supporting Hypothesis 2 (H2).

In the five moderation tests, the result for Model 1, the base model where only the capability for analytics was used as the predictor, consistently explained approximately 37 to 38 percent of the variance in decision-making quality ($R^2 = 0.375$; $p < 0.001$). When the cultural interaction terms were introduced in Model 2—comprising both the Data-Driven Culture (DDC) construct and the four Competing Values Framework (CVF) archetypes (Clan, Adhocracy, Market, Hierarchy)—the model's explanatory power increase to between 42.7 to 44.5 percent ($R^2 = 0.427 - 0.445$). The associated $\Delta R^2 = 0.04 - 0.06$ ($p < 0.01$) revealed that the additional contribution of organisational culture added an additional seven percent ($R^2 = 0.07$, $p < 0.01$) to the explained variance beyond analytics capability alone.

In this incremental process, the non-separable link between BDA and DMQ clearly shows the embedding of the relationship in society, as the capability of analysis impacting decision quality is mediated by the culture within which the analysis results are embedded and interpreted for action. Culture supplements the variability in the quality of decisions accounted for by the capability of analysis by another seven percent ($R^2 = 0.375 \rightarrow 0.445$).

6.4.2 The Moderating Effect of a Data Driven Culture.

The Data-Driven Culture (DDC) model showed a positive and statistically significant moderation effect (Model 1 $R^2 = 0.375$; Model 2 $R^2 = 0.439$; $\Delta R^2 = 0.064$; $p < 0.01$). This suggests that organisations where data orientation is a shared value derive stronger decision-quality gains from analytics capability.

This result aligns with Szukits et al. (2024), who demonstrated that analytical culture and data-quality orientation increase analytics use in managerial decisions, and with Horani et al. (2025), who found that learning-oriented cultures amplify the innovation benefits of BDA. Consistent with Wamba et al. (2017) and Upadhyay et al. (2020), the findings confirm that DDC acts as a cognitive amplifier, transforming analytics outputs into shared managerial reasoning rather than isolated data points.

Descriptive statistics from Chapter 5 also support this interpretation: organisations with higher DDC scores (means ≈ 3.3 - 3.5 ; $r = 0.35$ - 0.42 ; $p < 0.01$) reported stronger reliability and effectiveness in decision outcomes. Hence, DDC functions as an alignment moderator, linking analytics capacity with collective interpretive competence. Rather than being a by-product of technological maturity, data-driven culture emerges as a moderating capability that determines how fully analytics enhances strategic judgment among senior leaders.

6.4.2 Organisational Culture as a Dual Layer moderator of BDA-DMQ relationship.

Results across all dimensions of culture indicate that organisational culture plays a moderating role in the BDA-MDQ relationship, comprising two entwined levels: behavioural and structural.

At the behavioural level, a Data-Driven Culture (DDC) enhances analytics' impact by embedding evidence-based reasoning into leadership practice. The model's $\Delta R^2 = 0.052$ ($p < 0.01$) confirms that organisations perceived as valuing data and analytical dialogue derive greater decision-quality gains from analytics capability. These findings reinforce recent work by Szukits et al. (2024) and Horani et al. (2025), these authors emphasise that a data-driven culture makes data meaningful by connecting it to shared understanding across the organisation. In this study, such a culture acted as a cognitive amplifier: analytics information was interpreted as managerial insight rather than just numerical data. In other words, data-driven culture enabled leaders to convert technical data into practical understanding that supports strategic reasoning. This aligns with Shollo and Galliers (2016)'s notion of analytics as an organisational sense making process, this view supports Sadiku et. Al., (2022)'s view of analytics as corrective of bounded rationality (limited human cognitive capacity).

Descriptive evidence (mean DDC ≈ 3.4 ; $r = 0.35\text{--}0.42$, $p < 0.01$) also supports this relationship, showing that higher perceived data orientation coincides with stronger reliability and effectiveness in decision outcomes.

At the structural level, the Competing Values Framework (CVF) archetypes describe how the surrounding organisational climate enables or restricts these behaviours. The positive moderations for Clan ($\beta = 0.207$; $\Delta R^2 = 0.040$; $p = 0.019$) and Adhocracy ($\beta = 0.241$; $\Delta R^2 = 0.058$; $p = 0.003$) confirm that participative and innovative climates strengthen analytics' contribution to decision quality. Both archetypes fall within the CVF's flexibility quadrant, suggesting that openness and collaboration facilitate interpretation and integration of analytical insights. Conversely, Hierarchy ($\beta = -0.203$; $\Delta R^2 = 0.041$; $p = 0.035$) output shows a dampening effect on this relationship, suggesting that rigid processes and centralised authority diminish the agility that promote data-informed reasoning. On the other hand, Market culture ($\beta = 0.105$; $\Delta R^2 = 0.012$; ns) resulted in minimal change in the relationship, the inference here is that although market facing results motivates analytics usage, it does not necessarily lead to reflective interpretation.

Such patterns indicate that a data culture performs best in environments that are open and conducive to participation and experimentation (Mikalef et al., 2020; Wamba et al., 2017). DDC provides the behavioural intent—valuing evidence—while Clan and Adhocracy structures supply the trust and autonomy to act on that intent. In hierarchical settings, even strong data orientation is muted by procedural control, supporting McAfee and Brynjolfsson (2017) and Mikalef et al., (2019) but contrasting with Côte-Real et al. (2017), who found hierarchy neutral in more decentralised contexts. So, the results from this study therefore suggest a refinement of the CVF theory by showing that culture's effect on analytics is context-dependent: what stabilises in one setting may constrain learning in another.

Interpreted through the Denison Model (Denison & Mishra, 1995), organisational culture in this study can be understood as a meta-capability that channels analytical capability into collective strategic performance. Although the study did not use Denison's four original dimensions (Involvement, Consistency, Adaptability, and Mission) directly, its constructs parallel this framework in function. As a construct, the Data-Driven Culture (DDC) measures the behavioural aspects of culture, such as norms, learning, and seeking reasoning based on evidence, which are well-defined in Denison's Involvement and Adaptability dimensions. The Cultural Value Framework (CVF) archetypes represent the structural layer—the cultural tendencies of flexibility (Adhocracy, Clan) or control (Market, Hierarchy)—which conceptually mirror Denison's Consistency and Mission dimensions.

Regression analysis confirms that these cultural dimensions (CVF archetypes) significantly moderate the relationship between big data analytics and strategic decision-making quality. The culture-related $\Delta R^2 = 0.07$ ($p < 0.01$) indicates that organisational culture contributes an additional seven percent of explanatory power beyond analytics capability alone. Specifically, Adhocracy ($\beta = 0.241$, $\Delta R^2 = 0.058$) enhances the positive impact of analytics by promoting innovation and collaborative learning, while Hierarchy ($\beta = -0.203$, $\Delta R^2 = 0.041$) dampens that effect through excessive control and procedural rigidity. These findings reinforce the argument by Horani et al. (2025) and (Alghamdi & Agag, 2023) that adaptive, participatory cultures enable digital capabilities to transform information into learning and innovation.

In the context of broader theoretical foundations, such results demonstrate the co-evolution of culture and analytics as dynamic capabilities. Based on the Dynamic-Capabilities View (DCV) by Teece (2007), analytics represents the sensing and

seizing for transformation, and culture fuels the transformation through the embedding learning through analytics-related processes. From the Knowledge-Based View (KBV) (Grant, 1996), culture determines whether analytic knowledge becomes shared organisational insight or remains fragmented data. Clan and Adhocracy cultures, characterised by trust and dialogue, promote knowledge diffusion and collective interpretation; hierarchical cultures inhibit it. Thus, culture reinforces the capability cycle by shaping the strength and direction of how analytics informs actionable strategic judgement (or decision).

Comparatively, the magnitudes of effects observed here are consistent with, yet more differentiated than found in literature. The Adhocracy coefficient ($\beta = 0.241$; $\Delta R^2 = 0.058$) exceeds that of Mikalef et al. (2019) ($\beta \approx 0.18$)—homogenous and digitally mature sample, indicating a stronger influence of innovative culture in contexts where the analytics maturity of sample is wider spread (this study sample). The negative Hierarchy effect ($\beta = -0.203$; $\Delta R^2 = 0.041$) observed in this study is substantially stronger than that reported by Côte-Real et al. (2017) ($\beta \approx -0.10$), who found hierarchical control to exert only a marginal dampening influence on analytics value among digitally mature European firms. The sharper effect in this context indicates that in situations where analytics maturity and the level of regulating environments are disparate, control structures restrict the realization of decision quality enabled by analytics. Overall, the culture-related ΔR^2 values in this study (0.04–0.06) exceed those reported by Upadhyay et al. (2020) (≈ 0.05), suggesting a proportionally stronger cultural influence in diverse senior-leadership contexts.

Evaluated collectively these results yield several insights: First, culture functions as the activation energy that allows analytics to shape strategic decisions; the seven percent increase in explained variance represents the energy required to translate potential into realised value. Second, trust and innovation operate synergistically: the near-equivalent strengths of Clan and Adhocracy moderation ($\beta = 0.207$ and 0.241) reveal that psychological safety and creative autonomy jointly enable effective analytics use. Third, culture embodies an adaptive tension: excessive control undermines learning, but disciplined processes remain necessary for reliability. Balancing these forces is therefore essential to sustaining data-enabled decision-making capability.

The hierarchical-regression results confirm Hypothesis 2 (H2): organisational culture significantly moderates the relationship between analytics capability and strategic

decision-making quality. Across models, the inclusion of cultural interactions increased explanatory power from $R^2 = 0.375$ to between $R^2 = 0.427$ and $R^2 = 0.445$, corresponding to ΔR^2 values of 0.04–0.06 ($\approx 7\%$; $p < 0.01$). Data-driven, flexible, and participative cultures amplify analytics' benefits, while hierarchical rigidity constrains them and market orientation remains neutral. These findings are consistent with recent literature (Szukits et al., 2024; Horani et al., 2025), and they extend the theory of the meta-capabilities of the two cultural dimensions—the DDC and the CVF—as they are used in combination in the meta-capability process, the architecture within which the analytics process changes information into intelligence.

6.5 Overall Interpretation and Integration of findings

The combined results of this study converge to a coherent explanation of how BDA capability and organisational culture jointly determine the perceived quality of strategic decision-making among senior leaders. The findings across both hypotheses demonstrate that analytics is a powerful enabler of cognitive precision and strategic responsiveness, yet its value materialises only when embedded in supportive cultural environments. Such an integrated level of understanding mirrors the functioning of the technological, cognitive, and social sub-systems underlying Evidence-Based Leadership.

