Stockholm School of Economics
Master of Science in Business Management
Master Thesis, Spring 2022

Unpacking the "O" in VRIO: Organizational Deployment of Data Analytics and its Effect on Firm Performance

Authors:
Maria Tolkacheva (24127)
Beverly Law (41831)

Supervisor:
Sebastian Krakowski

Abstract

Drawing on the resource-based view (RBV) and the literature on data analytics (DA), this study provides a twofold contribution by studying the intersection between the RBV theory and DA. A review of past research unveils an under-researched and -theorized factor in the RBV's VRIO acronym, the "O" - organizational deployment. Furthermore, despite the high operational and strategic impacts promised by adopting DA, previous research has mainly focused on the technological aspects of the phenomena, ignoring vital managerial challenges. Consequently, this study fills a research gap within each respective field by investigating which organizational deployment practices of data analytics contribute to a firm's sustained competitive advantage. In total, 247 respondents contributed to a quantitive study where the primary findings show that the most influential and significant organizational practices are education and knowledge development and data-driven culture. Meanwhile, the planning and controlling practices of DA had an insignificant effect on firm performance. The study makes a theoretical contribution by providing insights into the under-researched "O" and offering a new perspective by linking RBV and data analytics literature. Second, this study makes an empirical contribution by testing the six most common organizational practices of DA and their effect on firm performance from an RBV and dynamic capabilities perspective.

Keywords: Data analytics, Firm performance, Organizational deployment, Resource-based view, VRIO-framework

Acknowledgements

We would like to thank all participating organizations and employees for partaking in our survey to enable the data collection for this thesis. Even though they remain anonymous, their contribution and efforts do not go unnoticed.

Furthermore, we would like to extend our sincerest gratitude to our supervisor Sebastian Krakowski for providing guidance and valuable insights throughout the whole process of writing this thesis. Your outstanding knowledge within the field and implacable encouragement during this process have contributed to a positive and memorable experience for us as authors.

Table of Contents

Definitions *6*

1. Introduction *7*

1.1 Problematization **9**

1.2 Purpose and Contribution **10**

1.2.1 Research Question 10

1.3 Delimitations **11**

1.4 Research Outline **12**

2. Literature Review & Theoretical Framework *13*

2.1 The Resource-Based View **13**

2.1.1 The Dynamic Capability Perspective 15

2.1.2 The RBV in Previous Literature Within the Technological Field 16

2.2 Data Analytics **17**

2.2.1 Data Analytics Management Skills 19

2.2.2 Data Analytics and Performance 19

2.3 Theorizing and Hypothesis Development **20**

3. Methodology *27*

3.1 Research Design **27**

3.1.1 Survey Design 29

3.2 Data Collection and Sample **36**

3.3 Data Analysis Using OLS: Regression Model **38**

3.3.1 Fulfilling the OLS Assumptions 39

3.4 Data Quality **43**

3.4.1 Reliability 43

3.4.2 Validity 44

3.4.3 Replicability 46

4. Results *47*

4.1 Analytical Tools **47**

4.1.1 Recoding Variables 47

4.2 The Final Model **48**

4.3 Hypothesis Testing **49**

4.3.1 Variables Comparison 52

5. Analysis and Discussion *54*

5.1 Adhering the Two-Fold Research Purpose **54**

5.1.1 The Importance of the ”O” for Firm Performance 54

5.1.2 Least influential and Insignificant Variables 55

5.1.2 Connections to Dynamic Capabilities and KBV 56

6. Conclusions *59*

6.1 Theoretical Contributions **60**
6.2 Managerial Implications **61**
6.3 Limitations **62**
6.3.1 Data Accessibility 62
6.3.2 Research and methodology design 63
6.4 Suggested Future Research Directions **63**
7. References ***65***
8. Appendix ***74***
Appendix 1: The VRIO-Framework **74**
Appendix 2: LinkedIn Post and Company E-mail Text **74**
Appendix 3: Survey **75**
Appendix 4: UNHCR Donation **82**
Appendix 5: ANOVA overview **83**

Definitions

Big data analytics (BDA)	*"Consists of extensive datasets, primarily in the characteristics of volume, variety, velocity, and/or variability, that require a scalable architecture for efficient storage, manipulation, and analysis. It includes advanced techniques that harness independent resources for building scalable data systems"* (NIST, 2018).
Business process (BP)	A set of activities which collectively contribute to the production of a certain output (Bititci & Muir, 1997).
Data analytics (DA)	*"The set of techniques focused on gaining actionable insights to make smart decisions from a massive amount of data"* (Duan & Da Xu, 2021:1).
Data analytics capabilities (DAC)	Organizational capabilities whose transformation is necessary to capture sufficient gains generated by application of data analytics (Mikalef et al., 2019).
Information systems (IS)	*"An IS is a work system whose processes and activities are devoted to processing information, that is, capturing, transmitting, storing, retrieving, manipulating, and displaying information"* (Steven, 2008).
Information technology (IT)	*"Any equipment or interconnected system or subsystem of equipment that is used in the automatic acquisition, storage, manipulation, management, movement, control, display, switching, interchange, transmission, or reception of data or information by the executive agency"* (NIST, 2006).
Return on investment (ROI)	A metric used to evaluate the effectiveness of an investment by comparing the costs of the investment to the gains that can be accounted for by the investment (Erdogmus et al., 2004).

1. Introduction

This chapter provides (i) an introduction to resource-based view and data analytics in the business field, (ii) the befitting theoretical and empirical problematization, (iii) the purpose and expected contribution, (iv) the delimitation, and (v) a brief research outline.

Today's business landscape is both turbulent and competitive, making organization's quest to achieve competitive advantage even more urgent than before (Aydiner et al., 2019; Malheiro et al., 2018). This has stirred firms to investigate how they should utilize, combine, and prioritize resources to become market leaders. The idea of looking at firms in terms of a broad set of resources mouths back to the '90s when Barney (1991) proved that a unique bundle of resources, if fulfilling a set of specific criteria, can help a company achieve a competitive advantage. A firm is said to have a competitive advantage when it enjoys greater success than current or potential competitors within the same industry (Peteraf & Barney, 2003). To empirically assess sustained competitive advantage, Barney (1991) developed the widely influential VRIO-framework, which evaluates the resources by assessing their value, rarity, imitability, and organizational deployment.

Looking at firms as an accumulation of different resources is captured by the theoretical perspective called the resource-based view (RBV). However, throughout the years of analyzing firms through the lens of the RBV, complementary extensions have been developed, namely the dynamic capability perspective (DC) and the knowledge-based view (KBV), which further help explain why certain resources are more likely to provide firms with a competitive advantage. RBV and the VRIO-framework have made foundational contributions in contexts such as strategic human resource management (Wright et al., 1994), entrepreneurship (Alvarez & Busenitz, 2001), marketing (Srivastava et al., 2001), and international business (Peng, 2001) in proving resources driving competitive advantage. In recent years, a new empirical field has gained significant attention from organizations and entered the realm of the RBV, namely data analytics (DA).

With the rise of the internet in the mid-20th century, society entered the information age characterized by the shift to an economy primarily dependent on knowledge, information, and advanced information processing technology (Hilbert, 2012). The increased amount of data available and the newly developed capacity to store data heightened the need for well-established data management and analytics (Hilbert & López, 2011). Collectively, the acceleration of information gathering and processing power transformed the economy to become service- and information-based, making DA a renowned topic among companies as well as scholars (Fosso Wamba et al., 2017; Ghasemaghaei et al., 2018; Gunay et al., 2019; Klatt et al., 2011).

DA is described as *"the set of techniques focused on gaining actionable insights to make smart decisions from a massive amount of data"* (Duan & Da Xu, 2021:1). With data being increasingly seen as an organizational asset that can be utilized to make more informed business decisions to optimize business performance (Lichtenthaler, 2020; Zhang et al., 2018), there is an expressed interest in examining whether DA is, in fact, a source of competitive advantage. With the widespread adoption of DA-enabled tools, technologies, and infrastructures such as mobile devices and social media networks, many companies have realized the possibility of finding sources of sustained competitive advantage by leveraging DA as a part of their business strategy (Fosso Wamba et al., 2017).

Companies who use DA tools can pinpoint and recognize the most significant variables among troves of data and thus identify relationships important for business success (Tyagi, 2002). For instance, sectors ranging from healthcare to marketing increasingly integrate customer data to become a fundamental component of the marketplace together with labor and capital (Ghorbani & Zou, 2019). As a result, data together with DA have become a fuel driving both technological and economic growth. Brown et al. (2011:1) even went so far as to claim DA to be *"the next frontier for innovation, competition, and productivity,"* which further explains the hype among today's corporations regarding the subject.

DA is still a novel subject, and while it has been concluded that DA poses technological challenges, the managerial challenges are said to be even greater (Mata et al., 1995; McAfee & Brynjolfsson, 2012). For example, leadership and strategy have been seen as factors that can serve either as obstacles or enablers for achieving success in DA projects (George et al., 2014). Consequently, important findings in understanding organizational drivers of firm value creation can be yielded by connecting the renowned RBV theory with the contemporary field of managerial practices related to DA.

1.1 Problematization

This study aims to contribute twofold by studying the intersection between the RBV theory and DA and consequently fill a research gap within each respective field. Complimentary extensions to the RBV theory, DC and the KBV, will also be included in this research as they further help to explain why certain resources are more likely to provide firms with a competitive advantage. Besides the features of the resources themselves, RBV emphasizes the way an organization deploys its resources. According to Barney (2007), the pioneer of modern RBV theory, to achieve a firm's full economic potential, businesses must be well-organized to maximize their resources and implement strategies - namely the “O” in the VRIO acronym. However, the “O” in the VRIO acronym has received little attention in the RBV theoretical and empirical literature (Anderson & Eshima, 2013; Barney & Mackey, 2005; Chatzoudes et al., 2017; Kim & Makadok, 2021). Nonetheless, recent studies prove the significance of studying organizational deployment further. What is known from recent studies is that personnel commitment in strategy implementation enhances the effect of strategy on firm performance (Kohtamaki et al., 2012), that middle managers acting as carriers of organizational responsibilities play a significant role in strategy implementation (Ahearne et al., 2014), and that organizational structure enhances the success of strategic plans (Ogbeide & Harrington, 2011). Furthermore, there is still, to date, a gap in the existing RBV literature of theoretically and empirically looking at the organizational deployment in the context of DA. Little is known regarding how DA management affects firm performance (Fosso Wamba et al., 2017; Duan & Da Xu, 2021). Therefore, this research will investigate the organizational deployment that allows for data to be translated into strategic actions leading to sustained competitive advantage, contributing to broadening the theoretical understanding.

Switching from the RBV theory to the emerging DA literature, thus far, previous research in DA (Chiang et al., 2018; Gunay et al., 2019: Ghasemaghaei et al., 2018; Kongar & Adebayo, 2021) has put a significant emphasis on the technical aspects of DA with little attention spared to the organizational changes to be made and how DA should be leveraged strategically. Even though DA appears to play a significant role in business, the understanding, with a few notable exceptions (Tambe, 2014), of how organizational deployment of DA influences firm performance has yet so far been limited (Grover et al., 2018; Zhang et al., 2018). As numerous forces, i.e., evolving customer needs, increased competition, and the need for strategic guidance (Aydiner et al., 2019), stimulate the demand for DA, there is still no consensus in existing literature regarding organizational best practices to manage DA to gain sustained competitive advantage. Hence, this study addresses the uncertainty surrounding which organizational practices allow the realization of a firm's performance benefits when adopting DA. This study examines the managerial aspect of DA practices and intends to determine which DA practices help translate DA into business value and increased firm performance.

1.2 Purpose and Contribution

This study aims to build upon previous literature and theory to enhance the understanding of how organizational deployment of DA influences firm performance by identifying DA practices with the largest impact on business performance. The expected contribution is thus (i) gaining an improved understanding of which DA-related organizational deployment practices used by firms have the most impact on firm performance in terms of financial and non-financial metrics, and (ii) shedding light on the under-researched "O" in the VRIO framework of the RBV theory by examining the managerial aspect of DA practices and determining how DA is translated into business value and hence contribute to a firm's sustained competitive advantage. Furthermore, this analysis will also incorporate complementary extensions of RBV, DC, and the KBV, to make a fruitful contribution to the discussion of the results. Thereby, the study is expected to contribute theoretically to the limited research of the "O" in the VRIO-framework and DA literature as well as empirically to practitioners aiming to maximize business value and performance in today's competitive environment.

1.2.1 Research Question

This study thus aims to answer the question of how organizational deployment of DA influences firm performance by determining which of the investigated organizational practices related to DA have the most impact.

Which organizational deployment practices of data analytics contribute to a firm's sustained competitive advantage?

1.3 Delimitations

Depending on a firm's needs and the industry it is operating in, the organizational deployment practices of DA might vary. For instance, some firms might focus merely on the technical aspects, such as advanced software or tools, while others focus on the managerial elements, i.e., how to implement and manage DA within firms. This study will focus on the latter by identifying different organizational practices, based on findings of previous studies, that are argued to have a more prominent impact on firm performance. Additionally, with a mere focus on the managerial aspects of DA, the delimitation of the VRIO-framework becomes apparent. Thus, this study will solely investigate the “O”. Next, the data collection is limited to personnel working in DA-intensive firms. Nonetheless, to obtain a large data sample, no limitations are placed on an industry- or hierarchical level.

Moreover, this study chooses to adopt subjective measures to determine firm performance. A subjective approach captures individuals’ collective perception as an indicator of the overall reality, i.e., aggregation of employees’ responses regarding firm performance metrics becomes the overall measure of firm performance. This is aligned with the microfoundation perspective stating that macro phenomena (firm performance) can be explained by a collection of micro-actions (the human capabilities) (Abell et al., 2008; Felin et al., 2012). Furthermore, previous studies investigating the relationship between DA and performance have adopted subjective approaches with the motivation of it accurately capturing the norm, including potential outliers (Chatzoudes et al., 2018; Fosso Wamba, 2017). Not to mention, prior studies have also indicated high validity in such approach (Dess & Robinson, 1984).

Finally, this research chooses to address the entire field of DA and not limit itself to subsections such as big data analytics (BDA). While DA covers the analysis of all types of data, BDA concerns the analysis of data characterized by volume, variety, velocity, and veracity (Chang & Grady, 2019). To date, most research within the field is executed with a focus on BDA (Gupta & George, 2016; Fosso Wamba et al., 2017). The same logic applies for information systems (IS) which is often used interchangeably with data analytics by organizations (Steven, 2008). However, as this research aims to study the organizational deployment aspects of DA and not the technical aspects, specific attributes of the data itself, as adhered to by BDA and IS, are not deemed relevant. This choice is further supported by previous studies investigating DA as a whole without limiting themselves to BDA or IS (Duan & Da Xu, 2021; Tambe, 2014).

1.4 Research Outline

Previously discussed problematization, purpose, and research question are explored using a quantitative approach directed towards personnel in various hierarchical levels in different firms and industries working with DA. The study adopts a deductive approach using hypotheses derived from existing literature and theory to analyze empirical data. The results are presented thematically according to the hypotheses tested and are followed by a discussion of the potential implications of these findings to tie back to the purpose and aim of this study. Finally, the study discusses potential limitations and suggests directions for future research. The study is divided into the following sections (i) Introduction, (ii) Theory, (iii) Methodology, (iv) Result, (v) Analysis and Discussion, and (vi) Conclusions.

2. Literature Review & Theoretical Framework

This chapter (i) dissects the RBV theory, (ii) presents a literature review of the data analytic field, and (iii) collectively applies previous research and the RBV to derive constructs and develop hypotheses.