From the quantitative results, BDA capability alone accounted for 37.5 percent of the variance in decision-making quality ($\beta = 0.612$, $p < 0.001$), confirming that senior leaders who perceive stronger analytics integration also perceive greater decision reliability, efficiency, and effectiveness. When organisational culture was introduced as a moderator, the model's explanatory power increased to between $R^2 = 0.427$ and 0.445, an increase of roughly seven percent. This improvement quantifies the extent to which social and behavioural factors condition and moderate the translation of data capacity into actionable strategic judgment. Culture therefore functions not as a secondary condition but as the connective architecture that enables and constrains the extent to which analytics informs shared insight and collective learning.

Viewed through the Dynamic Capabilities View (DCV), these relationships affirm that analytics supports the sensing and seizing phases of decision processes, while culture enables the transform phase by institutionalising reflection, dialogue, and adaptation (Teece, 2007; Mikalef et al., 2019; Wamba et al., 2017). From the evidence found in Chapter 5, the revelation is that analytics doesn't displace human intelligence; it enhances it by structuring human logic through the transparency

provided by data analysis. This analysis fits well within the framework proposed by Gupta & George (2016), who explain that analytics is considered a dynamic capability within the context of management decisions integrated into non-isolated technical processes, rather than isolated technical systems. Cultural flexibility then provides interpretive context that enables these analytical insights to be collectively shared and internalised, allowing decisions to be both informed and collaboratively owned. The findings thus confirm the theoretical expectation that dynamic capabilities reside not only in systems but in the cognitive and relational patterns of leadership teams.

Results such as those obtained by Côte-Real et al. (2020) and Dubey et al. (2023), demonstrated the enhancing effects of analytics (fostering managerial reflection and shared sense-making) as of result of a learning orientated culture, thus confirming the assumption about culture's role as an adaptive enabler in the capability system.

When interpreted through the Knowledge-Based View (KBV), the use of analytics makes it an important enabler for the integration of knowledge within a leadership group (Grant, 1996; Alharthi et al., 2017). The significant correlations across all decision-quality dimensions ($r = 0.35\text{--}0.42$; $p < 0.01$) show that analytics reinforces coherence in managerial reasoning. Yet this coherence is conditional on cultural context. Flexible/Participative and Clan/Adhocracy orientation-based cultures strengthen the process of knowledge integration in the organisation by fostering an environment of trust, dialogue, and experimentations. Hierarchical or control-dominant cultures, by contrast, limit the diffusion and synthesis of insights, thereby constraining the learning potential embedded in data as demonstrated by the results of this study. In this regard, culture signifies an environment for the mobilisation of knowledge, where collective intelligence emerges from the analysis of evidence (Mikalef et al., 2019; Gupta & George, 2016; Wamba et al., 2017; Denison & Mishra, 1995)

Integrating the Competing Values Framework (Cameron & Quinn, 2006) and the Denison Model (Denison & Mishra, 1995) further clarifies that culture operates as a dual-layer meta-capability. At the behavioural level, a data-driven orientation embeds evidence-based norms and cognitive discipline into leadership practice. At the structural level, flexible and adaptive cultures provide the organisational architecture that enables those behaviours to flourish. The empirical moderation effects (Clan $\beta = 0.207$; Adhocracy $\beta = 0.241$; Hierarchy $\beta = -0.203$) quantitatively

confirm that cultural flexibility amplifies, while rigidity constrains, the benefits of analytics capability. This aligns with contemporary evidence (Szukits & Móricz, 2024; Horani et al., 2025) showing that analytic systems achieve value only where cultures reward learning, cross-boundary collaboration, and transparent decision-making.

Comparative interpretation with literature also situates these results contextually (see Table 14). The results show that the moderating influence of cultural flexibility—specifically Clan and Adhocracy orientations—on the relationship between Big Data Analytics (BDA) capability and decision-making quality is stronger in this multi-industry leadership sample than in most single-region studies. The magnitude of the Adhocracy coefficient ($\beta = 0.241$; $\Delta R^2 = 0.058$) exceeds values reported by Mikalef et al. (2019) ($\beta \approx 0.18$), indicating that innovative culture exerts a proportionally stronger influence where analytics maturity is varied across organisations. Similarly, the Clan factor ($\beta = 0.207$) is slightly greater than similar research by Upadhyay et al. (2020). Conversely, the negative effect of Hierarchy ($\beta = -0.203$) is roughly double that reported by Côte-Real et al. (2017) ($\beta \approx -0.10$), showing that excessive control can significantly dampen the realisation of analytics value in diverse or regulatory-heavy contexts.

Table 14: Cross-Study Comparison of Cultural Moderation Effects on Analytics-Decision Link

Cultural Dimension (Moderator)	Current Study β (coefficient)	Literature β (coefficient)	Context / Source	Interpretive Comment
Data-Driven Culture (DDC)	0.231 ($p < 0.01$)			
Clan Culture	0.207 ($p = 0.019$)	0.16 (approx.)	Upadhyay et al. (2020) – India (knowledge-sharing culture)	Slightly stronger in this study, indicating that trust- and cohesion-based collaboration amplifies analytics value in diverse leadership contexts.
Adhocracy Culture	0.241 ($p = 0.003$)	0.18 (approx.)	Mikalef et al. (2019) – Europe (innovation culture)	Stronger moderation observed; suggests innovative culture exerts proportionally greater influence in environments with uneven analytics maturity.
Hierarchy Culture	-0.203 ($p = 0.029$)	-0.10 (approx.)	Côte-Real et al. (2017) – Europe (bureaucratic context)	Negative effect roughly double in magnitude, implying that rigid control structures more strongly dampen analytics impact in complex, compliance-intensive environments.
Note. Not many studies that have produced a β -coefficient for the moderating effect of DDC on BDA and DMQ relationship since most of the past studies regard DDC either as a direct variable or a mediator. As such the researcher could locate studies for comparative purposes.				

Overall, these contrasts reinforce that analytics outcomes are context-dependent: the same technological capability yields different strategic result depending on the cultural and organisation environment in which it is enacted.

By incorporating the Competing Values Framework (Cameron & Quinn, 2006), and the Denison Model (Denison & Mishra, 1995), it becomes clear that culture represents a meta-capability at the dual-layer level. Based on the theoretical frameworks, this study reveals a clear conceptual framework: BDA provides the information base for the process of strategic assessment, leadership provides the judgement required for the interpretation of information, and the culture of the organisation provides the context within which the insights are shareable and applicable in practice.

In Figure 7 below the relationships described above are illustrated, the illustration integrates both the direct and moderating effects tested in this study. The model consolidates the empirical findings from Chapter 5, showing how Big Data Analytics (BDA) capability directly enhances Decision-Making Quality (DMQ) (H_1), while Organisational Culture—comprising the Data-Driven Culture (DDC) dimension and Competing Values Framework (CVF) archetypes—moderates this relationship (H_2). The statistical values (β and p) shown along each path represent the strength and direction of these effects, indicating where cultural orientations amplify, is insignificant, or dampen BDA-DMQ relationship.

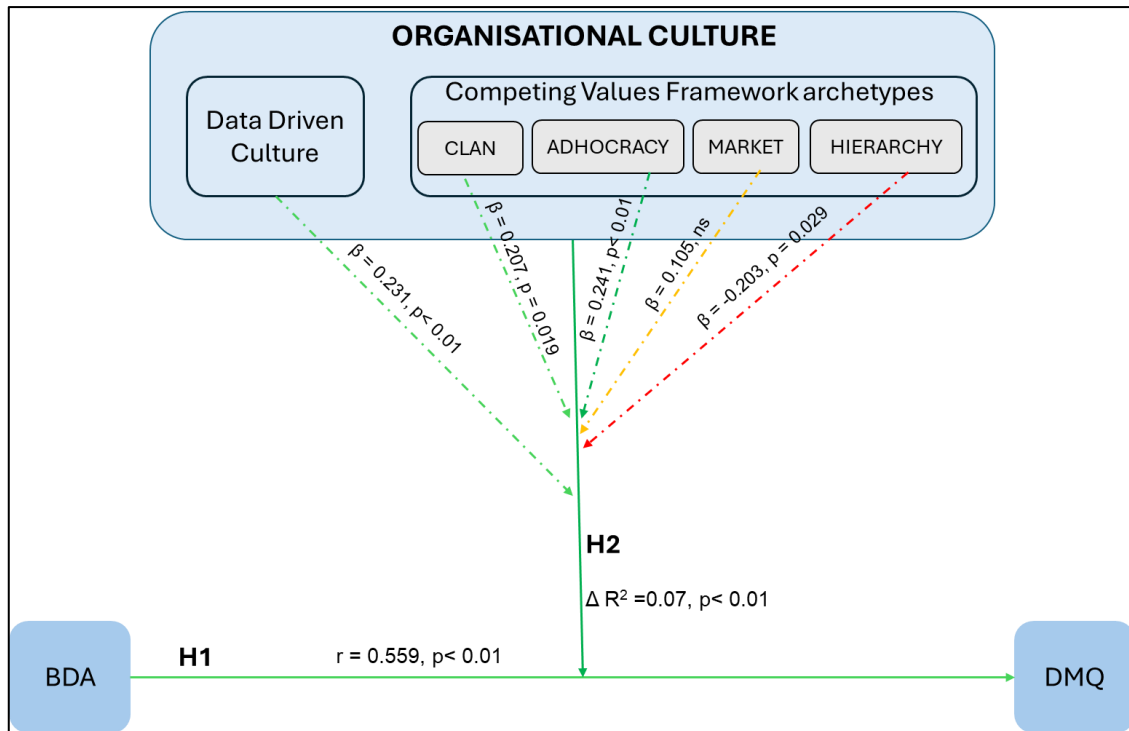


Figure 7: Research Model: Summary of empirical relationships between BDA, Organisational Culture and DMQ.

In summary, the integrated findings affirm both hypotheses and extend the theoretical frameworks that informed this research. Big Data Analytics enhances strategic decision-making quality (perceived) by enriching cognitive capacity and enabling knowledge integration, while organisational culture amplifies or constrains this influence through its behavioural norms and structural orientation. The results position culture as an interactive meta-capability that determines the translation of analytical potential into strategic action.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusions and implications of the study. It synthesises what the research has revealed about the intersection of analytics capability, leadership cognition, and organisational culture in shaping decision quality. The chapter answers the research questions, articulates conclusions and demonstrates the value of the study for both the business and leaders. The implications for academia as well as the study limitations are discussed. The Chapter concludes with study recommendations, proposes future research and outlines limitations.

At its heart, the study asked a deceptively simple question: *Why do organisations loaded with data still struggle to make good decisions?* The evidence now reveals that the answer lies not in technology, but in the cultural and cognitive conditions under which leaders interpret data. This chapter therefore argues, simply and practically, that cultivating a culture of analytical confidence is the defining leadership competency of the digital age.

7.1 What the Research Questions Have Answered

The first research question examined the extent to which Big Data Analytics (BDA) influences the quality of strategic decision-making (DMQ) at the senior leadership level. The analysis demonstrated that the relationship is strong, positive and significant, confirming both theoretical and practical predictions. Literature consistently proposed that integrating analytics into the decision making improves their quality and cognitive accuracy (Mikalef et al., 2019), the findings from this study reaffirms this proposition. Industry observations mirror this pattern: while the overall executive confidence in analytics-driven decisions remain limited as highlighted in Chapter 1, organisations that have embedded analytics in their decision-making routines report higher confidence levels and consistency in strategic choices (PWC, 2025; McKinsey & Company, 2025; Gartner, 2024). Thus, the study reinforces the consensus that BDA is a determinant of better decisions.

However, the second question concerned with the moderating effect of organisational culture on the interaction between DBA-DMQ, revealed a far more nuanced outcome. As anticipated, the influence of analytics on the quality of decisions was positively enhanced by adaptive and participative culture (Dubey et al., 2019). More surprising, perhaps, was the extent to which hierarchical and control-

oriented organisational culture dampened the influence of analytics quality on DMQ. Even instance where analytics capability where high, rigid structure and control-based cultures limited data driven senior managers deliberations. This finding contradicted early technological determinist assumptions (e.g., McAfee and Bynjolfsson, 2012) that sole use of analytics ensures rational and objective outcomes. Instead, this finding affirms that data value is contingent—that is, it is dependent on cultural climate where decision makers operate.

This alignment and divergence between expectations and observed reality reveal an important theoretical insight: BDA's impact on decision quality is not a universal law but a contextual relationship moderated by culture. The study thus reinforces existing theory while extending it into the behavioural domain of senior leadership decision-making.

7.2 Primary conclusions

Three integrated conclusions emerge from the analysis, reflecting both confirmation and extension of existing knowledge.

First, the study confirms that Big Data Analytics has evolved from a technical enabler into a strategic leadership capability. This finding supports the Dynamic Capabilities View (Teece, 2007) and aligns with the knowledge-based understanding that analytical competence allows organisations to sense and interpret environmental change. Yet, it extends prior theory by showing that the capability is enacted at the cognitive level of leaders—not only through organisational systems but through the interpretive habits of executive decision-makers.

Second, organisational culture remains the decisive mechanism that converts data into actionable wisdom. This outcome reinforces Denison and Mishra's (1995) and Cameron and Quinn's (2011) frameworks, which link adaptability and collaboration to performance, but extends them by revealing that these traits also condition how technology informs strategic reasoning. While this finding confirmed much of the expected relationship, it also exposed a contradiction: hierarchical control, once thought to improve consistency, now appears to restrict analytical integration and learning.

Third, the study contributes to the literature by proposing the idea that the measure of digital maturity lies not in the level of technology used, but in the quality of decisions made. This insight departs from the dominant industry narrative, which

equates digital transformation with system adoption. The study provides empirical weight to an emerging argument (McKinsey & Company, 2025; Gartner, 2024) that leadership culture—not infrastructure—is the ultimate differentiator in realising analytics value.

7.3 Value of the Study

The value of this study lies in its ability to connect what was theorised, what is observed in practice, and what is newly revealed.

Theoretically, it confirms the predictions of the Dynamic Capabilities and Knowledge-Based frameworks while extending them into the micro-foundations of culture and cognition. Prior studies implied that culture facilitates performance; this research demonstrates how culture functions as behavioural mechanism that activates analytics as a dynamic capability. As demonstrated in Chapter 5's moderation analysis, analytics capability improved decision-making quality most strongly under adaptive and participative cultural conditions, confirming that culture behaves as the enabling "activation mechanism" anticipated by the Dynamic Capabilities View. In Chapter 6, the process of leadership values and collective learning processes detailed how the above activation process takes place through the ability of organisations to 'sense, seize, and transform' information into strategy. The above key insight shifts the theoretical approach from abstraction to realism, as it indicates how analytical advantages are socially constructed via leadership culture

Managerially, the findings clarify that the cultural and cognitive dimensions of leadership must evolve alongside technological adoption. Industry discourse (PwC, 2025) had suggested this link, but this study provides empirical evidence of how it occurs. In Chapter 5, organisational-culture indicators associated with openness and collaboration correlated with higher decision-quality scores, while hierarchical indicators correlated negatively. Chapter 6 interpreted these results by showing that when leaders intentionally integrate analytics into collaborative decision routines, they transform data from an informational resource into a strategic asset. Such an example shows the importance of leadership behaviour in the process of turning investment in analytics into an improvement in decisions through open communications and analytical reasoning. By identifying the process through which analytical trust is built, the study provides practical guidance for organisations seeking to embed analytics into strategic deliberation and strengthen executive decision confidence.

In the social realm, the contribution of the study lies in the ethics of leadership during in a data age, in formally demonstrating that the quality of decisions is less dependent on the abundance of information at the disposal of the leaders, than to the morality of the process of interpreting the information at their command. This interpretation derives from the cultural profiles identified in Chapter 5, where participative and clan orientations—characterised by openness and trust—were associated with higher decision-making quality, underscoring the ethical dimension of evidence-based leadership.

In other words, the accountability of the leadership in the management of decisions encompasses the analytical process of the evidence used to justify decisions, such as the presentation, interrogation, and narration of the evidence used during the process.

Such environments should allow for the freewheeling discussions of the data presented, the consideration of dissenting views on the evidence presented, and the support of decisions for actions based on rational explanations rather than the provision of “proofs” based on the authority of the leadership’s decisions. This interpretive competence—what the study defines as “decision intelligence”—becomes the defining attribute of ethical and accountable leadership in a data-saturated society.

The outlined expectation represents a new standard of responsible leadership: the ability to use evidence not only to optimise performance, but also to uphold fairness, trust, and integrity in organisational decision-making.

7.4 Strategic Implications of the findings

The findings of the research contain a very profound and simplistic truth about the importance of the level of maturity of thought in the context of successful transformation: the success of digital transformation depends less on technological sophistication than on the maturity of leadership thinking. In the modern day and age where organisations are witnessing an unprecedented growth in the volume of their data, competitive advantage now stems from the ability to interpret it wisely and act responsibly. The research challenges the illusion of progress measured by technology alone and calls for a redefinition of leadership excellence in the digital age.

First, leaders must reclaim decision-making as a moral and cognitive act rather than a technical one. The study shows that analytics does not replace judgment—it refines it. The key take-home for senior leaders, is therefore to alter the culture of leadership from one that seeks certainty in data to one that seeks clarity through dialogue. This entails the humility to doubt one’s own assumptions, the boldness to solicit dissenting views, and the discipline to explain decisions through clear reasoning. Leadership behaviour of this kind not only improves decisions but also increases credibility and trust, both of which are intangibles that cannot be replicated by algorithms.

Second, organisations must treat culture as infrastructure. The evidence across this study makes clear that culture is not an accessory to analytics strategy but its foundation. Yet many firms still invest in systems before people, and data before dialogue. The rational argument is irrefutable: analytics delivers value only when cultural systems allow evidence to be shared, debated, and owned collectively. The true cost of neglecting this cultural alignment lies in what is lost when this does not happen—fragmented teams, reactive decisions, and disillusioned talent. Digital transformation starts not in the data warehouse, but in the conversations about how the data will be interpreted or understood.

Third, boards, educators, and policymakers must act with urgency. The pace of technological change is accelerating, but the pace of cultural adaptation remains slow. The findings of this study imply that leadership education and corporate governance must now include decision intelligence as a formal capability—training leaders not only to analyse data but to reason ethically with it. This argument is both moral and strategic: in a world governed by algorithms, human judgment remains the last line of accountability. By embedding evidence-based reasoning and moral reflection into decision frameworks, organisations ensure that progress remains human-centred.

Ultimately, the strategic message from this study is both rational and moral: analytics empowers, but culture enlightens. The core argument rests on balance—data may drive efficiency, but only wisdom drives legitimacy. Organisations who are able to integrate their level of technical capability with their level of cultural maturity are going to be able to make decisions not only faster than their competitors, but decisions that will last for years too.

The strategic takeaways highlighted above reiterate the importance of the human and cultural context within which data-informed decision-making takes place, having relevance for both leadership and Organisational practice. However, besides the significance for these aspects, the significance of the current study also lies in the theoretical contribution it makes. The theoretical contribution lies in the fact that the current study enhances the existing body of knowledge by identifying the underlying processes associated with the relationship between culture and analytics for decision quality.

7.5 Theoretical Implications

This study advances theoretical understanding at the intersection of strategic management, organisational culture, and leadership decision-making. It contributes new explanatory depth to existing frameworks by clarifying how culture and human judgment operationalise analytical capability within the firm.

It refines the Dynamic Capabilities View (DCV) by positioning organisational culture as a behavioural micro-foundation that enables dynamic sensing, seizing, and transforming. Rather than treating culture as context, the study conceptualises it as an activating mechanism that converts analytical resources into adaptive capacity. This insight specifies the social and cognitive conditions under which data capability becomes a source of strategic agility.

It extends the Knowledge-Based View (KBV) by redefining knowledge creation as a relational, interpretive process. Big Data Analytics is shown to function not merely as a technology for information storage but as a catalyst for knowledge integration across leadership boundaries. This reorientation moves the KBV beyond firm-level abstractions toward a model of collective sense-making that emphasises shared cognition and dialogue.

Additionally, the study enhances the theory of organisational culture by merging the theories proposed by Denison (1995) and Cameron & Quinn (2011). Adaptive, clan, and adhocracy culture profiles emerge from this combination as the culture archetypes associated with analytical learning and decision quality. The study thus enhances the theory of culture-performance by clarifying the culture archetypes associated with quality decisions in data environments based on evidence.

Lastly, the study presents the concept of “decision intelligence” as a theoretical bridge between analytics and leadership theories. The construct integrates analytical

acumen and ethical deduction, taking the conceptual models of decision-making from beyond rational optimisation to ethical and interpretive processes embedded within strategic decisions.