2.1 The Resource-Based View

The idea of looking at firms in terms of a broad set of resources goes back to work done by Penrose in 1959 who provides an explanatory logic covering linkages among a firm's resources, productive opportunities, and profitable firm growth (Kor & Mahoney, 2004). She defined resources as *"the physical things a firm buys, leases, or produces for its own use, and the people hired on terms that make them effectively part of the firm"* (Penrose, 1959:67). Even though the theory gained little attention at the time, it received more attention with Birger Wernerfelt's (1984) article *"A resource-based view of the firm."*

The RBV emerged to complement the industrial organization (IO) view (Bain, 1968; Porter, 1985). According to the IO view, firm performance is determined by external factors within the industry structure. The RBV embraces this view but explicitly shifts its focus to examining the firm's internal sources of sustainable competitive advantage and seeks to explain why firms in the same industry might perform differently (Barney, 2002; Mahoney & Pandian, 1992).

The RBV theory recognizes that a company's resources can serve as a source of sustained competitive advantage if adhering to certain difficult-to-imitate attributes (Barney, 1986; Hamel & Prahalad, 1996). This has also been confirmed by later research stating that specific resource combinations enable the achievement of a sustained competitive advantage (Friedmann & Olavarrieta, 2008; Kraaijenbrink et al., 2010). In this context, competitive advantage is defined as the benefits a firm gains when implementing a value-creating strategy that is not used or implemented by any current or potential competitor simultaneously (Barney, 1991). The notion of "sustained" does not refer to the time aspect but rather to the fact that it does not diminish even in cases of imitation by competitors (Barney, 1991).

In previous literature, resources have been broadly defined to include assets, organizational processes, firm attributes, information, or knowledge (Barney, 1991; Daft, 1983; Mata et al., 1995; Spanos & Lioukas, 2001). An organization is, in turn, a collection of physical, human, and organizational resources (Amit & Shoemaker, 1993). Barney (1986;1991) means that for a resource to be considered valuable it must contribute to improved financial performance, strategic performance, or effectiveness. Consequently, the RBV assists managers in understanding how the firm's assets can be used to improve its performance. The broad understanding of the term resource hence accepts that attributes related to past experiences, organizational culture, and competencies can be critical for the firm's success (Hamel & Prahalad, 1996). Grant (1996) further expanded the notion of knowledge as a strategic firm resource and argued that features such as transferability and appropriation of knowledge could result in competitive advantage. This laid the foundation for the knowledge-based view (KBV), an extension of the RBV.

According to the KBV, knowledge is created within the firm's boundaries, making it difficult to imitate (Grant, 1996). Hence, the KBV sees heterogeneous knowledge and capabilities as the main drivers of a firm's performance (Eisenhardt & Santos, 2002). The KBV complements the RBV by looking beyond the sole possession of the resource to also encapsulate the asset's transformation and reconfiguration and hence sees knowledge as simultaneously an asset and capability (Amit & Schoemaker, 1993; Curado & Bontis, 2006). Thus, KBV claims the integration between the specialized knowledge among employees and how it is coordinated and integrated in the organization to be difficult for competitors to replicate (Grant, 1996; Herden, 2020). This makes knowledge imitation difficult as competitors cannot access "*an organization's internal knowledge, combining specialized and common knowledge with knowledge integration mechanisms"* (Herden, 2020:168).

According to Barney (1991), resources that require an extended learning curve, a significant organizational change, or are hard to transfer are more difficult to imitate and therefore more likely to bring performance benefits. Barney (1991) developed the VRIO framework to categorize a firm's resources based on certain characteristics to determine whether they hold a competitive advantage or not. Hence, a competitive advantage is achieved if a unique bundle of resources fulfills the criteria suggested in the VRIO-framework. According to the RBV, these criteria are characterized by value, rarity, and imitability (Barney, 1991)(Appendix 1). Besides the features of the resources themselves, RBV also emphasizes the way an organization deploys its resources - namely the “O” in the VRIO acronym.

As explained by the VRIO-framework, firms should be organized (O) in a way that enables them to fully exploit and take advantage of resources and implement strategies. As such, a firm is thus only able to unlock its full potential on the market by mastering the “O” (Barney, 2007), and in contrast to the other VRIO criteria, the organizational deployment element is more dependent on the organization rather than the resource itself (Kim & Makadok, 2021). However, limited attention has been paid to the “O” in the RBV’s theoretical and empirical literature (Barney & Mackery, 2005; Kim & Makadok, 2021). In their literature review study, Armstrong & Shimizu (2007) conclude that the focus of empirical RBV studies has been mainly on the effects of firm-specific resources on firm performance, excluding a specific organizational deployment focus.

2.1.1 The Dynamic Capability Perspective

Some scholars (Cardeal & Antonio, 2012; Fainshmidt et al., 2019; Schilke, 2014; Titah & Ortiz, 2015) have studied the “O” and competitive advantage through dynamic capabilities, meaning that the way firms organize and bundle their resources constitutes the capability for competitive advantage. Dynamic capabilities can be seen as an extension of the RBV theory, where the primary difference lies in the view of a firm's resources. RBV primarily addresses a firm’s existing resources, meanwhile the dynamic capability perspective emphasizes the reconfiguration of these resources (Helfat & Peteraf, 2003). In other words, dynamic capabilities concern organizational routines that affect change in the firm’s existing resources (Eisenhardt & Martin, 2000; Helfat, 1997; Teece et al., 1997). Previous research on dynamic capabilities has investigated business processes such as product development, strategic decision-making, and alliance (Gruber et al., 2010; Helfat & Peteraf, 2009; Schreyögg & Kliesch-Eberl, 2007).

Furthermore, traditional literature assumes dynamic capabilities to have a universally positive effect on competitive advantage. Dynamic capabilities are suggested to create better matches between the configuration of a firm’s resources and external environmental conditions when replacing existing resources (Teece & Pisano, 1994). However, some researchers advocate for a more holistic view where the value of dynamic capabilities lies not only in organizational routines but also in the context in which these capabilities are deployed (Levinthal, 2000; Sirmon & Hitt, 2009). This stream of research recognizes the effective modes of organizational adaptation to be at least partly determined by environmental forces (Hrebiniak, 1985).

According to Eisenhardt and Martin (2000:1107), dynamic capabilities are *"important drivers behind criterion, evolution, and recombination of others into new resources of competitive advantage."* However, Teece (2007:1321) argues that such capabilities are difficult to develop and deploy in firms because their requirements *"must be necessarily incomplete, inchoate, and somewhat opaque due to know-how that is difficult to obtain and apply."* In highly competitive or fast-changing environments, firms must change more frequently to cope with competition and stay relevant in the market. Therefore, these environments provide more opportunities to execute dynamic capabilities and recuperate the cost of developing them (Darnevich & Kriauciunas, 2011; Wilden & Gudergan, 2015). Depending on the environment in which firms are operating, dynamic capabilities will contribute to competitive advantage to different extents (Schilke, 2014; Winter, 2012).

2.1.2 The RBV in Previous Literature Within the Technological Field

The RBV has been extensively used to analyze technological assets in firms. It started to appear in the information systems (IS) research field in the mid-1990s, where the emphasis was on identifying single sets of resources contributing to business value. Within this, Ross et al. (1996) identified human assets, technology assets, relationship assets, and IT processes, later complemented by Bharadwaj's (2000) findings to include IT infrastructure and IT-enabled intangibles. In addition, an extensive list of studies has explored the relationship between IS resources and firm performance, e.g., the management of external relationships (Bharadwaj et al., 1998; Benjamin & Levinson, 1993; Bharadwaj, 2000), market responsiveness (Ross et al., 1996; Zaheer & Zaheer, 1997), planning and change management (Mata et al., 1995; Marchand et al., 2000), and technical skills (Bharadwaj, 2000; Mata et al., 1995).

Being a novel topic, DA has been studied to a much lesser extent than its technological predecessor IS. The broader information system domain often refers to IT capabilities that capture a broader context of technology by looking at firms' ability to leverage different resources (Schryen, 2013).

Furthermore, it highlights that to understand how technological developments create business value, their particularities need to be thoroughly examined. Hence, the authors argue that exploring DA as a separate domain is important in order to make business applicable findings (Kamioka & Tapanainen, 2014).

Researchers have, by adopting the RBV, concluded that DA is simultaneously a resource and a capability that, if leveraged appropriately, serves as *"a major differentiator between high performing and low-performing organizations"* (Liu, 2014:40) and hence makes it a potential source of competitive advantage (Liu, 2014; McAfee & Brynjolfsson, 2012). In line with this, Fosso Wamba et al. (2015) and Gupta and George (2016) concluded that a combination of resources and capabilities is crucial for DA to deliver firm value. Building on this, Mikalef and Pateli (2017) conclude that DA, per se, can serve as a source of competitive advantage as it helps organizations renew their current organizational model for an ever-changing business environment.

Even though DA appears to play a significant role in business, the understanding, with a few notable exceptions (Tambe, 2014), of how organizational deployment of DA influences firm performance has so far been limited (Grover et al., 2018; Zhang et al., 2018). Previous research on DA (Chiang et al., 2018; Gunay et al., 2019; Ghasemaghaei et al., 2018; Kongar & Adebayo, 2021) has thus far put a large emphasis on the technical aspects of DA with little regard on how DA should be leveraged from a managerial and strategic aspect. Furthermore, as numerous market forces, i.e., evolving customer needs and preferences, increased competition, and the need for strategic guidance (Aydiner et al., 2019), are fueling the demand for DA, there is still no consensus in existing literature regarding organizational best practices to manage DA to gain sustained competitive advantage.

2.2 Data Analytics

DA has gained significant interest among business practitioners and hence became a field of interest for scholars. Over the years, DA has seen multiple definitions in the literature. Some authors categorized it into system infrastructure and analytic methods, where "*system infrastructure focuses on making data ready for analysis, while analytic methods focus on how to* *gain actionable insight from data"* (Duan & Da Xu, 2021:4), and others classify it by type of analyses used: descriptive, predictive, and prescriptive analytics (Aydiner et al., 2019). However, researchers have collectively concluded that DA enables firms to gain actionable insights and make decisions from data (Duan & Da Xu, 2021).

While being a relevant topic, DA is a relatively novel topic, and the amount of research executed on the subject is scarce and mainly focuses on big data analytics (BDA) (Gupta & George, 2016; Fosso Wamba et al., 2017). BDA is a subsection of DA where the attributes of the data itself have made it relevant to study as a separate subfield. Nonetheless, being an important part of DA, research about BDA still poses important findings for the entire field. Despite the attention surrounding BDA, research has focused mainly on the technological aspects, and less attention has been spared to how organizations need to adapt and function to embrace the technology (McAfee & Brynjolfsson, 2012). The authors further claim that not understanding under what conditions DA investments generate value hampers the true strategic potential that can be achieved by working with such tools.

Companies collect data for mainly two purposes - to monitor performance (reactive) and to innovate (proactive). While most companies use data for reactive purposes, the proactive agenda is carried out to a much lesser extent (Jackson, 2020). Though vast volumes of data are collected and stored by companies, some argue that lack of data organization and accessibility, as well as outcome reports being rather informational contra actionable, prohibit the extraction of strategic value from data (Lichtenthaler, 2020). Furthermore, collaborative research executed by McAfee & Brynjolfsson (2012) shows that companies who associate themselves with being data-driven to a greater extent gain better financial and operational results than their competitors. This did, in turn, steer the authors into understanding which capabilities underlie the difference in performance. By studying companies across different industries, researchers have concluded that while DA poses technical challenges, the managerial challenges are even greater (Mata et al., 1995; McAfee & Brynjolfsson, 2012).

2.2.1 Data Analytics Management Skills

In the case of DA, the managerial skills include management's ability to conceive of, develop, utilize, and exploit IT and DA applications to both support and enhance business functions and, thus, performance (Mata et al., 1995). For instance, important management skills to possess are (i) the ability to understand and appreciate the business needs of other stakeholders, such as functional managers, suppliers, customers, etc., (ii) the ability to work with other stakeholders to together develop DA applications, (iii) the ability to coordinate activities around DA, and (iv) the ability to anticipate future needs for DA development (Davenport & Harris, 2007; Davenport et al., 2012).

Management skills are often categorized as tacit knowledge, knowledge gained through experience, and hence difficult to extract. They involve making multiple decisions every day, making them hard to imitate or replicate (Castanias & Helfat, 1991). These skills are often developed over a more extended time through continuously gaining experiences (Katz, 1974). Management skills concerning DA are mainly developed through interaction and close internal relationships between managers in charge of the different functions (George et al., 2014). Thus, developing such capabilities is a socially complex and heterogeneous process that paves the way for sustained competitive advantage. Hence, it has been concluded that leadership and strategy are two obstacles that may prohibit firms from succeeding in DA projects (George et al., 2014). On the other hand, companies with a defined DA strategy, clear goals, and the ability to articulate the business case are more likely to succeed.

2.2.2 Data Analytics and Performance

Researchers have adopted different ways to measure firm performance, all with the same goal of evaluating how DA results in favorable outcomes (Bogdan & Borza, 2019). While some study decision-making effectiveness (Byrd & Wang, 2017), the most common approach is looking at the firm's financial and/or market performance (Côrte-Real et al., 2017; Fosso Wamba et al., 2017; Huang et al., 2018). The previous emphasis on this and the close connection to sustained competitive advantage motivates the further focus on the latter measures.

Looking at the financial impact of investments in DA, a large-scale survey of large- and medium-sized firms showed a statistical association between companies who invest in DA and their business performance (Davenport & Harris, 2007; Tambe, 2014). For instance, the International Data Corporation reported that analytics projects for production functions had a median ROI of 277%, while financial management functions yielded a median ROI of 139% (Morris, 2003; Davenport & Harris, 2007). While it is commonly recognized that data can generate value for companies and organizations, the process of value creation and capture still poses an issue for many businesses creating a demand to understand what drives the strategic value of data (Comuzzi & Patel, 2016; Brinch et al., 2021).

DA has been shown to bring large potential for various industries as a positive relationship has been established between firms adopting DA and their performance (Germann at el., 2014). For example, research shows how major retail firms have leveraged DA capabilities to improve the customer experience, reduce fraud, and make just-in-time recommendations (Tweney, 2013). Previous scholars have also found a positive connection between the deployment of customer analytics and firm performance (Germann et al., 2014) and are expecting DA to have a positive impact in various industries such as retail by increasing employee engagement (Coco et al., 2011; Tweney, 2013), healthcare by improving patient outcomes (Liu, 2014; Strome, 2013), and manufacturing by optimizing workflows (Davenport et al., 2012).

Much research on DA is executed as case studies within the retail industry, where firm-specific examples prove the positive relationship between DA and firm performance. Target, Amazon, and GE have all shown financial and operational benefits due to successful DA implementation (Liu, 2014; Wills, 2014; Ward, 2014). Richer customer profiles contribute to increased profits by better-predicting pricing strategies (Elmachtoub et al., 2021; Germann et al., 2014), and more robust customer loyalty programs are built to predict purchasing behaviors and future trends (Wills, 2014).

2.3 Theorizing and Hypothesis Development

DA has in the previous sections been demonstrated to entail business value for firms and requires certain capabilities to achieve these benefits. Several hypotheses are derived to address the aim of this study and provide consensus regarding organizational best practices to manage DA and achieve sustained competitive advantage. A revision of previous literature and theory resulted in six common themes being identified as especially important for successful organizational deployment and utilization of DA for enhanced company performance and thus competitive advantage. The following six themes focus on the management ability and a strategic management perspective of DA. The following themes are: planning, controlling, connectivity, leadership, data-driven culture, and education and knowledge development. The argument behind choosing each particular construct is explained below.

Internal knowledge sharing, planning, and controlling mechanisms as key capabilities

It is generally understood in the IS literature that IT resources per se do not enhance firm performance but rather act as key enablers of higher-order organizational capabilities or interact with other business units to enhance firm performance (Popovič et al., 2018). According to findings in previous studies in operation literature, previous scholars have shown that firms who utilize DA can conduct better forecasts of previously unpredictable outcomes and thus improve process performance, operations planning, inventory management, cost planning, etc. (Popovič et al., 2018). A more sophisticated analytical planning process characterizes higher-performing firms, while lower-performing firms acknowledge this competitive advantage (Klatt et al., 2011).