Taken together, these theoretical contributions provide a more integrated view of decision-making quality—one that unites capability theory, knowledge creation, and culture into a single behavioural framework. The study therefore shifts the academic conversation from “what analytics can do” to “how analytical capability becomes intelligent leadership.”

7.6 What Is Known and Not Known: New Learnings

The body of research on Big Data Analytics (BDA) has matured around organisational outcomes such as performance, innovation, and efficiency (Wamba et al., 2017; Mikalef et al., 2019; Dubey et al., 2019). This literature typically treats analytics as a firm-level capability embedded in processes and infrastructure. More recent studies (Alghamdi & Agag, 2023; Horani et al., 2025) recognise that organisational culture influences analytics effectiveness, yet the empirical focus remains largely at the organisational level. Far less is understood about the personal attributions and uses of analytics for strategic judgement among senior leaders.

is understood about the personal attributions and uses of analytics for strategic judgement among senior leaders. However, this study bridges the research gap by investigating the adoption and use of analytics at the leadership level, based on the moderating effects of culture on the relationship between the level of analysis use and the quality of their decisions. The findings reveal that the impact of analytics on decision-making quality is conditional: where it strengthens under an adaptive and participative culture; conversely, it declines under a hierarchical culture. This leadership-centred moderation analysis clarifies that analytics value is not an automatic organisational property—it depends on how leaders cognitively and behaviourally engage with data within their cultural environment.

In doing so, the study narrows a key gap between macro-level capability research and the micro-level realities of executive decision-making. It shows that culture operates as a behavioural amplifier of analytical reasoning among leaders rather than as an abstract organisational context. Still, new questions remain about the micro-processes through which leaders build trust in data, negotiate meaning with peers, and balance analytical evidence with experiential judgment. Future studies

could examine the underlying relationship and psychological processes to shed greater insight into the dynamic between analytics and the quality of decisions made at the highest leadership level.

7.7 Recommendations for Future Research and Practice

This study highlights that the importance of Big Data Analytics (BDA), within the context of decision-making, depends on the culture within which the executives are based. The results reveal both theoretical opportunities for further study and practical actions for leadership development.

From a research perspective, future work should deepen understanding of how culture influence the engagement of leaders with analytics. Qualitative and longitudinal studies could uncover the cognitive and behavioural processes—such as trust, reflection, and bias management—that underlie the moderating effect identified here. Comparative studies across industries or geographies could also determine whether these cultural patterns hold under different institutional conditions. Additional moderators such as leadership style, ethical reasoning, or organisational structure could refine the conditional model of analytics-driven leadership. Formal testing of the construct of decision intelligence would extend theory by integrating analytical, moral, and reflective dimensions of executive judgment.

From a practical perspective, the findings call for leadership development and organisational practices that align culture with analytical ambition. Senior leaders should be trained not only in data literacy but also in interpretive reasoning and collaborative decision routines that transform analytics into shared strategic insight. As emphasised by Mikalef et. al., (2021) and Wamba et al., (2017) building such capacity in leaders allows organisation to overcome resistance and lead easier organisation reconfiguration to sustain competitive advantage. Organisations should assess cultural readiness before investing in advanced analytics initiatives, focusing on psychological safety, openness, and learning orientation. Board-level governance processes should also evaluate the quality of reasoning and evidence supporting strategic choices, reinforcing accountability in data use.

In sum, both scholars and practitioners should move beyond the question of whether analytics improves decisions to explore under what conditions and through which behaviours it does so. Future studies should refine these processes, and the

leadership should institutionalise them. By doing so, the results of analytics will not only facilitate faster decision-making, but wiser decisions will be achieved as well.

7.8 Limitations

Even though the study objectives were met, there are several limitations associated with the study.

7.8.1 Cross-Sectional design

The study used a cross-sectional research design, where the relationship was measured at a single point in time. Although the study benefits from the fact that the research design enabled the examination of the moderating effects of culture in the relationship between Big Data Analytics and the quality of decisions, the research lacks the ability to infer causality and the passage of time to monitor the changes over time for culture and the level of analytics maturity's joint impact on leadership decision-making.

7.8.2 Self-Reported data (Bias)

The data collected via self-administered surveys among top executives. Though the participants are valid for the analysis of the strategic decision process, the possibility of both perceptual bias and the desirability of the response may be concerns for the objective assessment based on the findings through the survey questions among the executives themselves.

7.8.3 Sampling and Contextual Scope

The researchers employed a non-probability sampling technique among the selected set of business leaders from diverse sectors; however, they failed to capture the geographical location of the study participants. Consequently, the sampling approach used in the research fails to produce results generalizable to a broader population, and it's also impossible to identify regional/cultural differences in the moderating effects.

7.8.4 Model Scope and Variables

The conceptual framework was designed to examine the culture construct as the single moderating factor. Other contextual factors may affect the results, such as Organisational structure, management approach, and digital maturity, and could be accounted for in the framework. Future frameworks may be able to achieve greater theoretical specificity by taking these variables into consideration. In general, such

limitations do not impair the contribution of the study but rather serve to indicate the scope of the study within the context of the limitations.

7.9 Conclusion

This study demonstrated that the influence of Big Data Analytics (BDA) on strategic decision-making quality among senior leaders is conditional on organisational culture. Analytics strengthens decision quality only when embedded in adaptive, participative, and learning-oriented environments. By focusing on leaders rather than organisations, the study revealed that culture functions as a behavioural amplifier of analytical capability—shaping how evidence is interpreted, debated, and acted upon.

A combination of dynamic capability, knowledge-based theory, and culture theories offers a more humanistic approach to analytics—one where analytics is both a technology and a cognition process. In the context of the research's findings, what's important to note is the successful execution of a data-driven transformation must begin not in a place where an organisation invests in the technology, but where the behaviour of the leadership and the culture are ready for the transformation. Finally, the successful execution of digital leadership, according to the findings, must be based on the concept of decision intelligence.

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APPENDICES

Appendix A: Survey Instrument – Questionnaire

A1. Informed Consent

Research Survey

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA.

I am conducting research on how Big Data Analytics (BDA) influences strategic decision-making quality among senior leaders, and how organisational culture may moderate this relationship. To that end, you are asked to complete a survey with a set number of questions. This will help academic researchers better understand this relationship as well as provide industry-specific insights on dynamic capabilities influence on the success of digital transformation initiatives.

The survey should take no more than 10 minutes of your time. Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous, and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact my supervisor or me. Our details are provided below.

Researcher name: Ramaano Ishmael Rambiyana

Email: 24438503@mygibs.co.za

Research Supervisor: Rishal Balkissoon

Email: Rishal.balkissoon@gmail.com

A2: Questionnaire (Control Variables)

Current Age: ____ years

2. Gender:

- Male
- Female
- Prefer not to say

3. What is your current job title?

4. Which best describes your level in the organisation?

- Executive (e.g., CEO, COO, CFO)
- General Manager / Managing Director
- Head of Department / Business Unit
- Senior Manager
- Other (please specify): _____

5. How many total years of experience do you have in senior leadership roles?

- Less than 3 years
- 3–5 years
- 6–10 years
- More than 10 years

6. Which industry best describes your organisation's primary sector?

(e.g., Financial Services, Manufacturing, Public Sector, ICT, Healthcare, Mining, etc.)

7. How many full-time employees does your organisation have (globally or nationally)?

- 1–50
- 51–200
- 201–500
- 501–1,000
- 1,001–5,000
- 5,001–10,000
- More than 10,000

8. What is the approximate annual revenue of your organisation?

- Less than R10 million
- R10–50 million
- R50–200 million

- More than R200 million

9. How would you rate your organisation's current level of Big Data Analytics (BDA) adoption for strategic decision-making?

1 = No adoption at all, 5 = Fully embedded across leadership decisions

10. Have you received formal training or certification in data analytics or evidence-based decision-making?

- Yes
- No

A3: Constructs Survey Questions

Table 15: Questions used to test constructs, questions adapted from literature.

Survey Instrument Design			
	Likert Scale (1 to 5)	Ranging from 1=Strongly disagree to 5=Strongly Agree	
Construct	Dimension	Measurement Items	Source
Big Data Analytics (BDA) Capability	Data Infrastructure Capability	1. <i>Our Organisation has robust analytics systems infrastructure (e.g., cloud-based platforms).</i>	Wamba et al., 2017
		2. <i>Our analytics infrastructure facilitates the integration of large volumes of data from multiple sources.</i>	
		3. <i>Our Organisation frequently upgrades its analytics infrastructure to accommodate emerging technologies.</i>	
		4. <i>Our analytics infrastructure ensures flexibility and scalability to meet business demands.</i>	
	Managerial Capability	1. <i>Our senior management regularly examines innovative opportunities for the strategic use of Big Data Analytics.</i>	(Adapted from Akter et al., 2016; Wamba et al., 2017) Gupta & George, 2016
		2. <i>We continuously monitor the performance of our Big Data Analytics functions.</i>	
		3. <i>Our organisation effectively coordinates Big Data Analytics activities across different business units.</i>	
		4. <i>Our senior management has clear strategies for investment in Big Data Analytics capabilities.</i>	
Big Data Analytics Usage (BDAU)	Usage Frequency	1. <i>BDA insights frequently inform my strategic decisions.</i>	Shamim et al. (2019)
		2. <i>BDA is extensively embedded in our routine decision workflows.</i>	

		<i>3. Our organisation regularly relies on insights derived from BDA.</i>	
	Perceived Usefulness	<i>1. BDA significantly improves the accuracy of my strategic decisions</i> <i>2. BDA effectively reduces uncertainty in strategic decision-making.</i>	Wamba et al. (2017)
Decision Making Quality	Decision Completeness	<i>1. BDA provides all necessary information required for strategic decision-making.</i>	Li et al. (2021)
		<i>2. Our Organisation rarely encounters information gaps when utilizing BDA.</i>	
	Decision Accuracy	<i>1. Decisions based on BDA insights are consistently validated by subsequent outcomes.</i>	Nutt (2008)
		<i>2. BDA reduces the occurrence of errors in strategic judgments.</i>	
	Decision Effectiveness	<i>1. I believe that we make good decisions</i>	Shamim et al. (2019)
		<i>2. The decisions we make result in the desired outcomes</i>	
		<i>3. I am satisfied with the outcome of our decisions</i>	
		<i>4. Our decisions improve organisational performance</i>	
	Decision Efficiency	<i>1. Our decision-making cost is very low</i>	
		<i>2. We spend a lot of time in making decisions</i>	
		<i>3. We don't need a lot of people to make decisions</i>	
		<i>4. We make timely decisions</i>	
Organisational Culture (Data-Driven Culture)	Evidence-Based Norms	<i>1. Leaders in our Organisation consistently demand data-driven justifications for strategic decisions.</i>	Szukits & Móricz (2024)
		<i>2. Employees are actively rewarded for utilizing analytics insights in their decision-making processes.</i>	
		<i>3. Decision-makers consistently override intuition when it is contradicted by data insights.</i>	
	Strategic Orientation	<i>1. Senior leaders consistently emphasise making strategic decisions based on analytics insights rather than intuition alone.</i>	Gupta & George (2016)

		2. Senior leaders are willing to override their intuition or experience when presented with contradictory analytics insights. 3. Strategic decisions by senior leaders are primarily guided by analytics-based evidence. 4. Our senior leadership actively encourages the integration of analytics insights into strategic decision-making. 5. Senior leadership continuously assesses and refines business strategies based on insights generated from analytics. 6. Our senior leadership views data analytics as a critical asset for effective strategic decision-making.	
Organisational Culture (Competing Values Framework)	Clan Culture (Collaborative)	1. Our Organisation feels like an extended family with strong interpersonal relationships.	Cameron & Quinn, 2006
		2. Teamwork and employee participation are highly encouraged across departments.	
		3. Employee morale and commitment are high due to the supportive atmosphere.	
		4. Leaders mentor facilitate rather than direct and control	
	Adhocracy Culture (Innovative)	1. Innovation and experimentation are highly valued and encouraged within our organisation.	
		2. We proactively respond to market changes and embrace new approaches.	
		3. Our Organisation is known for creativity and entrepreneurial spirit.	
		4. Leaders are visionary, innovative, and willing to take risks.	
	Market Culture (Results-Oriented)	1. Our Organisation prioritises achieving strategic targets and measurable results.	
		2. Competitive performance and goal achievement are critical to our organisation's success.	
		3. We maintain a strong market presence through focused and decisive actions.	
		4. Leaders are hard driving, productive, and focus on winning	

	Hierarchy (Control Oriented	<i>1. Formal policies and procedures govern most aspects of our Organisational activities.</i>	
		<i>2. Stability, predictability, and efficiency are highly valued in our organisation.</i>	
		<i>3. Clear Organisational structure and defined roles are essential to our operations.</i>	

Appendix B: Sample Demographic

B1: Organisational Level

To ensure the data captured the target population in the proposed study, namely senior level leaders, every response describing organisational level in the questions with free-text response was coded. Responses were coded systematically according to their strategic impact and level of managerial seniority. On the one hand, job designations such as Founder and Senior Manager (Finance/Operations/Division Head) fell in the senior management category (codes 1–4) and were retained. Roles which did not satisfy the criteria of being inclusive of senior leaders were coded with 9; and excluded from the analysis. These include Middle Management, Supervisor, Team Leader, Process Specialist, and Line Manager. Thus, the screening ensured that in the final sample (n = 109) only those respondents were included who occupied decision-making positions.

Question: Which best describes your level in the Organisation:

Original Response	Final code	Notes
Founder	1	Treated as Executive
Senior Manager-Finance	4	Senior Manager variant
Middle Management	9	Below Senior Manager
Junior	9	Below Senior Manager
Team Leader	9	Below Senior Manager
Process Specialist	9	Below Senior Manager
Programme Manager	9	Below Senior Manager
Key account management	9	Below Senior Manager
Line manager	9	Below Senior Manager
Intermediate position	9	Below Senior Manager
Supervisor	9	Below Senior Manager

B2: Sector Coding

Industry/sector data was gathered in the form of free text entries but was then coded in standardized format to allow further descriptive and comparative analysis. Each response was coded with a final numerical code (1-9) representing a broad group of industries identified according to the South African Standard Industry Classification (SIC) and clustering principles. These include, for instance, Mining, Smelting, and Metallurgy, which belonged to Code 1 (Mining & Resources); Manufacturing, Construction, and Transport Logistics, which belonged to Code 2 (Manufacturing & Industrial); and Finance, Consultancies, and Professional Services, which belonged to Code 3 (Professional Services). The other major categories were Public Sector & Education (Code 4), ICT & Telecoms (Code 5), Consumer Goods & FMCG (Code 6), and Healthcare (Code 9). “Any UNCODED or ambiguous responses were assigned to Code 9 (‘Other’).” This facilitated the reporting of consistencies and ensured a degree of comparability between very different organisational settings.

Question: Which industry best describes your organisation’s primary sector? (e.g., Financial Services, Manufacturing, Public Sector, ICT, Healthcare, Mining, etc.)

Original Response	Final Code	Notes
Mining	1	Core mining sector
Smelting	1	Mining & resources variant
Minerals Processing	1	Mining & resources variant
Metallurgy/mining	1	Mining & resources variant
PGM Manufacturing	1	Mining & resources variant
Petrochemical and Energy	1	Treated as mining & resources due to extractives
Manufacturing	2	Manufacturing & industrial sector
Automotive	2	Manufacturing & industrial variant
Transport logistics	2	Industrial/logistics sector
Engineering	2	Industrial/technical sector
Construction	2	Industrial/infrastructure sector
Financial Services / Finance	3	Professional services (all variants grouped)
Government – Financial Services	3	Treated as professional services
Professional Services	3	Professional services category
Consulting	3	Professional services category
Marketing & Communications	3	Professional/business services
NGO / NPO	3	Non-profit, grouped under professional services
Gaming	3	Business/commercial services
Market Research	3	Treated as professional services
Public Sector	4	Public/government sector

SOE (State-owned Enterprise)	4	Public sector
Education	4	Education sector
Higher Education	4	Education sector
Utilities	5	Infrastructure/utilities sector
ICT	5	ICT sector
Telecoms	5	ICT sector
FMCG	6	FMCG & consumer goods
Food and Beverages	6	FMCG sector
Skincare	6	Healthcare/consumer goods
Healthcare	6	Healthcare
Agriculture	9	Coded as Other (miscellaneous)
Any uncoded responses	9	Default to Other

Appendix C

KMO = .920 (indicating excellent sampling adequacy). Bartlett's Test of Sphericity was significant ($\chi^2 = 777.876$, $df = 28$, $p < .001$), confirming that the correlation matrix is suitable for factor analysis.

Table 16: Kaiser-Meyer-Olkin (KMO) and Bartlett's Test for Sampling Adequacy BDA Capability)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.920
Bartlett's Test of Sphericity	Approx. Chi-Square	777.876
	df	28
	Sig.	<.001

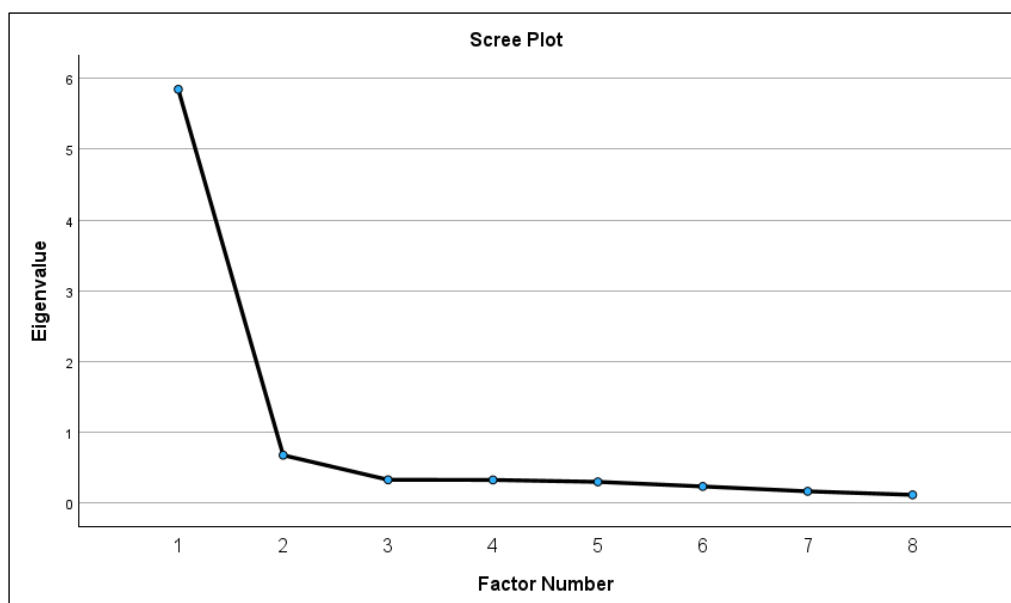


Figure 8: Scree Plot showing elbow at 1, indicating one factor solution for BDA.

Appendix D: Normality Assessment Output

In this appendix the histograms and Q-Q plots generated in SPSS for the all the constructs the research that were generated in SPSS are presented. The figures illustrate the shape of the data distribution (histogram) for each construct and how the data aligns with respect to the expected normality line (Q-Q plot). The visual patterns were consistent with the normality assessment in Table 9 that the data was approximately normally distributed.

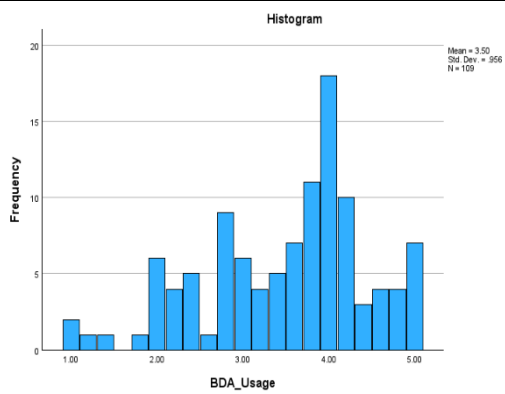


Figure 9: Histogram of BDA Usage

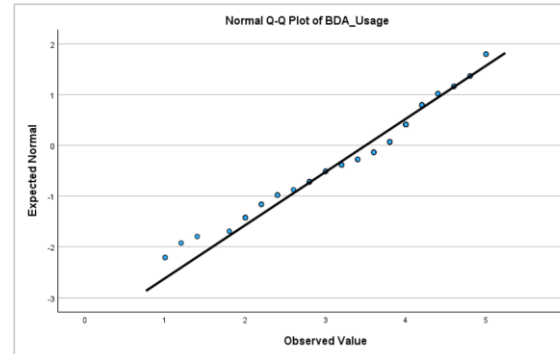


Figure 10: Normal Q-Q Plot of BDA Usage

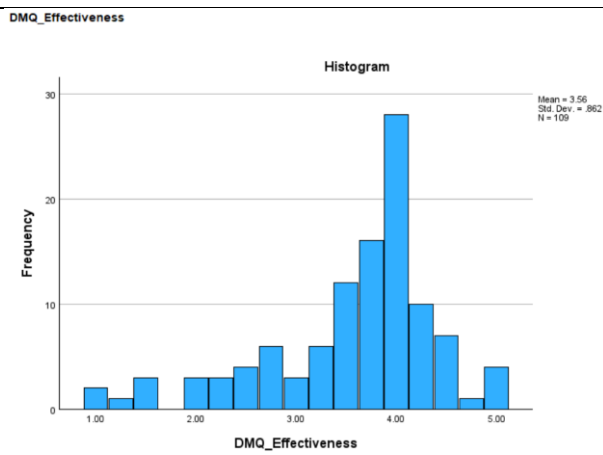


Figure 11: Histogram of DMQ-Effectiveness.