A firm's path towards gaining a competitive advantage in the market includes having well-defined data quality and strategy standards such as clear data, analytics strategies, and data information ethics. It is almost impossible to collect and analyze data throughout an enterprise and provide insights into where they are most required without adequate organizational structures and governance frameworks (Grover et al., 2018). DA necessitates centralized data collection and analysis, ensuring that all projects within DA use the same standards, protocols, procedures, and tools making planning and controlling practices, once institutionalized, operational by nature. Meanwhile, having a local, federated DA architecture for DA initiatives can help firms enhance analytics speed and ensure that learned information is available for decision-makers. As a result, firms must create a governance framework that standardizes DA processes across various operational domains while allowing for federated project delivery (Grover et al., 2018). Thus, the technical challenges are not merely the issue in becoming a data-driven firm.

Setting clear and appropriate targets from the beginning and frequently making sure these are met are crucial for firms to execute successful projects, e.g., meeting the data quality requirements. Hence, expectations management should not be overlooked (Bunder & Viaene, 2011).

Additionally, to improve DA outcomes, it is vital for firms to implement practices that enable IT professionals to understand business users' work styles, behavior, and needs. Such practices entail shadowing, agility working, and/or co-locating (Wixom et al., 2013).

Furthermore, authors within the IS literature emphasize the importance of shared knowledge between IT and customer service units and identify this as a key IT capability that optimizes customer service process performance (Ray et al., 2005). Firms need to align their DA capabilities with their business strategy and DA departments - composed of business analysts, data scientists, and IT staff - to create business value (Vidgen et al., 2017). Moreover, internal sharing of the acquired experiential knowledge amongst decision-makers using DA impacts firm performance and the ability to create sustainable DA-enabled competitive differentiation (Marjanovic, 2022). Connectivity practices facilitate knowledge sharing, which consequently enables new combinations of skills and knowledge that are shown to have a positive impact on the transformation of technological capabilities (Protogerou et al., 2011).

Based on the aforementioned arguments and aligning with previous scholars, this study intends to investigate the effect of planning, controlling, and connectivity mechanisms on firm performance. These constructs will be explored through the following hypotheses:

H1: ***Planning,*** *as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.*
H2: ***Connectivity****, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.*
H3: ***Controlling****, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.*

Practices fostering education and knowledge development as key capabilities

Talent management has, in recent years, emerged as an organizational challenge, even more so in data-driven organizations where processing and understanding data calls for data-specific capabilities (Ali et al., 2020). Hence, human capital practices cannot be ignored when investigating successful organizational capabilities in relation to DA.

Researchers have noticed organizations' active involvement in competing for talented employees during today's technological business landscape and have detected a connection between successful data management and talent within organizations (Mikalef et al., 2019). Davenport & Shapiro (2010) further showed that a workforce with an analytical mindset drives more business value from DA practices. A study by Fosso Wamba et al. (2015) even showed that the personnel's expertise was the most critical DA capability, strongly influencing firm performance.

Furthermore, the dynamic nature of the technological landscape makes continuous learning an important factor for organizations investing in DA (Vidgen et al., 2017). This is further supported by Teece et al. (1997) who state that learning processes lead to quicker problem resolution and opportunity identification. According to the researchers, the value of learning processes comes from their dynamic and multilevel nature (Teece et al., 1997). This implies importance for organizational practices fostering education and knowledge development.

Previous research indicates knowledge being an important factor affecting organizational performance. Hence, this study will test whether there is a relationship between educating and fostering knowledge development practices and firm performance. This will be examined through the following hypothesis:

H4: ***Educating and knowledge development****, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.*

Importance of leadership for sustained competitive performance

Leadership decisions regarding the utilization of organizational resources have been shown important for successful strategic management practices (Ferigotti et al., 2020). Moreover, especially in uncertain and rapidly changing market environments, leadership ability is a core contributor to high firm performance in firms operating in data-driven contexts (Mikalef et al., 2019). Sotarauta (2005) also showed the importance of leadership for expanding and progressing organizational members' capabilities in dynamic markets.However, leadership itself can take many shapes and forms, making it dynamic in nature (Breevaart et al., 2016; Tepper et al., 2018).

Moreover, Prescott (2014) showed that data-analytic thinking ability goes beyond data scientists and needs to be instilled throughout the organization, particularly for employees in managerial positions. Furthermore, Davenport & Shapiro (2010) notably characterized analytical leaders as having the ability to apply analytical perspectives to the business and guide employees into more rigid thinking. Additionally, analytical leaders are shown to more successfully take leadership of initiatives or projects to increase the use of DA for organizational gain (Davenport & Shapiro, 2010).

Multiple previous studies have shown a positive relationship between leadership and firm performance (Fosso Wamba et al., 2015; Mikalef et al., 2019; Ali et al., 2020). Nonetheless, the broad encapsulation of the term leadership has allowed the studies to investigate slightly different aspects of the umbrella phenomena that is leadership. While Fosso Wamba et al. (2015) looked at leadership through the lens of coordination and control, Mikalef et al. (2019) instead investigated to what extent management understands the business needs of different functions and their ability to set a strategic direction based on new insights. In this study, leadership relates to managers' understanding and ability to drive DA-related initiatives.

In line with the exploration of the *organizational* factor in the RBV theory, as well as the identified connection between leadership and firm performance, we propose the following:

H5: ***Leadership,*** *as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.*

Importance of a data-driven culture for DA and sustained competitive performance

Grover et al. (2018) see having a culture that welcomes data- and evidence-driven approaches to business choices, as well as governance that clearly defines data responsibility and accountability as a prerequisite to extracting value from DA. In fact, multiple studies have proven the relationship between organizational culture and firm performance (Ali et al., 2020; Martinsons & Westwood, 1997). Furthermore, previous literature studying workplace outcomes in digital adopting organizations has also highlighted that performance is not only affected by the technology used but also by the organizational culture (Alotaibi et al., 2020; Thomas & Chopra, 2020). Hence, organizational culture can serve both as a support or hindrance in adopting efficient DA practices.

The purpose of organizational culture in a data context is to enable the firm to generate and use innovative ideas (Erevelles et al., 2016). A lack of supportive culture has also been identified as one of the largest barriers faced by managers when implementing data initiatives, as it prohibits the development of critical insights (Kiron, 2017). Previous research within the DA field has discovered multiple practices indicating the significance of organizational culture for the successful utilization of data and DA. Hopkins et al. (2011) showed that having a data-driven culture is a key determinant for continuing projects in organizations working extensively with data. The reason for this is that companies with such a culture use data in a pervasive way and develop processes facilitating for employees to acquire the necessary information and make decisions, and hence enabling the reconfiguration of necessary capabilities and new ideas (Chatterjee et al., 2021; Hopkins et al., 2011). As an example, by making data-driven decisions, firms have increased cost savings and firm efficiency (Ward, 2014). This is further supported by McAfee and Brynjolfsson (2012), whose research shows that organizational culture and governance are crucial in establishing the right atmosphere for DA projects to succeed.

As a part of a data-driven culture, Mikalef et al. (2019) showed a positive relationship between embedding evidence-based decision-making in an organization's core values and its performance. This has also been demonstrated in previous studies (Hopkins, 2010; Kettinger et al., 2011). Furthermore, clear strategies regarding DA, as well as a data-driven approach and mindset, have been identified as critical components under uncertain market conditions (Mikalef et al., 2019). Such conditions surround many companies relying on DA. Hence, based on the earlier discussion, the following hypothesis is proposed:

H6: ***Data-driven culture****, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.*

Table 1: Decription of independent variables

Independent variables	Abbreviation	Description
Planning	PL	Systematic enforcement of adequate plans for DA where DA plans are frequently adjusted to suit organizational conditions.
Connectivity	CN	Facilitated communication of DA insights and collaboration across different functions of the organization.
Controlling	CL	Well defined DA responsibilities where workstreams are regularly monitored and measured.
Education & knowledge development	E&KD	Presence of frequent DA-related learning opportunities.
Leadership	LS	Manager's understanding and ability to drive DA related initiatives.
Data-driven culture	DDC	Instilled sense of evidence-based decision making and understanding of DA's role within the organization.

Table 2: Summary of hypotheses

Relationship	Hypothesis
Planning and firm performance	H1: Planning, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.
Connectivity and firm performance	H2: Connectivity, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.
Controlling and firm performance	H3: Controlling, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.
Education and knowledge development and firm performance	H4: Educating and knowledge development, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.
Leadership and firm performance	H5: Leadership focus on DA has a distinct effect on firm performance compared to the other organizational practices measured.
Data-driven culture and firm performance	H6: Data-driven culture, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.

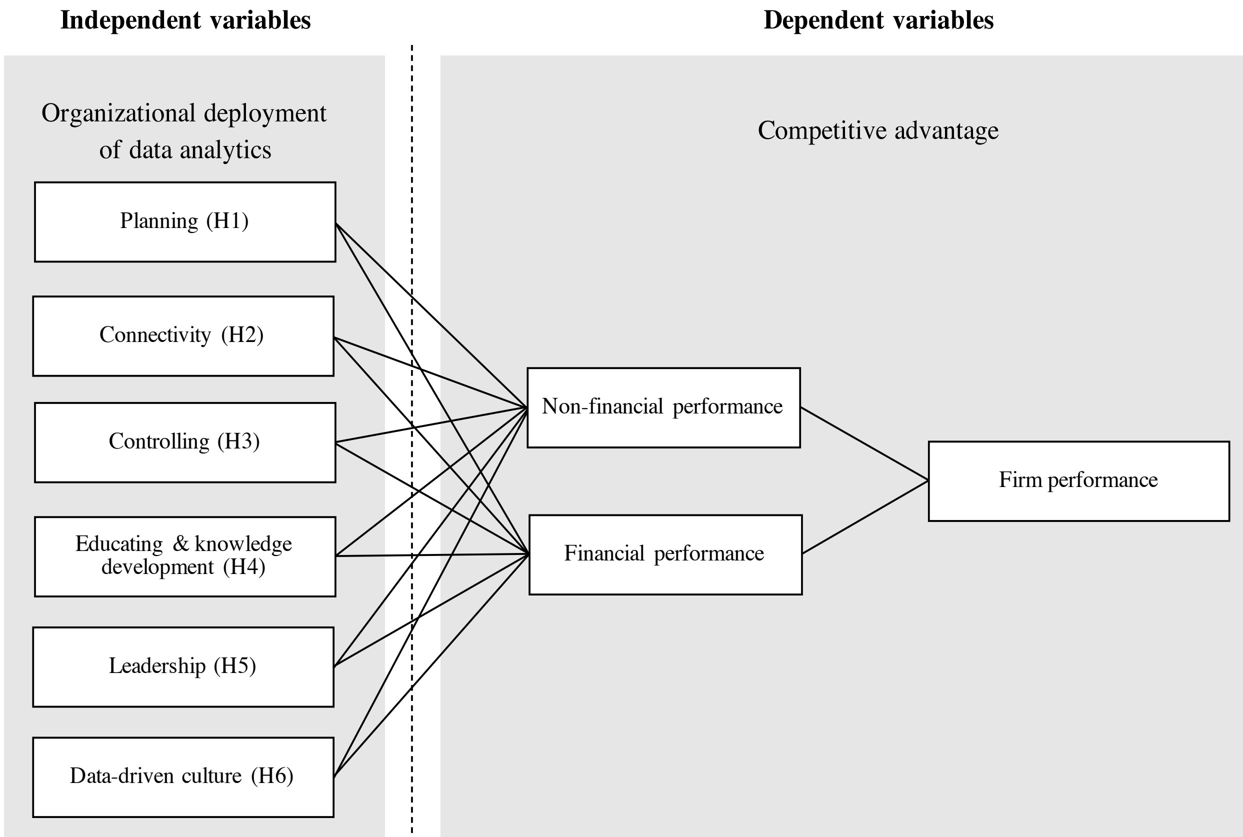

Figure 1: Visual representation of theoretical framework

3. Methodology

This chapter describes the study's methodological approach by presenting (i) the chosen research approach, (ii) data collection and sample, (iii) data analysis and justification, and a (iv) data quality discussion.

3.1 Research Design

This study is based on a positivist research approach which assumes that the world of phenomena has an objective reality that can be expressed in casual relationships and measured in data (Straub et al., 2004). Hence, the authors of this study argue for organizations being objects of external reality in which findings are observed as naturally derived and therefore independent of an external reality (Moses & Knutsen 2007). The research question is approached through a survey as it manages to capture the objective and social reality of organizational practices of DA and their effect on firm performance. The hypotheses were developed using a deductive approach. This is demonstrated by the researchers combining theory and existing research across fields such as DA, competitive advantage, and organizational practices to derive hypotheses that will answer the research question (Creswell & Creswell, 2017). By gathering data and empirically testing the hypotheses, the researchers could support or reject statements allowing for revision or expansion of previous theory (Bryman & Bell, 2011).

To test the hypotheses, the researchers gathered quantitative data through an online self-completion survey which was further refined through a pilot test (Section 3.1.5). The self-completion survey is the most common method to collect quantitative data and the motivations for using a survey are its cost- and time-efficiency, quick administration processes and the fact that it runs smoothly without the researchers' physical presence (Bryman & Bell, 2011). However, the researchers are aware of the risks associated with data collection through surveys such as limited possibility for assistance of respondents participating in the survey, respondent fatigue and the fact that the survey only measures what is specifically asked and no other contextual findings will be detected. Furthermore, self-reporting does also pose risks to respondent dishonesty (Dillman et al., 2014). However, by being mindful of the potential risks and biases throughout the creation and distribution of the survey (Section 3.1.1), the researchers believe the benefits outweigh the potential drawbacks. As complete anonymity is promised to the respondents, the temptation of dishonesty should be limited. Furthermore, the method's contextual advantages, such as allowing for data collection from a broad set of respondents and capturing complex observable data (Bhattacherjee, 2012), additionally justify the researchers' choice to use the self-completion questionnaire as means to fulfill the purpose of this study.

Although organizational practices can be captured through a qualitative method, the intention of explaining and finding correlation to firm performance is highly difficult with such. Researchers have adopted both quantitative and qualitative methodologies in previous research on DA and the RBV, depending on the research purpose (Creswell & Creswell, 2017; Rouse & Daellenbach, 2002). However, in the research context of investigating the relationship between practices and performance, a quantitative measure has been preferred as it, to a greater extent, enables capturing of causal relationships between constructs and provides generalizable statements on the research setting (Fosso Wamba et al., 2017; Pinsonneault & Kraemer, 1993). Additionally, the relatively large scope of industries and respondents captured in this study for generalizability pose the quantitative approach to be superior to the qualitative. All the aforementioned motivates using a quantitative methodology for this study's specific research purpose.

3.1.1 Survey Design

The aim of the survey design is to construct measures to capture the variables of interest (Bryman & Bell, 2011). However, as the variables, to a great extent, are unobservable (i.e., latent), multiple indicators have been instilled, allowing for more concrete measures than relying on single-numbered measures. Furthermore, to promote the reliability and validity of this study, all indicators were inspired by previous studies and have hence been recognized in previous research (Saunders et al., 2009). In total, three statements accompanied each theoretical construct to measure the variables.

The self-completion survey was designed across 12 sections (Figure 2), starting with an introduction, relevant definitions, and consent, followed by eight modules corresponding to each of the dependent and independent variables, and ending with quality and demographics questions. Each block of the independent variables, namely *internal knowledge sharing, planning, controlling, education and knowledge development, leadership,* and *data-driven culture,* consisted of three questions and used a seven-point Likert scale to measure the presence and quality of the listed organizational practices (Lietz, 2010). All questions for the independent variables were randomly displayed to the respondents to decrease the risk of potential question order bias (Perreault, 1975/76). The dependent variables, *non-financial performance* and *financial performance,* consisted of six and four statements, respectively, to which the respondent yet again answered using the seven-point Likert scale.