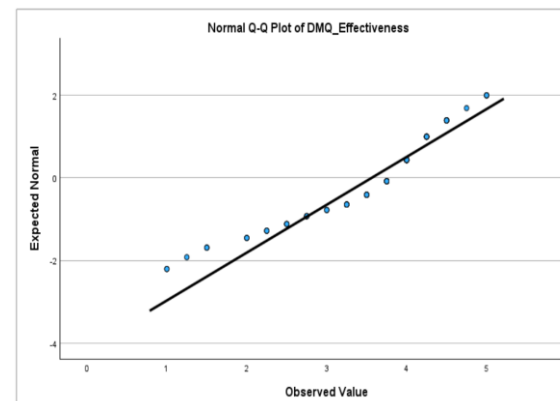


Figure 12: Normal Q-Q Plot of DMQ-Effectiveness

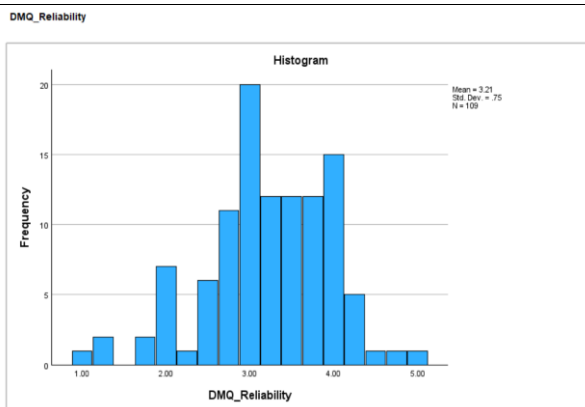


Figure 13: Histogram of DMQ-Reliability.

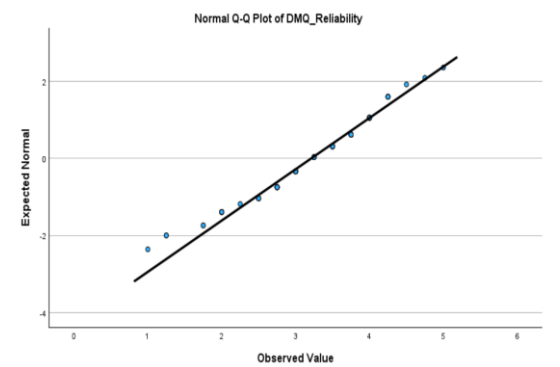


Figure 14: Normal Q-Q Plot of DMQ-Reliability.

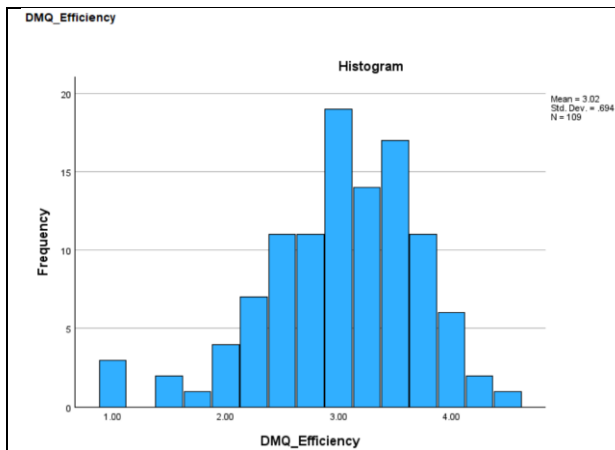


Figure 15: Histogram of DMQ-Efficiency.

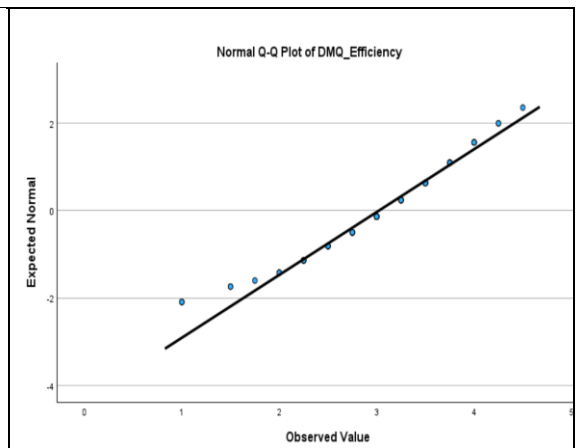


Figure 16: Normal Q-Q Plot of DMQ-Efficiency.

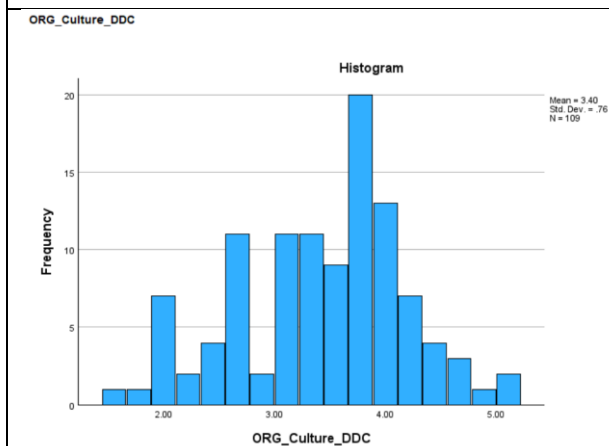


Figure 17: Histogram of organisational Culture Data Driven Culture.

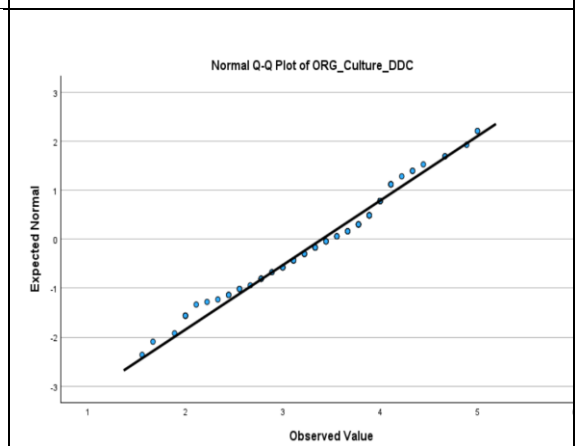


Figure 18: Normal Q-Q Plot of Culture Data Driven Culture.

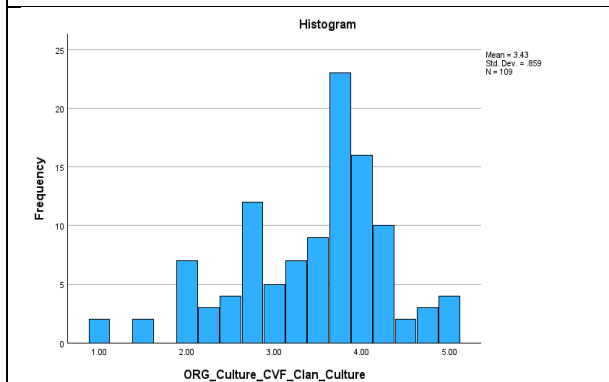


Figure 19: Histogram of organisational Culture CVF Clan Culture.

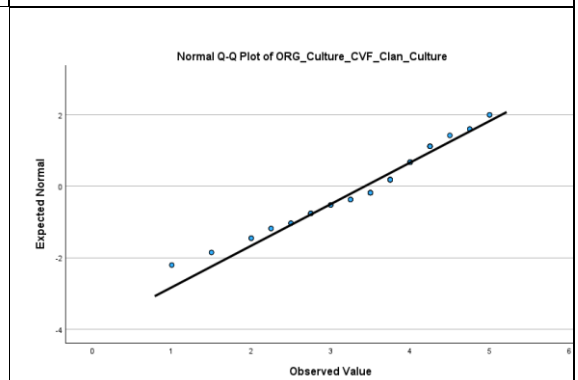
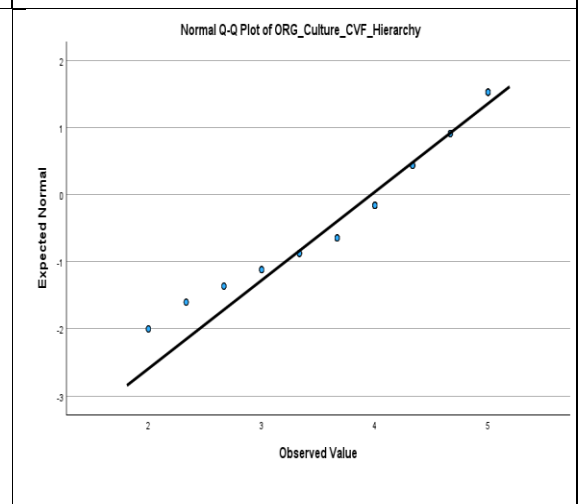
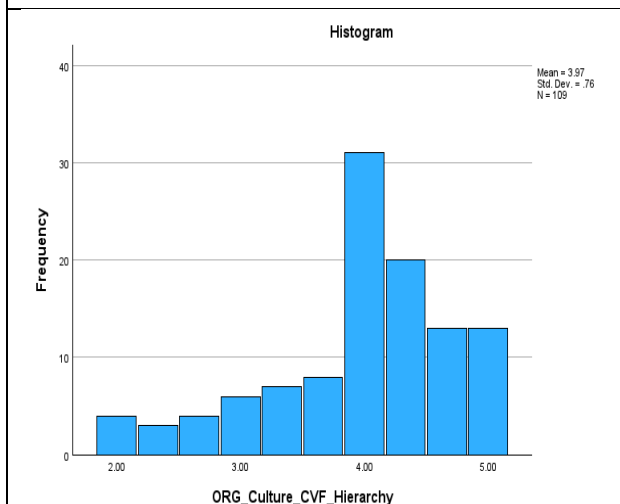
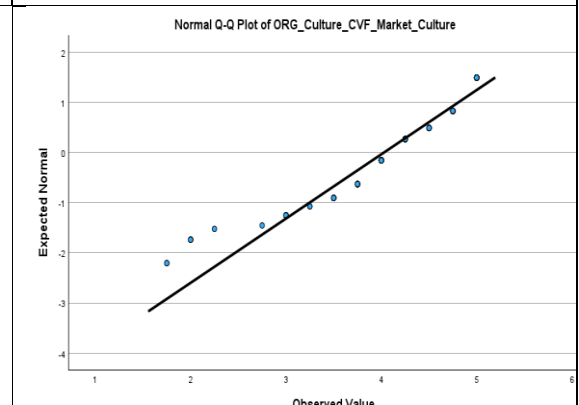
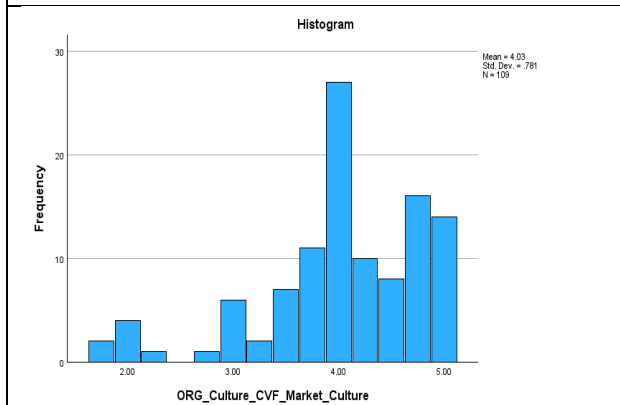
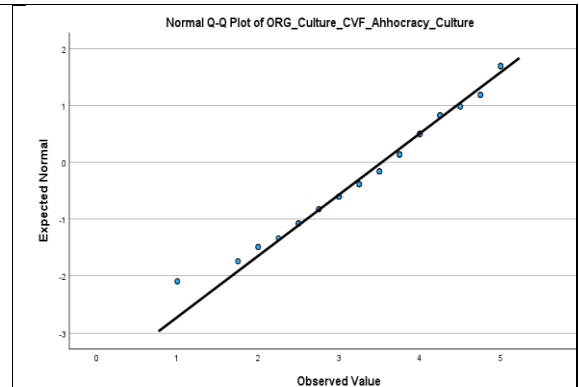
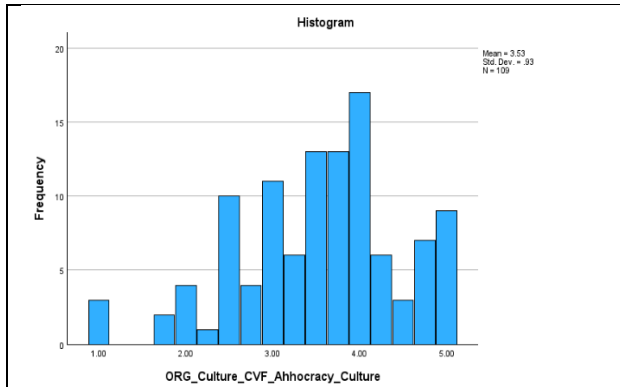


Figure 20: Normal Q-Q of Plot organisational CVF Clan Culture



Appendix E: Descriptive Statistic

Table 17: Descriptive Statistics for Study Constructs.

Descriptives				
			Statistic	Std. Error
BDA_Cap	Mean		3.3383	0.09668
	95% Confidence Interval for Mean	Lower Bound	3.1467	
		Upper Bound	3.5299	
	5% Trimmed Mean		3.3647	
	Median		3.5000	
	Variance		1.019	
	Std. Deviation		1.00940	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.38	
	Skewness		-0.356	0.231
	Kurtosis		-0.691	0.459
BDA_Usage	Mean		3.5009	0.09160
	95% Confidence Interval for Mean	Lower Bound	3.3194	
		Upper Bound	3.6825	
	5% Trimmed Mean		3.5377	
	Median		3.8000	
	Variance		0.915	
	Std. Deviation		0.95631	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.40	
	Skewness		-0.564	0.231
	Kurtosis		-0.221	0.459

DMQ_Effectiveness	Mean		3.5619	0.08258
	95% Confidence Interval for Mean	Lower Bound	3.3982	
		Upper Bound	3.7256	
	5% Trimmed Mean		3.6142	
	Median		3.7500	
	Variance		0.743	
	Std. Deviation		0.86211	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		0.75	
	Skewness		-1.091	0.231
	Kurtosis		1.018	0.459
DMQ_Reliability	Mean		3.2110	0.07185
	95% Confidence Interval for Mean	Lower Bound	3.0686	
		Upper Bound	3.3534	
	5% Trimmed Mean		3.2359	
	Median		3.2500	
	Variance		0.563	
	Std. Deviation		0.75013	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.00	
	Skewness		-0.496	0.231
	Kurtosis		0.375	0.459
DMQ_Efficiency	Mean		3.0229	0.06651
	95% Confidence Interval for Mean	Lower Bound	2.8911	
		Upper Bound	3.1548	
	5% Trimmed Mean		3.0572	
	Median		3.0000	
	Variance		0.482	
	Std. Deviation		0.69434	
	Minimum		1.00	
	Maximum		4.50	
	Range		3.50	
	Interquartile Range		1.00	
	Skewness		-0.691	0.231
	Kurtosis		0.711	0.459

ORG_Culture_DDC	Mean		3.4037	0.07280
	95% Confidence Interval for Mean	Lower Bound	3.2594	
		Upper Bound	3.5480	
	5% Trimmed Mean		3.4115	
	Median		3.4444	
	Variance		0.578	
	Std. Deviation		0.76004	
	Minimum		1.56	
	Maximum		5.00	
	Range		3.44	
	Interquartile Range		1.11	
	Skewness		-0.349	0.231
	Kurtosis		-0.320	0.459
ORG_Culture_CVF_Clan_Culture	Mean		3.4312	0.08223
	95% Confidence Interval for Mean	Lower Bound	3.2682	
		Upper Bound	3.5942	
	5% Trimmed Mean		3.4578	
	Median		3.7500	
	Variance		0.737	
	Std. Deviation		0.85856	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.25	
	Skewness		-0.628	0.231
	Kurtosis		0.175	0.459
ORG_Culture_CVF_Ahhocracy_Culture	Mean		3.5298	0.08905
	95% Confidence Interval for Mean	Lower Bound	3.3533	
		Upper Bound	3.7063	
	5% Trimmed Mean		3.5688	
	Median		3.7500	
	Variance		0.864	
	Std. Deviation		0.92966	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		1.00	
	Skewness		-0.501	0.231
	Kurtosis		0.111	0.459

ORG_Culture_CVF_Market_Culture	Mean		4.0298	0.07479
	95% Confidence Interval for Mean	Lower Bound	3.8816	
		Upper Bound	4.1781	
	5% Trimmed Mean		4.0938	
	Median		4.0000	
	Variance		0.610	
	Std. Deviation		0.78079	
	Minimum		1.75	
	Maximum		5.00	
	Range		3.25	
	Interquartile Range		1.00	
	Skewness		-1.069	0.231
	Kurtosis		1.126	0.459
ORG_Culture_CVF_Hierarchy	Mean		3.9694	0.07277
	95% Confidence Interval for Mean	Lower Bound	3.8252	
		Upper Bound	4.1137	
	5% Trimmed Mean		4.0166	
	Median		4.0000	
	Variance		0.577	
	Std. Deviation		0.75977	
	Minimum		2.00	
	Maximum		5.00	
	Range		3.00	
	Interquartile Range		0.67	
	Skewness		-0.869	0.231
	Kurtosis		0.375	0.459

Appendix F: Correlations for Study Constructs

Table 18: SPSS Output Pearson Correlations between Study Constructs.

		Correlations						
		BDA (Capability & Usage mean)	Decision- Making Quality (mean of Effectiveness, Reliability, Efficiency)	BDA_Cap	BDA_Usage	DMQ_Reliabilit y	DMQ_Effective ness	DMQ_Efficienc y
BDA (Capability & Usage mean)	Pearson Correlation	1	.559**	.930**	.922**	.577**	.527**	.212*
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	.027
	N	109	109	109	109	109	109	109
Decision-Making Quality (mean of Effectiveness, Reliability, Efficiency)	Pearson Correlation	.559**	1	.503**	.533**	.758**	.878**	.757**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001
	N	109	109	109	109	109	109	109
BDA_Cap	Pearson Correlation	.930**	.503**	1	.714**	.520**	.481**	.182
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	.059
	N	109	109	109	109	109	109	109
BDA_Usage	Pearson Correlation	.922**	.533**	.714**	1	.550**	.496**	.213*
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	.026
	N	109	109	109	109	109	109	109
DMQ_Reliability	Pearson Correlation	.577**	.758**	.520**	.550**	1	.508**	.310**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	.001
	N	109	109	109	109	109	109	109
DMQ_Effectiveness	Pearson Correlation	.527**	.878**	.481**	.496**	.508**	1	.552**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001
	N	109	109	109	109	109	109	109
DMQ_Efficiency	Pearson Correlation	.212*	.757**	.182	.213*	.310**	.552**	1
	Sig. (2-tailed)	.027	<.001	.059	.026	.001	<.001	
	N	109	109	109	109	109	109	109

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Appendix G: Simple slope graphs