The uneven seven-point Likert scale was chosen to allow for higher differentiation in answers and provided the respondents with a neutral alternative (Lietz, 2010). Furthermore, it has been used in a similar research context when studying the relationship between DA and performance (Fosso Wamba et al., 2017; Ali et al., 2020), proving its suitability for such studies. To avoid confusion, the two extreme options were accompanied by a qualitative description, i.e., fully disagree vs. fully agree. In total, the survey consisted of 32 questions for the respondents to answer, and the questionnaire was carefully reviewed multiple times before distribution to avoid any mistakes.

In terms of language, even though most respondents were native Swedish speakers, the survey was constructed in English. As the questionnaire included previously proven and scientifically recognized measures and questions, wrongly executed translations could negatively affect the study's replicability, validity, and reliability. Furthermore, as the respondents were all expected to be highly proficient in English, considering the international staffing of the many participating organizations, having the survey in English was not assumed to pose any challenges for the respondents. Nonetheless, the risk of misunderstandings was further mitigated by pre-testing the survey on both native and non-native English speakers.

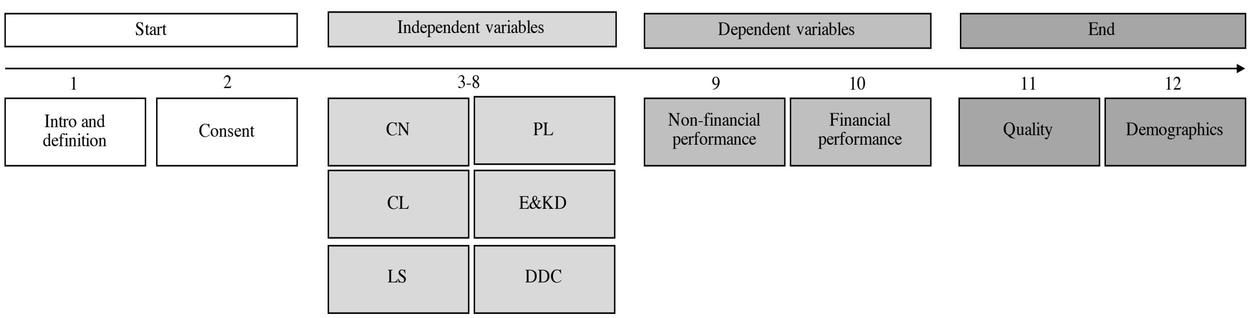

Figure 2: Visual illustration of survey build-up

3.1.2. Indicators of the Independent Variables

Planning (PL)

An organization's planning routine in relation to its DA practices is measured using three indicators (i) *the organization enforces adequate plans for the utilization of data analytics,* (ii) *our organization performs data analytics planning processes in systematic ways,* and (iii) *data analytics plans are frequently adjusted to better adapt to changing conditions.* These are inspired by previous research investigating organizations' planning practices regarding IT and big data (Popovič et al., 2018; Klatt et al., 2011).

Connectivity (CN)

Inspired by previous research proving the significance of intra-organizational knowledge sharing for service process optimization in companies deploying IS and DA (Ray et al., 2005; Marjanovic, 2022), this survey assesses connectivity through the same but contextually adapted indicators. The three indicators employed by the authors were (i) *there are no identifiable communications bottlenecks within our organization for sharing analytics insights,* (ii) *information is shared across our organization, regardless of the location,* and (iii) *in our organization, data analysts and employees from various departments regularly attend cross-functional meetings.*

Controlling (CL)

How the organization sets out control measures to ensure that goals are reached and expectations are managed is determined through the following indicators (i) *in our organization, different responsibilities regarding analytics development are well-defined and assigned*, (ii) *workstreams involving data analytics are monitored regularly,* and (iii) *clear performance criteria are set regarding workstreams involving data analytics.* These are inspired by previous studies (Bunder & Viaene, 2011; Grover et al., 2018).

Education and Knowledge Development (E&KD)

These measures address the organization's active involvement in its personnel's education and knowledge development as proven important in previous research which also inspires this study's indicators (Davenport et al., 2012; Fosso Wamba et al., 2015). The three indicators are (i) *employees are regularly encouraged to draw knowledge and make decisions based on data,* (ii) *personnel are regularly educated in technological trends, new technologies, or data analytics,* and (iii) *the organization ensures that personnel have the required knowledge about the business environment and customer needs.*

Leadership (LS)

Leadership focus on DA was measured using the three indicators (i) *our leadership are able to understand the business need of managers and customers to determine opportunities that data analytics might bring to our business* (ii) *our managers frequently examine innovative opportunities for the strategic use of data analytics,* and (iii) *our managers are able to understand* *where to apply data analytics.* These indicators are formulated based on previous studies and align with the “organizational deployment” from the VRIO-framework (Fosso Wamba et al., 2015; Mikalef et al., 2019; Ali et al., 2020).

Data-Driven Culture (DDC)

Organizational culture has been proven to influence organizational performance (Alotaibi et al., 2020; Martinsons & Westwood, 1997; Thomas & Chopra, 2020). Consequently, to which extent organizations foster a data-driven culture and the relationship between cultural factors and firm performance is further investigated in firms working extensively with big data (Ali et al., 2020; Mikaelf et al., 2019). Hence, the indicators for measuring data-driven culture within firms are inspired by studies mentioned above, and these indicators are the following (i) *decisions are based on data rather than on instinct,* (ii) *all personnel are willing to override their own intuition when data contradicts their viewpoints* and (iii) *all personnel know which role data analytics play in the firm's business strategy.*

Table 3: Summary indicators for independent variables

Variable	Indicator
Planning	1. The organization enforces adequate plans for the utilization of data analytics
	2. Our organization performs data analytics planning processes in systematic ways
	3. Data analytics plans are frequently adjusted to better adapt to changing conditions
Connectivity	1. There are no identifiable communications bottlenecks within our organization for sharing analytics insights
	2. Information is shared across our organization, regardless of the location
	3. In our organization, data analysts and employees from various departments regularly attend cross-functional meetings
Controlling	1. In our organization, different responsibilities regarding analytics development are well-defined and assigned
	2. Workstreams involving data analytics are monitored regularly
	3. Clear performance criteria are set regarding workstreams involving data analytics
Education & knowledge development	1. Employees are regularly encouraged to draw knowledge and make decisions based on data
	2. Personnel are regularly educated in technological trends, new technologies, or data analytics
	3. The organization ensures that personnel have the required knowledge about the business environment and customer needs
Leadership	1. Our leadership are able to understand the business need of managers and customers to determine opportunities that data analytics might bring to our business
	2. Our managers frequently examine innovative opportunities for the strategic use of data analytics
	3. Our managers are able to understand where to apply data analytics
Data-driven culture	1. Decisions are based on data rather than on instinct
	2. All personnel are willing to override own intuition when data contradicts their viewpoints
	3. All personnel know which role data analytics play in the firm's business strategy

3.1.3. Indicators of the Dependent Variables

Non-Financial and Financial Performance

To assess firm performance, both financial and non-financial performance measures are considered as DA is said to bring multiple benefits to an organization: financial, service, and process benefits (Fosso Wamba et al., 2015; Klatt et al., 2011; Mikaelf et al., 2019). Furthermore, to capture the essence of the RBV theory and the accompanying ”O” in the VRIO-framework, firm performance is assessed relative to their competitors and over three years for all indicators.

This study uses indicators for firm performance based on previous research (Morris, 2003; Davenport & Harris, 2007), where non-financial performance is made up of the six indicators (i) acquisition of new customers/users more quickly, (ii) customer retention (iii) customer satisfaction, (iv) market share, (v) introduction of new products or services to the market faster, and (vi) the success rate of our new products or services, and financial performance is made up of the four indicators (i) sales growth, (ii) profitability, (iii) return on investment and (iv) overall financial performance.

Table 4: Summary indicators for dependent variables

Variable	**Indicators**
Non-financial performance	*Using data analytics improved ____ during the last 3 years relative to competitors*
	Acquisition of new customers/users more quickly
	Customer retention
	Customer satisfaction
	Market share
	Introduction of new products or services to the market faster
	The success rate of our new products or services
Financial performance	*Using data analytics improved ____ during the last 3 years relative to competitors*
	Sales Growth
	Profitability
	Return on investment
	Overall financial performance

3.1.4. The Control Variables

Control variables are external factors to the primary study but might still affect the dependent variable. Unless controlled for, those factors can bias the findings as they can cause changes in the dependent variable that go unnoticed (Atinc et al., 2012). Hence, including control variables facilitates the establishment of possible correlations between the independent and dependent variables and increases the internal validity of a study (Pedhazur & Schmelkin, 1991). This study has two themes of control variables (i) industry and (ii) hierarchical level. First, by including different industries, the researchers aim to capture any potential intra-industry discrepancies where, e.g., organizations in more technical fields such as IT might be more used to working with DA than traditional industries such as retail or education. The selection and categorization of relevant industries are based on previous DA studies executed by Mikalef et al. (2019) and Fosso Wamba et al. (2017). Next, the purpose of taking the different hierarchical levels of respondents into account is to capture potential differences in knowledge about the performance metrics, e.g., higher hierarchical levels might know more about metrics such as ROI or profitability. However, in this study, in-depth analysis of control variable estimates is omitted for brevity.

Table 5: Summary of control variables.

Control Variable	Alternatives
Industry	Agriculture
	Media & Entertainment
	Construction
	Education
	Energy
	Oil & Gas
	Finance & Insurance
	Healthcare
	Manufacturing
	IT & Tech
	Retail & E-commerce
	Logistics
	Consumer Goods
Hierarchical Level	C-suite
	Vice President
	Director
	Manager
	Individual Contributor (e.g., associate, analyst)
	Other

3.1.5. Pilot Testing

Before gathering data for the main study, a pilot test of the planned questionnaire was conducted. This was done to ensure that the final data collection is of desired quality, i.e., that the proposed sets of questions are clearly phrased, free of misunderstandings, and utilize appropriate measures (Saunders et al., 2009). Furthermore, as the data is collected through an online self-completion survey in which the respondents do not receive any simultaneous assistance from the authors, conducting a pilot test is of crucial importance (Dillman et al., 2014).

A total of seven respondents participated in the pilot test, answering the questions that would be found in the final survey. The respondents stemmed from three industries (consumer goods, education technology, and retail) and across hierarchical levels. Due to time constraints, the respondents were people within the researchers' private networks. Nonetheless, Saunders et al. (2009) encourage pilot-testing with one's network to the alternative of not conducting a pilot test.

As part of the pilot testing, an additional open-ended question was added to the survey: *"Is there any feedback you would like to share with the researchers regarding the survey?"* The feedback from the pilot test indicated some minor changes which were incorporated into the final survey. For example, an explicit definition of the term "data analytics" was added to the introduction to prohibit the respondents from ambiguous interpretations of the phenomena. Lastly, spelling errors and some minor adjustments in the phrasing of a few questions were adhered to before the publication of the main survey.

3.2 Data Collection and Sample

Before collecting the data, a research setting was established, and suitable respondents were identified (Christensen et al., 2014). The empirical field was narrowed down by a set of criteria covering the organizations' operational status of DA. This is to ensure that the respondents' perspectives on the organizational practices of DA are of sufficient nature. The two selection criteria were (i) the organization uses DA extensively as a part of its business strategy, and (ii) the organization has done so for at least three years. These criteria were communicated both in the initial communication (Appendix 2) as well as in the survey to reduce confusion amongst respondents and ensure comparability between their answers.

A cross-sectional self-completion survey served as the source for data collection to which respondents could fill in their answers through the online-survey tool Qualtrics (Appendix 3). Furthermore, the researchers included a control question, *”choose the option ’5’”,* amongst the ordinary survey questions to ensure focus and caution of the respondents.

The survey was distributed through e-mail and the social media platform LinkedIn. To ensure a diverse list of companies to e-mail, the researchers combined organizational lists from startup incubators, mid-size and large companies in Sweden across all major industry sectors. In total, 232 companies were contacted through e-mail. LinkedIn was deemed suitable as its users align with this research’s target group of working professionals across different fields and industries. Hence, participants for this research were recruited based on a non-probability convenience sampling approach where availability and ease of access to respondents drive volume (Chandler & Shapiro, 2016). Furthermore, as this method is favorable in situations with time and cost constraints and is frequently used in management research (Bryman & Bell, 2011), it is considered suitable by the researchers. However, to decrease potential biases of convenience sampling and increase the sample size (Saunders et al., 2009), the researchers also enforced snowball sampling by encouraging respondents to re-share the survey link in their professional networks. To further increase participation rates, a non-egoistic incentive was offered to participants (Christensen et al., 2014), where 2 SEK was donated to UNHCR with each completed survey (Appendix 4).

The data collection lasted a total of 26 days (1/4/21 -26/4/21), during which a total of 247 responses were collected. However, after removing respondents for not agreeing to GDPR (n=7), having not worked with DA for at least three years (n=18), and incorrect quality answers (n=16), the total number of responses used in the data analysis constitutes 205. The complete responses pose a diverse sample with variety amongst gender, industry, and hierarchical level. However, industries such as IT & tech, finance & insurance, retail & e-commerce, and consumer goods, as well as the lower hierarchical levels, are clearly dominating amid the sample (Table 6).

Table 6 - Sample description

Demographics	**Categories**	**Sample (N=205)**	**Percentage (%)**
Gender	Female	111	54.41%
	Male	93	45.59%
	Other	0	0.00%
Industry	Agriculture	2	0.98%
	Media & Entertainment	14	6.86%
	Construction	7	3.43%
	Education	12	5.88%
	Energy	4	1.96%
	Oil & Gas	4	1.96%
	Finance & Insurance	28	13.73%
	Healthcare	12	5.88%
	Manufacturing	15	7.35%
	IT & Tech	40	19.61%
	Retail & E-commerce	28	13.73%
	Logistics	12	5.88%
	Consumer Goods	24	11.76%
Hierarchical level	C-suite	9	4.41%
	Vice president	8	3.92%
	Director	30	14.71%
	Manager	66	32.35%
	Individual contributor (e.g., consultant, associate analyst, representative)	81	39.71%
	Other	10	4.90%

3.3 Data Analysis Using OLS: Regression Model

The relationship between the different organizational deployment variables and firm performance was tested using an ordinary least squares (OLS) regression model. In OLS regression, the estimated equation "*minimizes the sum of the squared residuals,*" which enables to derive *"unbiasedness, consistency, and other important statistical properties relatively easily"* (Wooldridge, 2009:31-32). This type of regression is deemed suitable for studying potential relationships between independent and dependent variables and was therefore considered by the authors. Furthermore, the authors are aware of the rising concern of the OLS model being applied without fulfilling the necessary assumptions of multiple linear regressions (MLR), creating inaccurate results (Barry, 1993; Hardy, 1993). This is especially prominent in contemporary research, where increased use of mixed categorical and continuous variables may create conditions under which the assumptions are not met (Agresti, 1990; Barry, 1993; Huselid & Day, 1991). Hence, before interpreting the results using the OLS regression model, the researchers concluded that the estimators met all necessary assumptions of MLR.

3.3.1 Fulfilling the OLS Assumptions

Assumption MLR 1: Linear in Parameters

This assumption captures the fact that the independent variable indeed affects the dependent variable (Wooldridge, 2009). The independent variables derived from previous studies (Section 3.1.2) have shown linear relationships to firm performance across various studied fields. Moreover, a scatter plot of the overall model also shows a clear linear relationship (Figure 3), proving fulfillment of the first MLR assumption.

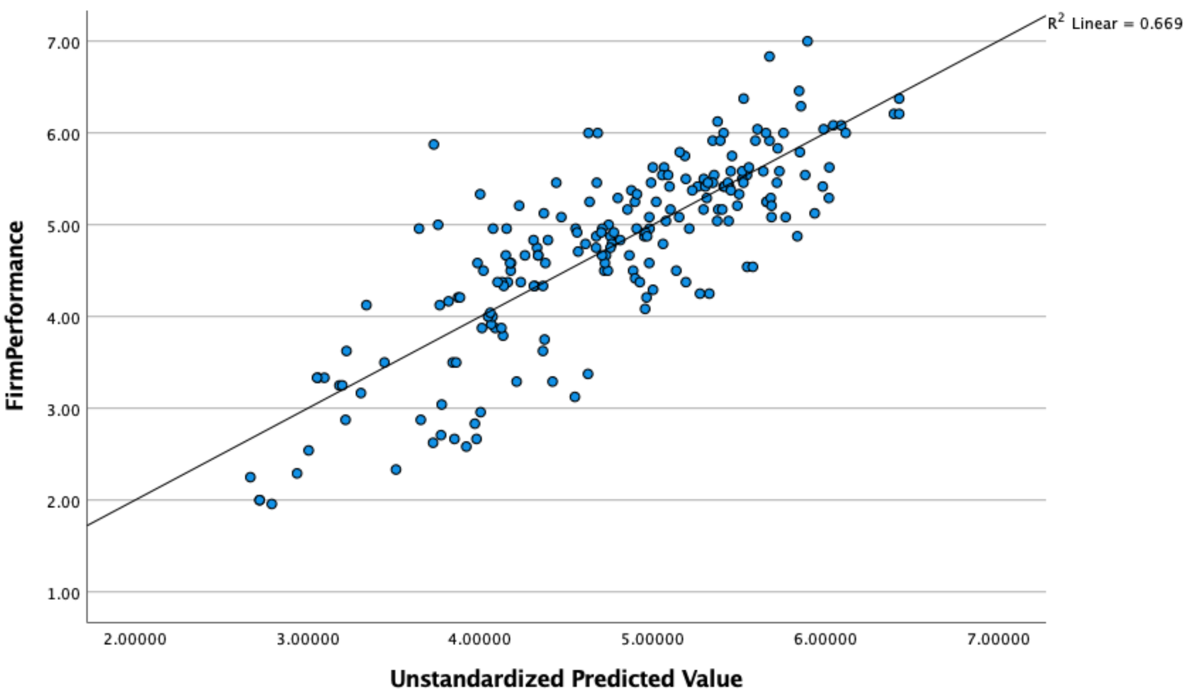

Figure 3: Scatter plot of overall regression model

Assumption MLR 2: Random Sampling

A Durbin-Watson test was undertaken to ensure a random sample (Ali, 1987). The Durbin-Watson statistic checks for autocorrelation in the residuals. If a sample is random, the error terms of one observation should not be influenced by the error term of another observation. However, if correlated, the standard errors will be underestimated, and variables might be found significant even when, in reality, they are not. The Durbin-Watson statistic for this particular model is DW = 1,96, indicating no autocorrelation and hence fulfilling the second MLR assumption (Wooldridge, 2009).

Assumption MLR 3: No Perfect Collinearity

This assumption checks for perfect collinearity between the independent variables of the model. If present, it becomes impossible to understand how each of the perfectly correlated variables individually affects the dependent variable (Wooldridge, 2009). The variance inflation factor (VIF) is used to indicate multicollinearity between the independent variables. VIF indicates to what extent the variance of a variable is affected by correlation with other variables. Hence, increased multicollinearity results in higher VIF-values. To exclude multicollinearity, the VIF values should be below ten and preferably below five (Belsley, 1991).

The initial model showed high VIF-values for the control variable "industry," indicating high multicollinearity. However, as some industries only had a few respondents ($n<10$), the researchers excluded these from the model. The new model, only including industries with more than ten respondents as control variables, satisfied the assumption of no multicollinearity as all VIF-values were below five. This was hence the regression model used in the analysis.

Additionally, Table 7 further demonstrates the correlation between the different variables of this study. As seen in the Table, there are no perfectly correlated variables. Education & knowledge development and data-driven culture, and education & knowledge development and leadership have the highest correlations of $r=0.744$ and $r=0.669$, respectively.

Table 7 - Summary of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FP	1.000						
(2) PL	0.352	1.000					
(3) CL	0.472	0.586	1.000				
(4) CN	0.398	0.354	0.423	1.000			
(5) E&KD	0.641	0.510	0.593	0.407	1.000		
(6) LS	0.499	0.590	0.617	0.292	0.669	1.000	
(7) DDC	0.633	0.335	0.506	0.478	0.744	0.561	1.000

Note: FP=Firm performance, PL=Planning, CL=Controlling, CN=Connectivity, E&KD=Education and knowledge development, LS=Leadership, DDC=Data-driven culture

Assumption MLR 4: Zero Conditional Mean

The error terms should follow a normal distribution for valid inferences to be made from the regression. In other words, the difference between the predicted and actual value given by the model should have the expected value of zero (Poole & O'Farrell, 1971). The P-P plot (Figure 4) indicates normal distribution as the values conform to the diagonal normality line, showing that the theoretical distribution closely aligns with the sample data. Consequently, the data fulfills the assumption of zero conditional mean.

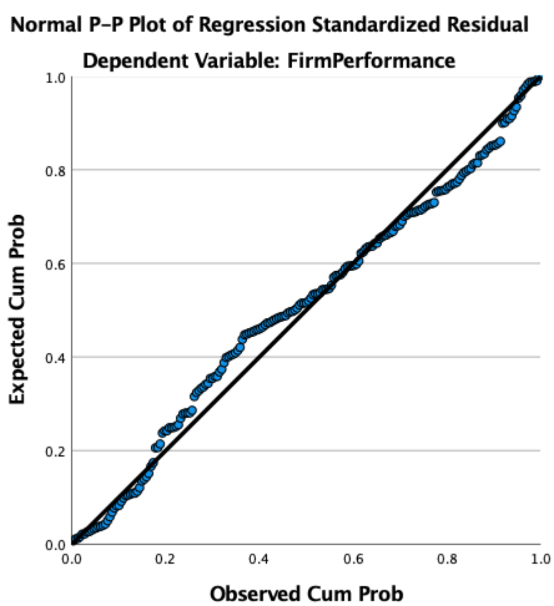

Figure 4: P-P plot showing normal distribution of residuals.

Assumption MLR 5: Homoscedasticity

Whereas the previous assumption refers to the expected value of the residuals, this assumption concerns the variance of the error terms and hence to what extent they are equally distributed or concentrated around certain values (Wooldridge, 2009). By plotting the predicted values and residuals on a scatter plot, homoscedasticity in the data can be concluded (Tranmer et al., 2020). As no pattern can be identified between predicted values and residuals, the assumption of homoscedasticity is fulfilled.

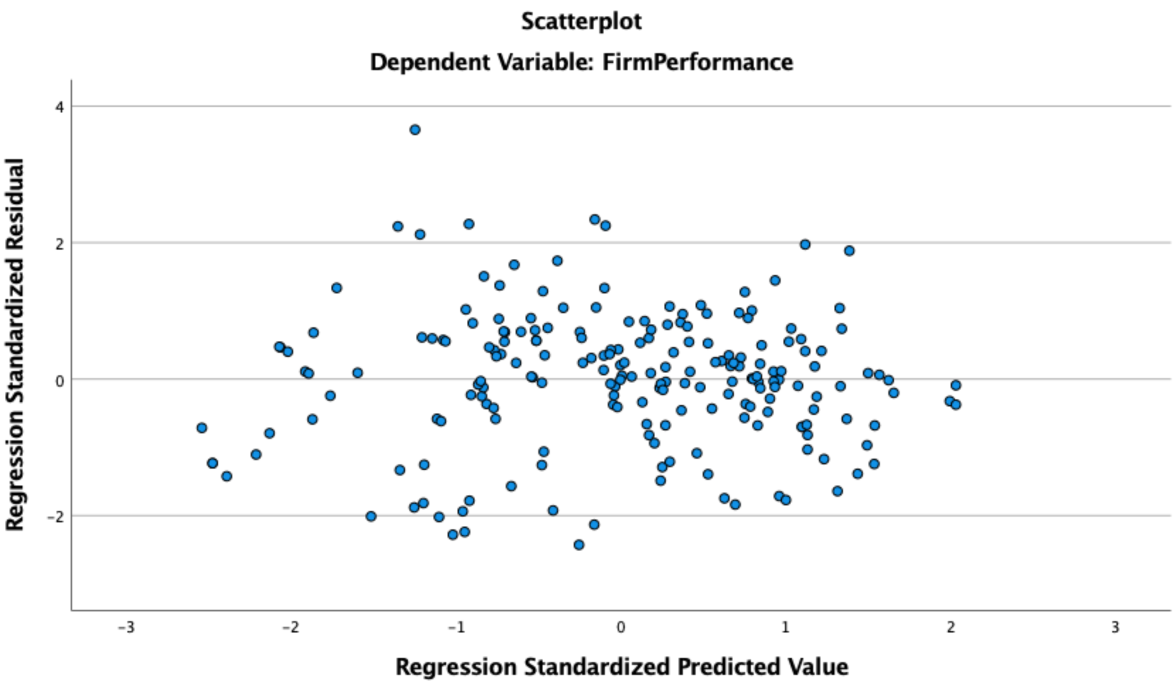

Figure 5: Residual plot to check ensure linearity in parameters

Assumption MLR 6: Normality

The last MLR assumption states that the population error should be independent of the explanatory variables and be normally distributed with zero mean and variance (Wooldridge, 2009). To test for this, the researchers conducted a Kolmogorov–Smirnov test which is deemed appropriate when testing for normality of sample sizes of n>50 (Mishra et al., 2019). The test's null hypothesis is that the population is normally distributed, and as p<0.01, the statement is supported. Furthermore, the researchers analyzed the skewness, lack of symmetry in the normal distribution, and kurtosis, the peakedness of the distribution, to assess the overall symmetry of the distribution. The skewness and kurtosis of this data set are -0.74 and 0.28, respectively, which fall within the appropriate values of +/- 1 for the population to be considered approximately normal and hence satisfying the normality assumption (Mishra et al., 2019).

3.4 Data Quality

Reliability, validity, and replicability are common concerns regarding the quality of data in quantitative studies, which need to be addressed before findings can contribute to the research field (Daft, 1983). The following section will address how the authors approached the three constructs respectively.

3.4.1 Reliability

The concept of reliability centers around ensuring that the measures used are accurate, stable, and consistent over time (Saunders et al., 2009). Reliability is further divided into three sub-sections: (i) stability, (ii) internal reliability, and (iii) inter-observer consistency, all of which are addressed below.

Stability

As indicated by the term itself, stability assesses whether a measure is stable over time and hence results relating to that measure pose little variation in case of a re-administration of the study (Bryman & Bell, 2011). Organizational practices are the core of this study and should be relatively stable over time due to the tacit knowledge and inertia associated with their existence (Godkin & Allcorn, 2008). Furthermore, the RBV theory clearly argues for sustained competitive advantage, which further indicates the stability of the investigated field (Barney, 1991). Hence, to adhere to the stability of this study, measured constructs are argued to be stable prior to being administered as part of this study.

Internal Reliability

Internal reliability ensures that multiple-indicator measures, in fact, are related to the same thing and hence when aggregated, provide coherence (Creswell & Creswell, 2017). To ensure the internal reliability of this study, the indicators are tested using Cronbach's Alpha which *"calculates the average of all possible split-half reliability coefficients"* (Bryman & Bell, 2011:159) and where the indicator intercorrelations become an estimate for reliability. Values above 0.70 are considered satisfactory to signify internal reliability, while values below 0.60 are seen as unsatisfactory (Cronbach, 1951). As seen in Table 8, this study achieved satisfactory levels of internal reliability for all constructs. This is not very surprising as almost all questions have been used in earlier studies across the IT, BDA, or IS fields.

Table 8 – Summary of Cronbach's alpha

Variable	Cronbach's Alpha
Planning	0.882
Connectivity	0.785
Controlling	0.898
Education & knowledge development	0.872
Leadership	0.888
Data-driven culture	0.826

Inter-Observer Consistency

This construct addresses issues of subjectivity faced in research where multiple observers record and process data (Bryman & Bell, 2011). In this study, a check for inter-observer consistency delivers no value as the self-completion survey leaves no need for manual observations and hence eliminates the risk of contamination from the authors' personal biases or interpretations. Furthermore, any potential inconsistencies in data processing were limited due to the automatic transfer of data from the survey software to IBM SPSS Statistics.

3.4.2 Validity

Validity is highly important for research. It reflects to what extent the chosen indicators assess the considered variable and hence how much integrity can be appointed from the conclusions drawn from the research (Creswell & Creswell, 2017). Validity is further divided into four subsections: (i) measurement validity, (ii) internal validity, (iii) external validity, and (iv) ecological validity, which all have been considered by the authors and will be addressed below (Wentland, 1993).

Measurement Validity

Measurement validity is especially important in quantitative research and reflects whether the chosen measures really reflect the concept intended to be captured in the study (Wentland, 1993).

In this study, all measures were derived from well-established existing literature and theory. Moreover, through confirmatory and iterative discussions, regarding the measurements' applicability to the study's explicit concepts, with people close to the researchers (e.g., the supervisor, fellow students, and colleagues), their affirmation could ensure face validity (Bryman & Bell, 2011). Hence, the authors argue that all measures capture the intended concepts of this study.

Internal Validity

The concept of internal validity refers to the subject of causality between the constructed variables and investigates whether the independent variable solely affects the dependent variable and not vice versa (Saunders et al., 2009; Bryman & Bell, 2011). Due to the relationship between the tested variables, the authors argue for sufficient internal validity. With the dependent variables being clearly outcome-oriented by nature, financial and non-financial firm performance, organizational practices delivering such results are assumed to serve as contributors, at least to some extent. Furthermore, as demonstrated in the hypothesis's development (Section 2.3), all casual relationships being tested in this survey have in previous research been proven to affect firm performance to some extent ensuring a single-sided cause-effect connection.

External Validity

External validity questions to what extent the findings of a study can be generalized beyond the sample used in that particular study (Cristensen et al., 2014). Although external validity represents a greater challenge in qualitative research, which is often characterized by using smaller samples and case studies to collect data, it is also important in quantitative research (Creswell & Creswell, 2017). Regardless of following a non-probability approach to sampling, the researchers argue for strong external validity. By incorporating respondents across industries and sectors, risks of firm-specific findings can be eliminated. Additionally, all individuals working at organizations with DA are given equal opportunity to participate in the study, further promoting randomization.

Ecological Validity

The construct of ecological validity displays whether the study's results can be transferred to people's real-life natural settings (Bryman & Bell, 2011). By familiarizing with the different types of organizational practices related to DA in both previous research and popular literature (e.g., Ali et al., 2020; Fosso Wamba et al., 2015; Klatt et al., 2011; Mikalef et al., 2019; Popovič et al., 2018), the authors ensure as much as possible that the statements present in the questionnaire reflect the respondents' everyday work environment. Nonetheless, ecological validity may be limited due to, firstly, potential dishonesty in the respondents' answers and secondly, the use of a questionnaire creating a gap between the respondents and their natural environment. By promising complete anonymity to both the organizations and the researchers respectively, the issue of dishonesty could be addressed. Moreover, an introductory text was included at the beginning of the survey to set the context and bridge the distance between their current state of mind and their natural work environment.

3.4.3 Replicability

The concept of replicability refers to other researchers being able to replicate the study by employing a similar methodology and approach and consequently gaining similar results (Bryman & Bell, 2011; Bettis et al., 2016). By explicitly documenting, outlining, and sharing the chosen research approach, the data collection process, survey design, and measures, satisfactory replicability is argued for. Furthermore, should another researcher wish to replicate the study, sufficient guidance is to be found regarding theory, method, and empirics.