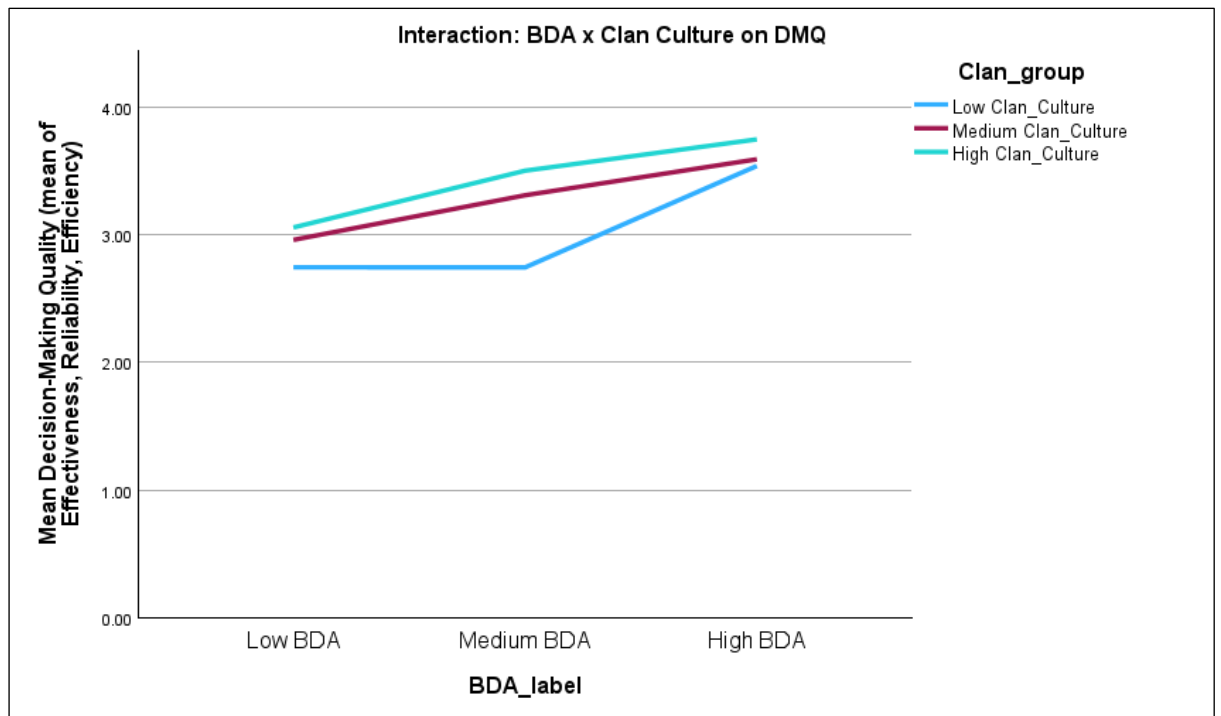


Figure 27: Simple Slope Plot Illustrating the Moderating Effect of Clan Culture on the Relationship Between Big Data Analytics and Decision-Making Quality

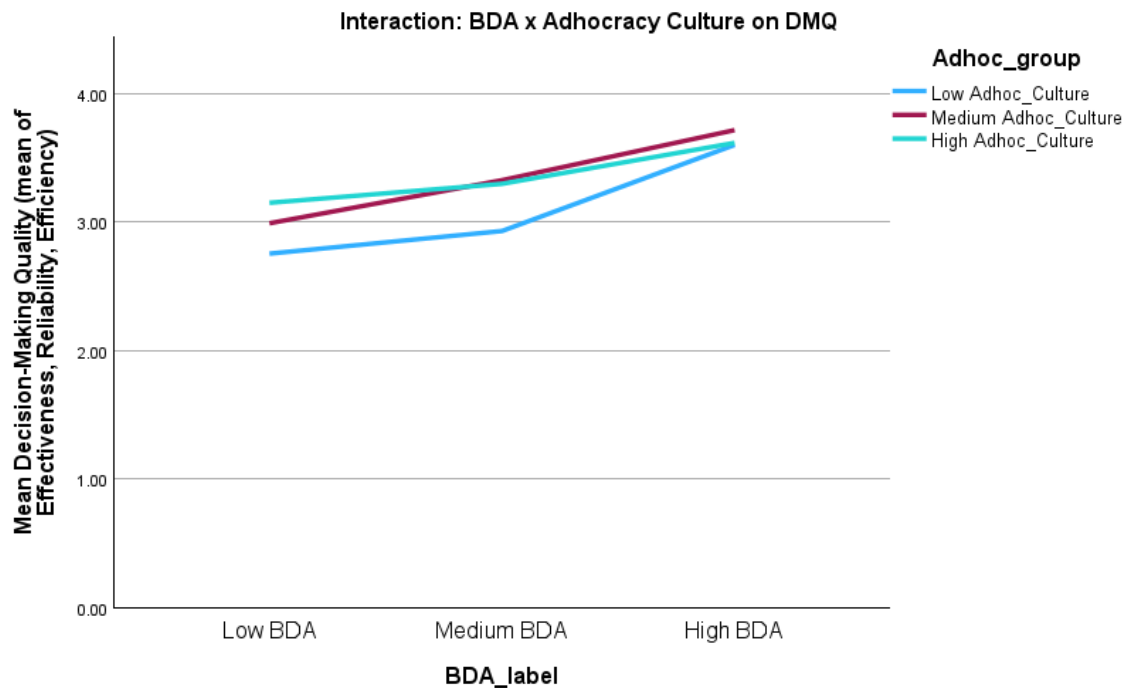


Figure 28: Simple Slope Plot Illustrating the Moderating Effect of Adhocracy Culture on the Relationship Between Big Data Analytics and Decision-Making Quality.

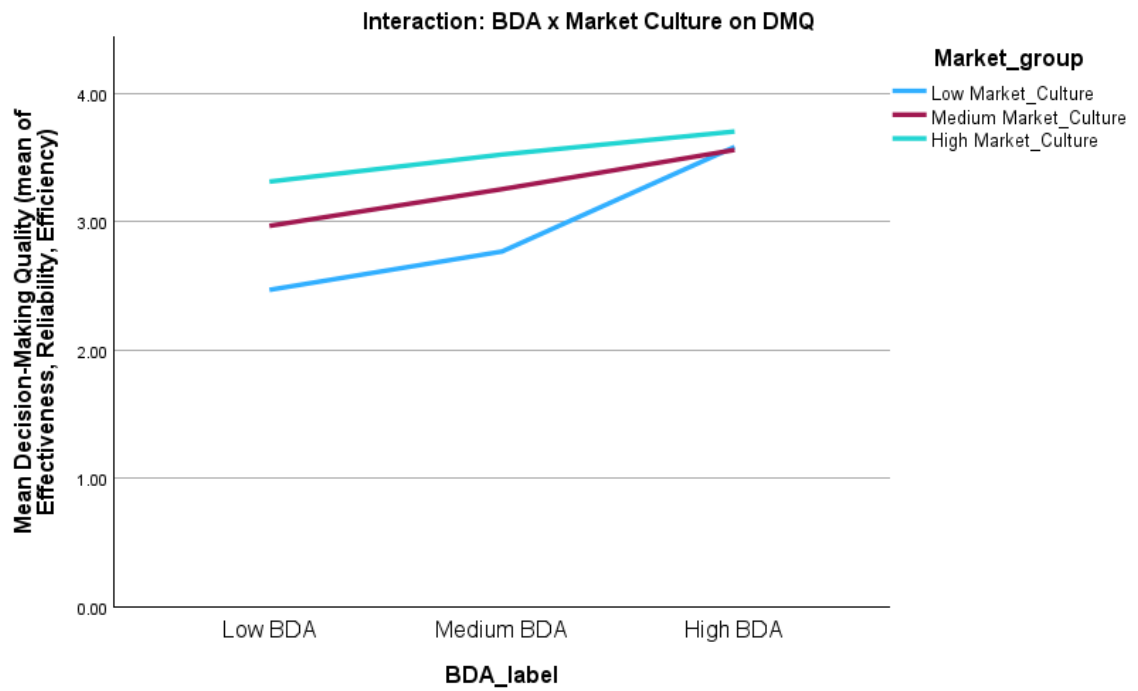


Figure 29: Simple Slope Plot Illustrating the Moderating Effects of Market and Hierarchy Cultures on the Relationship Between Big Data Analytics and Decision-Making Quality.

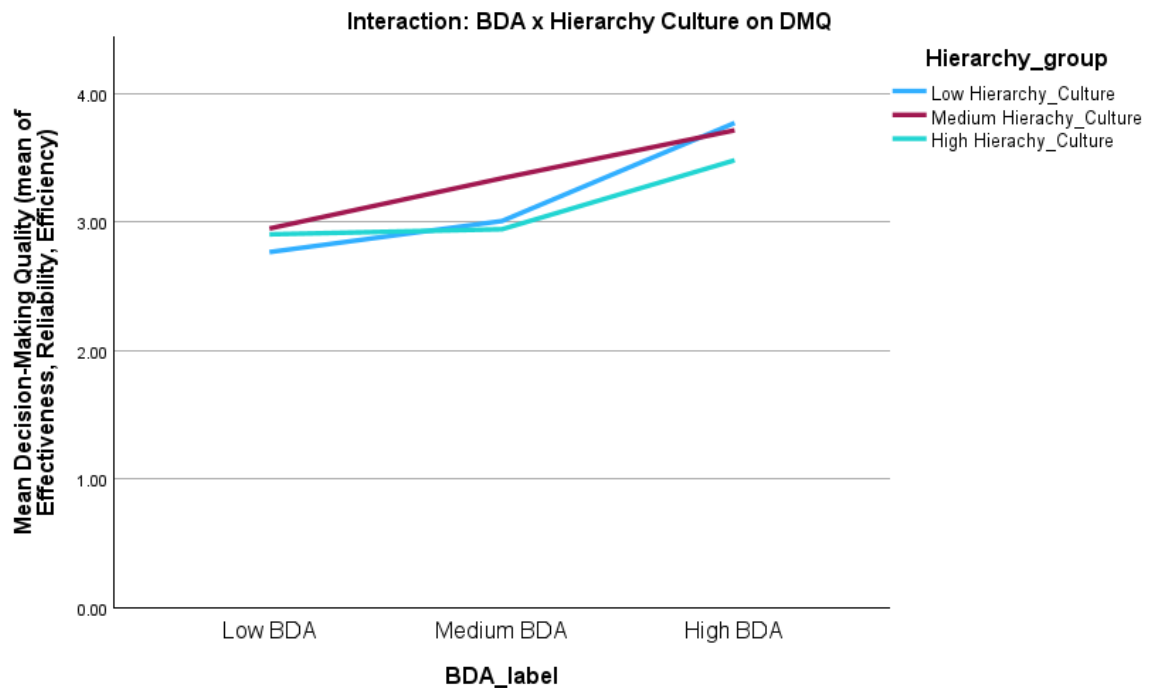


Figure 30: Simple Slope Plot Illustrating the Moderating Effects of Market and Hierarchy Cultures on the Relationship Between Big Data Analytics and Decision-Making Quality.