4. Results

The following section presents the empirical findings by (i) describing the analytical tool and preparatory data work, followed by (ii) a presentation of the main model including (iii) conducted empirical analysis devoted to hypothesis testing.

4.1 Analytical Tools

After manually eliminating the data set from incomplete responses and wrongly answered control questions, the data was analyzed using the software tool SPSS. As the sample size fulfills the Kolmogorov–Smirnov test and the criteria for normality (Section 3.3.1), the data could be analyzed by conducting statistical tests such as the t-test, correlation tests, and regression-based tests. Before initiating regression analysis, recoding of variables took place to transfer indicators into the independent variables as well as translate categorical variables into nominal counterparts.

4.1.1 Recoding Variables

All questions were answered using the seven-point Likert scale, ensuring comparability between the answers without any need for transformation (Pedhazur & Schmelkin, 1991). Hence, when the multiple item indicators were to be combined into final independent variables, this was achieved by calculating the mean where values again could range from 1 to 7. Next, each of the performance measurements, financial and non-financial performance, were compiled in a similar manner by calculating the mean of their respective items. The final dependent variable, i.e., overall firm performance, was consequently compiled by taking the mean of financial and non-financial performance. Calculating the mean when compounding indicators is a common practice in research that yields result for statistical tests (Pedhazur & Schmelkin, 1991).

After compiling multiple-item measures, the 13 industry options and six hierarchical level options, i.e., each categorical variable, were recorded and converted into dummy variables to create a two-dimensional binary matrix where each column represents a particular category. Each industry and hierarchical level option was coded into the binary scale where the number “1” indicated the presence and “0” absence of that particular industry or hierarchical level.

4.2 The Final Model

To assess the relationship between DA practices and firm performance to determine the most influential factors, i.e., the strength of the relationships between the independent and dependent variables, the study applied an OLS regression model as it was deemed to be appropriate and suitable for the study's research question (Section 3.3). The final model included all independent, dependent- and control variables in the same model.

In total, six different regression models were analyzed where the organizational practices were mapped against: firm performance, non-financial performance, and financial performance, each with and without the control variables. As indicated in Table 9, all models are statistically significant with $p<0.05$. When examining R^2, a measure assessing the goodness-of-fit for linear regression models, i.e., *"the percentage of the variance in the dependent variable that the independent variables explain collectively"* (Wooldridge, 2009:177), all models fulfill the adequate goodness-of-fit as they exceed the 0.36 suggested by Zikmund (2000). As seen in the table, the model accounting for the overall firm performance provides the highest collective explainability ($R^2 = 0.66$).

Table 9: Summary of statistics of the six regression-models

Model	**R^2**	**F**	**Std. Deviation**	**p**
Firm performance without control variables	0.66	66.82	0.59	<.001
Firm performance with control variables	0.65	20.12	0.59	<.001
Non-financial performance without control variables	0.61	54.57	0.71	<.001
Non-financial performance with control variables	0.60	16.09	0.72	<.001
Financial performance without control variables	0.46	30.49	0.79	<.001
Financial performance with control variables	0.48	10.41	0.78	<.001

Furthermore, collinearity and correlation diagnostics were conducted (Table 7). The analysis of multicollinearity shows that the variance inflation factor (VIF) falls below the acceptable cut-off point (VIF<5)(Hair et al., 2006), meaning that multicollinearity is not an issue in this study. Next, the correlation matrix (Table 7) shows that the highest inter-construct correlation is between data-driven culture and education and knowledge development at (r=0.744). Though being high, this study is not having issues of common method bias which is being evidenced by extremely high correlations (r<0.90)(Bagozzi et al., 1991).

4.3 Hypothesis Testing

The following hypotheses testing is divided thematically according to the main model illustrated in the theoretical framework (Figure 1). Moreover, each hypothesis is analyzed with various statistical measures such as t-test, p-value, and VIF.

Planning and Firm Performance

To investigate the significance of hypothesis 1, which is: *Planning, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured* - an independent t-test and VIF was conducted. The results do not show a significant difference (t=-0.386, p=0.700) between the organizational practice measured and firm performance. As a result, no conclusion can be drawn in terms of the planning of DA affecting firm performance. **Hypothesis 1 is therefore rejected.** To validate this statement further, another model was conducted where the effect of planning on firm performance was isolated by excluding the highly correlating variable controlling (r=0.59). Even when this variable was excluded from the model, the variable planning appeared insignificant. This proves that planning as a practice in itself is insignificant for predicting firm performance and that it has nothing to do with its high correlation with other variables.

Table 10 – Summary of statistical tests on organizational practice - Planning

<table>
<tr><th>Planning</th><th>N</th><th>Mean</th><th>Std. Deviation</th><th>t</th><th>p</th><th>VIF</th></tr>
<tr><td>Without control variables</td><td rowspan="2">205</td><td rowspan="2">4.21</td><td rowspan="2">1.5</td><td>-0.298</td><td>0.766</td><td>1.876</td></tr>
<tr><td>With control variables</td><td>-0.386</td><td>0.700</td><td>2.172</td></tr>
</table>

Connectivity and Firm Performance

To test the link between connectivity and firm performance, hypothesis 2 was formulated as follows: *Connectivity, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.* To investigate whether this organizational practice has a significant impact on firm performance, an independent t-test was conducted. The results show a statistically significant difference on the five percent significance level (t=2.744, p=0.007) in connectivity's (M=4.44, SD=1.52) effect on firm performance. The results suggest that the deployment of connectivity is likely to have a significant positive effect on firm performance in relation to other organizational practices of DA. **Thus, hypothesis 2 is not rejected.**

Table 11 - Summary of statistical tests organizational practice – Connectivity

Connectivity	N	Mean	Std. Deviation	t	p	VIF
Without control variables	205	4.44	1.52	2.476	0.014	1.433
With control variables				2.744	0.007	1.562

Controlling and Firm Performance

To investigate whether an organization's controlling mechanisms have a significant effect compared to other organizational practices, an independent t-test was conducted, and the results do not show a significant relationship (t=0.805, p=0.422) between the organizational practice measured and firm performance. Hence, no conclusions can be drawn about whether controlling mechanisms significantly affect firm performance; therefore, **hypothesis 3 is rejected.** To further validate these results, additional models were constructed where potentially correlated variables were excluded to isolate the effect of the investigated variable. In all the conducted models, controlling still showed no significant difference in its impact on firm performance (p>0.05).

Table 12 - Summary of statistical tests on organizational practice - Controlling

Controlling	N	Mean	Std. Deviation	t	p	VIF
Without control variables	205	4.32	1.55	0.659	0.511	2.074
With control variables				0.805	0.422	2.242

Education and Knowledge Development and Firm Performance

To test whether managerial efforts of educating and enabling knowledge development contributed to firm performance, a t-test was conducted where the results showed that education and knowledge development of DA has a significant effect on firm performance ($t=5.153$, $p=<0.001$). In fact, education and knowledge development appear to have the highest measured correlation ($r=0.641$) and coefficient ($\beta=0.284$) to firm performance. Thus, hypothesis 4 - *Educating and knowledge development, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured* - **is not rejected**.

Table 13 – Summary of statistical tests on organizational practice – Educating and knowledge development

Educating & knowledge development	N	Mean	Std. Deviation	t	p	VIF
Without control variables	205	4.67	1.37	4.94	<0.001	3.048
With control variables				5.153	<0.001	3.299

Leadership and Firm Performance

The fifth hypothesis of this study is as follows: *Leadership focus on DA has a distinct effect on firm performance compared to the other organizational practices measured.* The conducted t-test showed that leadership's focus on DA significantly affects firm performance ($t=2.099$, $p=0.037$). **Thus, hypothesis 5 is not rejected.**

Table 14 - Summary of statistical tests on organizational practice – Leadership

Leadership	N	Mean	Std. Deviation	t	p	VIF
Without control variables	205	4.63	1.37	2.472	0.014	2.37
With control variables				2.099	0.037	2.537

Data-Driven Culture and Firm performance

The final and sixth hypothesis tested is the following: *Data-driven culture, as an organizational practice of DA, has a distinct effect on firm performance compared to the other organizational practices measured.* In line with the analysis of the other variables, to investigate whether a data-driven culture has a significant effect on firm performance, an independent t-test was conducted. The result showed a statistically significant difference on the five percent significance level ($t=4.261$, $p<0.001$), suggesting that fostering a data-driven culture is likely to have a significant positive effect on firm performance. **Hence, hypothesis 6 is not rejected.**

Table 15 - Summary of statistical tests on organizational practice – Data-driven culture

Data-driven culture	N	Mean	Std. Deviation	t	p	VIF
Without control variables	205	4.59	1.3	4.828	<0.001	2.599
With control variables				4.261	<0.001	2.804

4.3.1 Variables Comparison

As shown by the mean of the different constructs, organizations seem to work relatively equally and be equally good at the various practices ($M\approx4.5$). However, when comparing the beta (β) of each construct, data-driven culture and education & knowledge development are the most significant organizational practices affecting firm performance. On the other hand, planning and controlling were proven insignificant. Even if the result turns out to be statistically significant, it is equally important to address the economic significance of the results. The coefficient of each variable indicates how firm performance is affected by a one-unit increase in employees' perception of the respective variable. As a result, a one-unit increase in perceived connectivity is associated with a 9.4% increase in firm performance. This suggests that a one-unit increase in perceived connectivity is related to the operationalization in the variable overview (Table 1). A similar interpretation can be applied analogously to all the statistically significant variables (Table 16).

Table 16 - Summary of coefficients

Independent Variable	β	95.0% Confidence Interval for β	
		Lower Bound	Upper Bound
Planning	-0.016	-0.096	0.065
Controlling	0.032	-0.047	0.112
Connectivity	0.094	0.026	0.161
Leadership	0.101	0.06	0.196
Data-driven culture	0.227	0.122	0.332
Educating & knowledge development	0.284	0.175	0.392

5. Analysis and Discussion

This chapter will discuss the results of the hypothesis testing in the light of previous research and the theoretical framework.

5.1 Adhering the Two-Fold Research Purpose

This study aims to contribute two-fold, both to the novel field of DA and the understudied factor of organizational deployment in the RBV theory. Furthermore, to assess DA as a potential source of competitive advantage, the researchers will connect the findings to the intersection of the two.

5.1.1 The Importance of the ”O” for Firm Performance

This study shows that organizational deployment practices do matter for firm performance in the context of DA applications. Taking a RBV perspective, a likely explanation is that distinctive firm-specific capabilities cannot be readily assembled through markets, enabling them to serve as sources of competitive advantage and increased firm performance (Mikalef et al., 2019). Nonetheless, the results also indicate that not all practices that are currently undertaken by organizations and that have been proven important in other contexts are of significance when related to DA. Education and knowledge development have the largest effect on firm performance, followed by data-driven culture, leadership, and connectivity, while controlling and planning practices were proven insignificant.

As mentioned, educational and knowledge development efforts were found to influence firm performance the most among the organizational practices measured. This finding is supported by previous research where human capital practices and educational efforts have been claimed to have a meaningful effect on developing successful organizational capabilities (Ali et al., 2020; Mikalef et al., 2019). In fact, a workforce with an analytical mindset has been proven to drive more business value and maintaining analytical capabilities and implementing procedures to foster knowledge have been found to be crucial factors for improved organizational performance (Fosso Wamba et al., 2015).

As mentioned previously, the second most influential organizational practice impacting firm performance is the existence of a data-driven culture. This aligns with Kiron's (2017) statement of culture being a factor that can serve as both an enabler or hindrance for unlocking business value from DA. Furthermore, Mikalef et al.'s (2019) findings show that organizations that embed an evidence-based approach and foster a data-driven decision-making process as their core values improve their performance significantly, which can explain why a data-driven culture impacts firm performance to such an extent. As employees acknowledge the business value of using DA and understand how it might increase efficiency, firms can convince their personnel to work with it in a way that improves firm performance. Erevelles et al. (2016) also mean that a data-driven culture enables and promotes the generation and implementation of innovative ideas, creating opportunities for increased firm value. As many firms adopting DA are active in dynamic markets such as IT & tech, finance & insurance, retail, e-commerce, etc., the point of continuous innovation becomes even more important than in more stable markets.

Next, the results of this study advocate previous leadership findings and theory as it turns out to be the third most influential organizational practice impacting firm performance and thus potentially a sustained competitive advantage. In fact, leadership decisions have shown to be crucial for successful strategic management practices (Ferigotti et al., 2020). An analytical leader can impose the appropriate procedures suited for the organization and lead employees into more rigid thinking (Davenport & Shapiro, 2010). Though leadership was proven less important than knowledge development and having a data-driven culture, it is the leaders i.e., higher hierarchical levels that enable the existence of the two. Davenport et al. (2012) underline this by stating that how an organization's resources are utilized to maximize its value is highly affected by decisions made by the leadership.

5.1.2 Least influential and Insignificant Variables

Contrastingly, the least influential but still significant organizational factor on firm performance is connectivity, which captures cross-functional and internal knowledge sharing. In the context of this study, connectivity occurs when different functional managers and departments interact with each other during, e.g., cross-functional meetings. Compared to other relevant organizational practices for DA, connectivity does not seem to impact firm performance to the same extent as the previously mentioned variables. This contrasts Ray et al.'s (2005) findings from the IS field, where shared knowledge between the organizational departments was identified as a key IT capability for optimizing process performance.

Nonetheless, the fact that connectivity was proven significant still aligns with Marjanovic's (2022) research findings within the DA field, showing that shared knowledge enhances the ability to establish differentiation which can positively impact firm performance. However, when comparing it to the most impactful practices - educating and knowledge development and data-driven culture, these are all practices that involve the single individual to a great extent. This might, in turn, indicate that it is more impactful when each employee possesses the necessary knowledge of how to manage and act on DA, which consequently makes cross-functional meetings or internal knowledge sharing less significant. Hence, this study opens up the possibility that employee involvement affects the extent to which firm performance is affected.

Lastly, according to this study, planning and controlling practices were both shown to have an insignificant effect on firm performance. These are surprising findings as the hypotheses were anchored in previous empirical evidence showing that, i.e., high-performing firms are characterized by more sophisticated analytical planning processes (Klatt et al., 2011) and that clear implementation and monitoring of targets are crucial for successful project implementation (Bunder & Viaene, 2011). Nonetheless, these were proven insignificant in the context of the executed study. Interestingly, this ignites a discussion of whether planning and controlling practices are insignificant in the context of DA or if the employees' perception of these practices is less established than other practices. The latter would suggest that each construct depends on the managerial efforts to communicate each practice within the organization or externally in media. While planning and controlling practices are likely to be less visible and/or acknowledged by employees, education and organizational culture are likely to be more widely discussed.

5.1.2 Connections to Dynamic Capabilities and KBV

By looking at the results of this study through the lens of dynamic capabilities, another explanatory dimension can be added to understanding the outcome. As mentioned in the theorizing and hypotheses development section (Section 2.3), all significant variables, educating and knowledge development, data-driven culture, leadership, and connectivity, are practices that are transformed and reconfigured frequently, making them dynamic by nature (Helfat & Peteraf, 2003). In comparison, practices being more operational in nature, such as planning and controlling, i.e., once a regulatory system is implemented and in place, it generally takes longer time for it to be modified or reconfigured, were shown insignificant. Hence, the results of this study indicate a link between dynamic capabilities and firm performance. Such claims find additional support in traditional literature stating that dynamic capabilities have a universally positive effect on a firm achieving competitive advantage (Teece & Pisano, 1994).

The dynamisms of the most influential practice, education and knowledge development also tie to Grant's (1996) contribution to the RBV, the KBV, claiming that knowledge per se can be a source driving firm performance. In this study, knowledge development was seen as to what extent organizations foster and provide knowledge-generating opportunities for their employees, resulting in all employees possessing relevant knowledge regarding both technological and business aspects. In other words, this captures the ongoing transformation and reconfiguration of knowledge occurring within the organizations, which according to Grant (1996) and Herden (2020), provides uniqueness leading to increased firm performance. The added perspective of KBV hence offers additional support for a potential link between dynamic capabilities and increased firm performance in DA contexts.

However, on the other hand, another possible explanation for the significance of all dynamic variables lies in the firms' operating environment. The majority of the results from this study steamed from industries such as IT and tech, finance and insurance, retail and e-commerce, etc., which can be regarded as highly competitive and/or fast-changing environments compared to, e.g., logistics or education. Such fast-paced environments require firms to change more frequently to cope with competition and stay relevant in the market. Hence these environments provide opportunities to execute dynamic capabilities and recuperate the cost of developing them (Darnevich & Kriauciunas, 2011; Wilden & Gudergan, 2015). Therefore, another potential explanation is that dynamic capabilities will contribute to competitive advantage to different extents depending on the firm's operating environment (Schilke, 2014; Winter, 2012). Connecting back to this study, this would imply that the "O" in the context of DA and its contribution to firm performance could potentially be explained by dynamic capabilities.

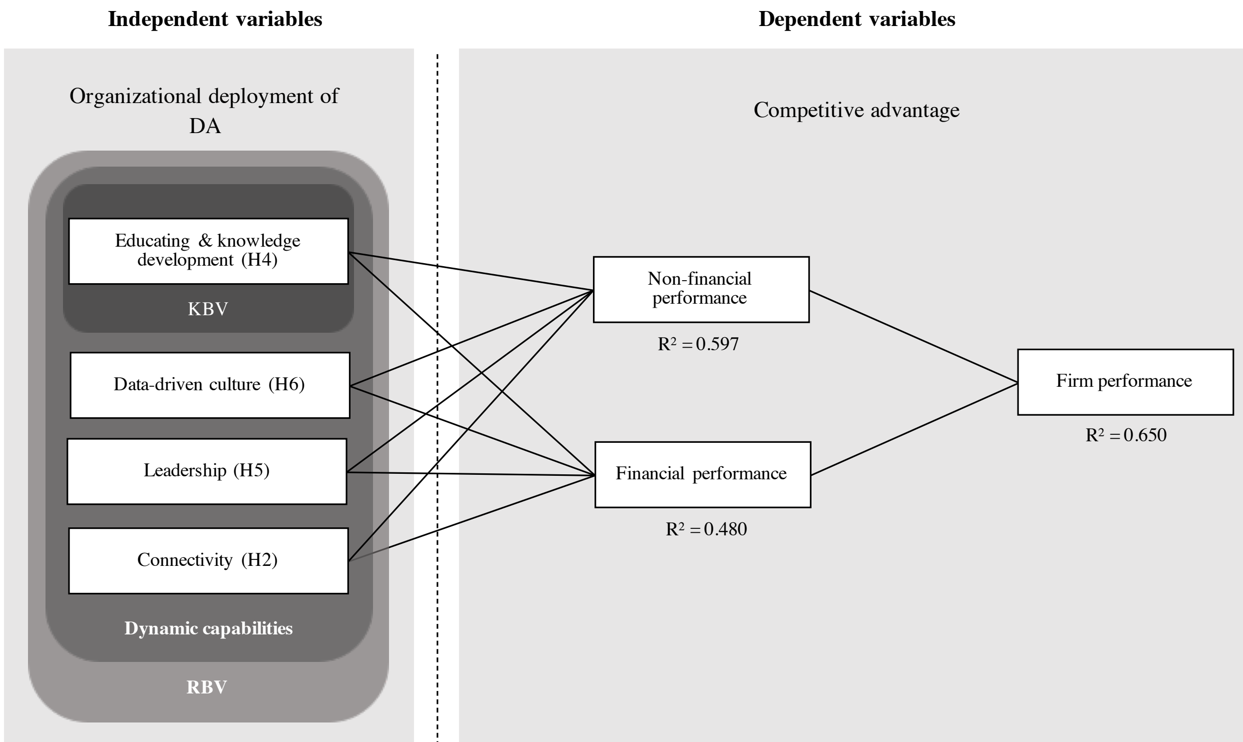

Figure 6 – Final model with significant variables

6. Conclusions

The following sections will present the (i) conclusions of this study and summarize the key findings from the analysis section in an effective way by connecting back to the purpose and research question of the thesis, (ii) address the theoretical contribution, (iii) the managerial implications, (iv) limitations of the study, and (v) suggestions for future research directions.

The fundamental motive of this study was derived from a combination of the existing RBV theory, the under-researched "O" and the emerging DA literature. Together, they motivated this study to have a twofold contribution by studying the intersection between the RBV theory and DA to consequently fill a research gap within each respective field and contribute to (i) the under-researched "O" by shedding light on insight and new perspectives, and (ii) the limited understanding of the strategic managerial aspects of DA practices of *how* DA management is translated into business value and competitive advantage.

In terms of theory, this research investigates the organizational deployment that allows for data to be translated into strategic actions leading to sustained competitive advantage, contributing to broadening the theoretical understanding of the "O" in the VRIO-framework. On the DA literature side, this study examines the managerial aspect of DA practices and intends to determine organizational best practices to determine how DA is translated into business value and firm performance. Thus, the research question was formulated to gain insights into *which organizational deployment practices of DA contribute to a firm's sustained competitive advantage?*

The result showed that the most influential significant organizational practices of DA for firm performance were having a data-driven culture and maintaining educational and knowledge developing efforts. Meanwhile, the least influential, significant organizational practice was connectivity, while planning- and controlling practices appeared to be insignificant in this study. The key findings mostly corroborate previous DA theory when comparing DA's six most common organizational practices, drawn from previous DA literature, and investigating them from the RBV perspective.

When applying a dynamic capabilities perspective and KBV to the key findings, all significant organizational practices were dynamic by nature, while the insignificant practices were operational and static. Thus, the results of this study indicate a link between dynamic capabilities and firm performance. This does imply that “O” ’s contribution to sustained competitive advantage in the context of DA could be explained by dynamic capabilities.

6.1 Theoretical Contributions

The theoretical contributions of this thesis are grounded in the executed literature review and identified research gap, which claims that (i) organizational deployment practices have been under-studied compared to the other VRIO-components in the RBV theory, especially in a contemporary context as DA, and (ii) ambiguity surrounding the relationship between management's efforts within DA and the firm’s performance. Based on this research gap, the thesis's main theoretical contribution comes from linking the most impactful practices on firm performance and analyzing them through the RBV.

In terms of RBV, this study has shed light on the importance of firms being seen as a unique bundle of resources (Barney, 1991) where the linkages between the different resources together contributed to sustained competitive advantage. By unpacking the “O,” this study questions and examines the role and contribution that the “O,” i.e., organizational deployment has in creating this unique bundle of resources claimed by Barney (1991). Indeed, the results of this study reveal that the “O” does make an important contribution to DA as a resource by making it more valuable through managing it in a strategic, impactful way by prioritizing the most effective DA practices. This also contributes to making it rare and difficult for competitors to imitate. Importantly, it is the organizational resources, specifically the human capabilities, that enable DA as a resource to be fully utilized. These insights extend the view of Amit and Shoemaker (1993), where organizations are seen as a collection of physical, human, and organizational resources by showing that some recourses might function as enablers for others.

Secondly, this study shows that dynamic practices are more likely to generate business value, as pointed out by both extensions of the RBV - dynamic capabilities and the knowledge-based view. Adding on to that, the findings of this study indicate that for DA to have distinct positive effects on firm performance, emphasis needs to be put on practices that are both dynamic in nature and directly affect and are practiced by all employees of the organization, e.g., culture and knowledge. Hence, this study opens up for further theoretical investigation within the RBV to explore the relationship between dynamic capabilities and sustained competitive advantage and whether it is affected by employee involvement or mainly stemming from the management side.

Finally, this thesis also fills the empirical gap by complementing previous literature in the technological field. The findings indicate some discrepancies between what has been seen as successful organizational practices regarding IT and IS and what was found to affect firm performance when working with DA. This further opens up a discussion to what extent findings from research across different technological applications can be transferred and hence to what extent management needs to adapt their strategies when working with various tools. Concludingly, this thesis contributes by providing a better understanding of how management should work with DA to positively impact firm performance and initiates further interesting discussions broadening the field of RBV and management-technology research.

6.2 Managerial Implications

By shedding light on the previously inconclusive relationship between organizational practices regarding DA and firm performance, clear managerial implications for leadership working with DA can be drawn from the results of this study. As pointed out by Fosso Wamba et al. (2015) and Mikaelf et al. (2019), organizations perform multiple organizational practices simultaneously without analyzing what actually drives performance. Similar patterns could be seen in this study, where the small variation between the means of the different constructs indicates an equal emphasis on the different practices.

The results of this study do, however, clearly show that managers should prioritize some practices over others and deprioritize some practices altogether to maximize firm performance. Spending time on planning- and controlling practices did not significantly contribute to firm performance, and hence managers should place considerably less effort on these tasks. On the other hand, educating and knowledge development, fostering a data-driven culture, leadership understanding of DA, and having structures for sharing learnings and insights were all proven to contribute to firm performance significantly.

Education and knowledge development and fostering a data-driven culture were the two practices having the largest effect on firm performance, which is interesting as they, in contrast to planning and controlling, which were proven insignificant, to a great extent involve the entire organization and are institutionalized "bottom-up." Hence, this research indicates that involving the organization as a whole is important for significant results to be seen in a firm's performance as a result of deploying DA.

6.3 Limitations

6.3.1 Data Accessibility

Similar to other studies, this study comes with certain limitations. The first limitation is related to the data collection. Gaining access to participants was proven difficult as the longitudinal nature of establishing a competitive advantage from the utilization of a resource demanded the participants to work at companies having used DA for an extensive period of time. To gain a significant number of respondents, people across all hierarchical levels of the organization were considered suitable participants as long as their organization actively used DA. This does, however, assume that all employees have the same knowledge of the firm's performance which might not be the case in reality. Measures such as ROI, profit improvements, etc., might only be known by people in the higher hierarchical levels, resulting in lower hierarchical levels leaving ambiguous answers to such metrics. However, due to the otherwise limited participant pool and the validation from previous studies (Ali et al., 2020; Fosso Wamba et al., 2017) having successfully used this methodology for measuring performance, the approach was deemed acceptable for this study.

Next, studies on sustained competitive advantage are ideally longitudinal and hence require more extended time periods to capture the phenomenon. However, due to the given time constraint, this study captured firm performance as a set of financial and non-financial performance factors, e.g., market share, revenue growth, perceived competitive advantage, etc., and used it to measure potential competitive advantage. The assumption made is that firm performance is associated with a sustained competitive advantage in the long term (Davenport & Harris, 2007; Fosso Wamba et al., 2017; Gupta & George, 2016). Nonetheless, collecting data from one point in time might not be optimal for measuring long-term causal relationships. Lastly, due to accessibility, only Swedish companies were approached to answer the survey. This indicates that careful consideration should be taken when applying findings to new geographical contexts or other technological practices.

6.3.2 Research and methodology design

The following limitations are related to the research design. Having a self-completion survey does leave space for potential dishonesty, subjectivity, and biases in the responses, which can cause over-or under-optimistic relationships between organizational deployment practices and firm performance. Executing a complementing text analysis of press releases and annual reports could be a way to further validate the respondents' views on firm performance. However, by considering multiple factors to assess firm performance, this research still manages to shed light on the subject holistically. Furthermore, the self-completion survey also leaves space for biases in who decides to respond to the survey. There is a risk that systematics in who chooses to answer the survey, e.g., lower hierarchical levels, people passionate about DA, etc., might not represent the entire population.

6.4 Suggested Future Research Directions

Building upon the findings and limitations of this study, this research lays the ground for several future research directions. To begin with, this study deploys a quantitative methodology that was deemed appropriate to identify and rank organizational practices affecting firm performance. Now that it is known which practices are important, a qualitative study could provide a further understanding of how organizations realize each of the constructs internally. Thus, future research may follow up with interviews to fully explore each construct and how their day-to-day organizational practices are related to competitive advantage.

The next suggestion for future research is to incorporate industry-specific performance metrics to measure firm performance more accurately. DA might be utilized differently in different firms depending on the firm's needs and external environment. Thus, the indicators to measure firm performance and sustained competitive advantage might vary among various industries. Another interesting research direction includes investigating potential differences amongst different business models. For example, DA's unique bundle of resources and organizational practices might vary and have different emphases for digital- vs. traditional business models such as platform-, freemium-, brick and mortar, etc.

Furthermore, the authors believe that this thesis opens for interesting future research within the grounds of both the RBV and the successively more integrated tech and business landscape. Firstly, this thesis suggests further investigation of whether employee engagement matters for achieving a sustained competitive advantage. This study indicates a positive relationship between organizational practices involving the entire organization and firm performance. Lastly, discrepancies in findings between the field of DA and IS, when it comes to organizational practices' effect on firm performance, encourage additional empirical studies to take place.

The authors believe that this study *"Unpacking the "O" in VRIO: Organizational deployment of data analytics and its effect on firm performance"* contributes to the management research field and hope that it will inspire new studies to take form within the field of RBV and DA.

7. References

Abell, P., Felin, T., & Foss, N. (2008). Building microfoundations for the routines, capa- bilities, and performance links. *Managerial and Decision Economics*, 29(6), pp. 489–502.

Agresti, A. (1990). *Categorical data analysis.* New York: John Wiley & sons.

Ahearne, M., Lam, S.K. & Kraus, F. (2014). Performance impact of middle managers' adaptive strategy implementation: The role of social capital. *Strategic Management Journal*, 35(1), pp. 68-87.

Ali, M. (1987). Durbin-watson and generalized durbin-watson tests for autocorrelations and randomness. *Journal of Business & Economic Statistics,* 5(2), pp. 195-203.

Ali, M., Ali, S., Jamshed, S., Nasir, N., Naz, S., & Nisar, Q.A. (2020). Big data management and environmental performance: role of big data decision-making capabilities and decision making quality. *Journal of Enterprise Information Management,* 34(4), pp. 1061-1096.

Alotaibi, S., Mehmood, R. & Katib, I. (2020). The role of big data and twitter data analytics in healthcare supply chain management. *Smart Infrastructure and Applications,* Springer Nature Switzerland AG, Cham.

Alvarez, S., & Busenitz, L. (2001). The entrepreneurship of resource-based theory, *Journal of Management,* 27(6), pp. 755-75.

Amit, R., & Schoemaker, P.J.H. (1993). Strategic assets and organizational rent. *Strategic Management Journal,* 14(1), pp. 33-46.

Anderson, B.S., & Eshima, Y. (2013). The influence of firm age and intangible resources on the relationship between entrepreneurial orientation and firm growth among Japanese SMEs. *Journal of Business Venturing,* 28(3), pp. 413-429.

Armstrong, C.E., & Shimizu, K. (2007). A review of approaches to empirical research on the resource-based view of the firm. *Journal of Management,* 33(6), pp. 959-986.

Atinc, G., Simmering, M.J., & Kroll, M.J. (2012). Control variable use and reporting in macro and micro management research. *Organizational Research Methods*, 15(1), pp. 57-74.

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, 96(3), pp. 228-237.

Bagozzi, R.P., Yi, Y., & Phillips, L.W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, 36(3), pp. 421-458

Bain, J.S. (1968). *Industrial organization.* Hoboken: John wiley & sons.

Barney, J.B. (1986). Strategic factor markets: Expectations, luck, and business strategy. *Management Science,* 32(10), pp. 1231-1242.

Barney, J.B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), pp. 99-120.

Barney, J.B. (2002). Strategic management: from informed conversation to academic discipline. *The academy of management executive,* 16(2), pp. 53-57.

Barney, J.B. (2007). *Gaining and Sustaining Competitive Advantage* (3rd ed.).. Pearson Prentice Hall.

Barney, J.B., & Mackey, T.B. (2005). Testing resource-based theory. In: D.J. Ketchen, Jr. & D.D. Bergh (Eds.), *Research methodology in strategy and management,* (pp. 1–12). Elsevier Ltd.

Barry, W. (1993). *Understanding regression assumptions.* (1ed.). SAGE Publications.

Belsley, D.A. (1991). *Conditioning diagnostics: Collinearity and weak data in regression*,

(1ed.). Wiley-Interscience.
Benjamin, R.I., & Levinson, E. (1993). A framework for managing IT-enabled change. *Sloan Management Review*, 34(4), pp. 23-33.
Bettis, R.A., Helfat, C.E., & Sharver, J.M. (2016). The necessity, logic, and forms of replication. *Strategic management journal, 37(11), pp. 2193-2203.*
Bharadwaj, A.S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly,* 24(1), pp. 169-196.
Bharadwaj, A.S., Sambamurthy, V., & Zmud, R.W. (1998). IT Capabilities: Theoretical perspectives and empirical operationalization. In R. Hirsch heim., M. Newman., & J.I. DeGross (Eds.) *Proceedings of the 19th International Conference on Information Systems,* (pp. 378-385). SciTePress.
Bhattacherjee, A. (2012). *Social science research: Principles, methods, and practices* (2nd.). Tampa, FL: CreateSpace.
Bititci, U. & Muir, D. (1997). Business process definition: a bottom-up approach. *International Journal of Operations & Production Management,* 17(4), pp. 365-374.
Bogdan, M., & Borza, A. (2019). Big data analytics and organizational performance:A meta-analysis study. *Academy of Economic Studies,* 4(2), pp. 1-13.
Breevaart, K., Bakker, A.B., Demerouti, E., & Derks, E. (2016). Who takes the lead? A multi-source study on leadership, work engagement, and job performance. *Journal of organizational behaviour,* 37, pp. 309-325.
Brinch, M., Gunasekaran, A., & Fosso Wamba, S. (2021). Firm-level capabilities towards big data value creation. *Journal of Business Research,* 131(7), pp. 539-548.
Brown, B., Bughin, J., Chui, M., Dobbs, R., Hung Byers, A., Manyika, J., & Roxburgh, C. (2011). *Big data: The next frontier for innovation, competition and productivity*. McKinsey Global Institute. Retrieved from: https://bigdatawg.nist.gov/pdf/MGI_big_data_full_report.pdf
Bryman, A., & Bell, E. (2011). *Business research methods.* (3rd ed.). Oxford University Press.
Bunder, A., & Viaene, S. (2011). The secret to managing business analytics projects. *MIT sloan management review*, 53 (1), pp. 65.
Byrd, T.A., & Wang, Y. (2017). Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care. *Journal of Knowledge Management,* 21(3), pp. 517-539.
Cardeal, N., & António, N. (2012). Valuable, rare, inimitable resources and organization (VRIO) resources or valuable, rare, inimitable resources (VRI) capabilities: What leads to competitive advantage?. *African Journal of Business Management*, 6(37), pp. 10159-10170.
Castanias, R.P., & Helfat, C.E. (1991). Managerial resources and rents. *Journal of management,* 17(1), pp. 155-171.
Chandler, J., & Shapiro, D. (2016). Conducting clinical research using crowdsourced convenience samples. *Annual Review of Clinical Psychology,* 12(3), 53-81.
Chang, W., & Grady, N. (2019). *NIST Big Data Interoperability Framework: Volume 1, Definitions, Special Publication (NIST SP),* National Institute of Standards and Technology, Gaithersburg.
Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research*. Springer.

Chatzoudes, D., Chatzoglou, P., Sarigiannidis, L., & Theriou, G. (2017). The role of firm-specific factors in the strategy-performance relationship: Revisiting the resource-based view of the firm and the VRIO framework. *Management Research Review,* 41(1), pp. 46-73.

Chiang, H.L.R., Grover, V., Liang, T.P., & Zhang, D. (2018). Special Issue: Strategic Value of Big Data and Business Analytics. *Journal of Managemnet Information Systems,* 35(2), pp. 383-387.

Christensen, L.B., Turner, L.A., & Burke Johnson, R. (2014) *Research Methods, Design, and Analysis.* (12th ed.) Pearson Education.

Coco, C.T., Jamison, F., & Black, H. (2011). Connecting people investments and business outcomes at Lowe's: Using value linkage analytics to link employee engagement to business performance. *People & Strategy,* 34 (2), pp. 28–33.

Comuzzi, M., & Patel, A. (2016). How organizations leverage: Big data: A maturity model. *Industrial Management and Data Systems,* 116(8), pp. 1468–1492.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of big data analytics in European firms. *Journal of Business Research*, 70(1), pp. 379-390

Creswell, J.W., & Creswell, J.D. (2017). *Research Design: Qualitative, Quantitative and Mixed Method Research.* (5th ed.). Thousand Oaks, CA: Sage Publications

Cronbach, L.J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), pp. 297–334.

Curado, C., & Bontis, N. (2006). The knowledge-based view of the firm and its theoretical precursor. *International Journal of Learning and Intellectual Capital*, 3(4), pp. 367-381.

Daft, R.L. (1983). Learning the craft of organizational research. *The Academy of Management Review,* 8(4), pp. 539-546.

Darnevich, P.L. & Kriauciunas, A.P. (2011). Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance. *Strategic Management Journal*, 32(3), pp. 254-279

Davenport, T.H., Barth, P., & Bean, R. (2012). How 'big data' is different. *MIT Sloan Management Review,* 54(1), pp. 43-46.

Davenport, T.H., & Harris, J.G. (2007). *Competing on analytics: The new science of winning*. (6th ed.). Boston, Mass: Harvard Business School Press

Davenport, T.H & Shapiro, J. (2010). Competing on talent analytics. *Harvard Business Review,* 88(10), pp. 52-8.

Dess, G.G., & Robinson, R. (1984). Measuring organizational performance in the absence of objective measures: the case of the privately-held firm and conglomerate business unit, *Strategic Management Journal*, 5(3), pp. 265-273.

Dillman, D.A., & Smyth, J.D., & Christian, L.M. (2014). *Internet, Phone, Mail, and Mixed-mode surveys: The tailored design method.* (4th ed.) John Wiley & Sons Inc.

Duan, L., & Da Xu, L. (2021). Data analytics in industry 4.0: A survey. *Information System Frontiers, Early publication,* pp. 1-17.

Eisenhardt, K.M., & Martin, J.A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, 21(10/11), pp. 1105–1121.

Eisenhardt, K.M. & Santos, F.M. (2002). Knowledge-based view: A new theory of strategy. *Handbook of Strategy and Management,* 1(1), pp. 139-164.

Elmachtoub, A.N., Gupta, V., & Hamilton, M.L. (2021). The value of personalized pricing. *Management Science,* 67(10), pp. 6055-6070.

Erdogmus, H., Favaro, J., & Strigel, W. (2004). Return on Investment. *IEEE Computer Society.* 21(3) pp. 18-22.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing, *Journal of Business Research*, 69(2), pp. 897–904.

Fainshmidt, S., Wenger, L., Pezeshkan, A., & Mallon, M.R. (2019). When do dynamic capabilities lead to competitive advantage? The importance of strategic fit. *Journal of Management Studies,* 56(4), pp. 758-787.

Felin, T., Foss, N. J., Heimeriks, K.H., & Madsen, T.L. (2012). Microfoundations of routines and capabilities: Individuals, processes, and structure. *Journal of Management Studies*, 49(8), pp. 1351–1374.

Ferigotti, C.M., Da Cunha, S.K., & Dos Santos, J.S. (2020). Dynamic capabilities and business model in the transition to sustainability: The case of Bosch/Curitiba-Brazil. *International Business, Trade and Institutional Sustainability,* Springer Nature Switzerland, Cham.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How "big data" can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics,* 165(7), pp. 234–246.

Fosso Wamba, S., Gunasekaran, A., Akter, S., Ren, S.J., Dubey, R., & Childe, S.J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research,* 70(1), pp. 356–365.

Friedmann, R., & Olavarrieta, S. (2008). Market orientation, knowledge-related resources and firm performance. *Journal of Business Research,* 61(6), pp. 623-630.

George, G., Haas, M.R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*, 57(2), pp. 321–326.

Germann, F., Lilien, G.L., Fiedler, L., & Kraus, M. (2014). Do Retailers Benefit from Deploying Customer Analytics? *Journal of Retailing,* 90(4), pp. 587–593.

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems,* 27(1), pp. 101-113.

Ghorbani, A., & Zou, J. (2019). Data shapley: Equitable valuation of data for machine learning. In 36th *International Conference on Machine Learning*, International Machine Learning Society (IMLS), pp. 4053–4065.

Godkin, L., & Allcorn, S. (2008). Overcoming Organizational Inertia: A Tripartite Model for Achieving Strategic Organizational Change. *The journal of applied business and economics,* 8(1), pp. 82-96.

Grant, R.M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal,* 17(S2), pp. 109-122.

Grover, V., Roger, H.L., Chiang, T.P.L., & Dongsong, Z. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of management information systems,* 35(2), pp. 388-423

Gruber, M., Heinemann, F., Brettel, M., & Hungeling, S. (2010). Configurations of resources and capabilities and their performance implications: an exploratory study on technology ventures. *Strategic Management Journal*, 31(12), pp. 1337–1356.

Gunay, H.B., Shen, W., & Newsham, G. (2019). Data analytics to improve building performance: A critical review. *Automation in Construction,* 97(1), pp. 96-109.

Gupta, M., & George, J.F. (2016). Toward the development of a big data analytics capability. *Information & Management,* 53(8), pp. 1049–1064.

Hair, J.F., Tatham, R.L., Anderson, R.E., & Black, W. (2006). *Multivariate data analysis.* (6ed.). NJ: Pearson Prentice Hall.
Hamel, G., & Prahalad, C. (1996). *Competing for the Future*, Harvard Business School Press.
Hardy, M. (1993). *Regression with dummy variables.* Sage Publications.
Helfat, C.E. (1997). Know-how and asset complementarity and dynamic capability accumulation: the case of R&D. *Strategic Management Journal,* 18(5), pp. 339–360.
Helfat, C.E., & Peteraf, M.A. (2003). The dynamic resource-based view: capability lifecycles. *Strategic Management Journal,* 24(10), pp. 997-1010.
Helfat, C.E., & Peteraf, M.A. (2009). Understanding dynamic capabilities: progress along a developmental path. *Strategic Organization,* 7(1), pp. 91–10.
Herden, T.T. (2020). Explaining the competitive advantage generated from analytics with the knowledge-based view: The example of logistics and supply chain management. *Business Research,* 13(1), pp. 163-214.
Hilbert, M. (2012). *How much information is there in the "information society"?* Blackwell Publishing Ltd.
Hilbert, M., & López, P. (2011). The world's technological capacity to store, communicate, and compute information. *Science*, 332(6025), pp. 60-65.
Hopkins, M.S. (2010). Interview with Eric Brynjolfsson: The four ways that IT is innovation. *MIT Sloan Management Review,* 51(3), pp. 51-56.
Hopkins, M.S., LaValle, S., Lesser, E., Shockley, R., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 52(2), p. 21.
Hrebiniak, L.G., & Joyce, W.F. (1985). Organizational adaptation: strategic choice and environmental determinism. *Administrative Science Quarterly,* 30(3), pp. 336-439.
Huang, C.K., Wang, T., & Huang, T.Y. (2018). Initial Evidence on the Impact of Big Data Implementation on Firm Performance. *Information Systems Frontiers*, 22(2), pp. 475-487.
Huselid, M., & Day. N. (1991). Organizational commitment, job involvement, and turnover: A substantive and methodological analysis. *Journal of Applied Psychology*, 76(3), pp. 380-391.
Jackson, J. (2020). *Businesses have more data than ever before, but do they measure what they manage?* Forbes. Retrieved 2022, February 18, from: https://www.forbes.com/sites/jarretjackson/
Kamioka, T., & Tapanainen, T. (2014). Organizational use of big data and competitive advantage—exploration of antecedents. *Pacific Asia conference on information systems*, *Association for Information Systems,* pp. 372
Katz, R.L. (1974). Skills of an Effective Administrator. *Harvard Business Review*, 52(5), pp. 90-102.
Kettinger, W.J., Zhang, C., & Marchand, D. (2011). CIO and Business Executive Leadership Approaches to Establishing Company-wide Information Orientation. *MISQ Executive,* 10(4), pp. 157-174.
Kim, J., & Makahok, R. (2021). Unpacking the "O" in VRIO: the role of workflow interdependence in the loss and replacement of strategic human capital. *Strategic Management Journal, Early publication.*
Kiron, D. (2017). Lessons from becoming a data-driven organization. *MIT Sloan Management Review,* 58(2), pp. 1-13.

Klatt, T., Schaefke, M., & Moeller, K. (2011). Integrating business analytics into strategic planning for better performance. *Journal of Business Strategy,* 32(6), pp. 30-39.
Kohtamaki, M., Kraus, S., Makela, M., & Ronkko, M. (2012). The role of personnel commitment to strategy implementation and organisational learning within the relationship between strategic planning and company performance. *International Journal of Entrepreneurial Behavior & Research*, 18(2), pp. 159-178.
Kongar, E., & Adebayo, O. (2021). Impact of social media marketing on business performance: Hybrid performance measurements approach using data analytics and machine learning. *IEEE Engineering Management Review,* 49(1), pp. 133-147.
Kor, Y.Y., & Mahoney, J.T. (2004). Edith Penrose´s (1959) contributions to the resource-based view of strategic management. *Journal of management studies,* 41(1), pp. 183-191.
Kraaijenbrink, J., Spender, J.C., & Groen, A.J. (2010). The resource-based view: a review and assessment of its critiques. *Journal of Management*, 36(1), pp. 349-372.
Levinthal, D.A. (2000). Organizational capabilities in complex worlds. In G, Dosi., R.R, Nelson., S.G,Winter (Eds.), *The Nature and Dynamics of Organizational Capabilities*, (pp. 363–379), Oxford University Press.
Lichtenthaler, U. (2020). Mixing data analytics with intuition: Liverpool football club scores with integrated intelligence. *Journal of Business Strategy,* 34(1), pp. 10-14.
Lietz, P. (2010). Research into questionnaire design: A summary of the literature. *International Journal of Market Research*, 52(2), pp. 249-272.
Liu, Y. (2014). Big data and predictive business analytics. *Journal of Business Forecasting,* 33(4), pp. 40-42.
Mahoney, J.T., & Pandian J.R. (1992). The resource-based view within the conversation of strategic management. *Strategic Management Journal,* 13(5), pp. 363-380.
Malheiro, A., Ribeiro, F., Jamil, G.L., Rascao, J.P., & Mealha, O. (2018). *Handbook of Research on Knowledge Management for Contemporary Business Environments.* IGI Global.
Marchand, D.A., Kettinger, W.J., & Rollins, J.D. (2000). Information Orientation: People, technology and the bottom line. *Sloan Management Review,* 41(4), pp. 69-80.
Marjanovic, O. (2022). A novel mechanism for business analytics value creation: improvement of knowledge-intensive business processes. *Journal of Knowledge Management*, 26(1), pp. 17-44.
Martinsons, M.G., & Westwood, R.I. (1997). Management information systems in the Chinese business culture: an explanatory theory. *Information and Management,* 32(5) pp. 215-228.
Mata, F.J., Fuerst, W.L., & Barney, J.B. (1995). Information technology and sustained competitive advantage: A resource-based analysis, *MIS Quarterly,* 19(4)*,* pp. 487-505.
McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review,* 90(10), pp. 4.
Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management,* 30(2), pp. 272-298.
Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: findings from PLS-SEM and fsQCA, *Journal of Business Research*, 70, pp. 1-16.

Mishra, P., Pandey, C.M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of cardiac anaesthesia*, 22(1), pp. 67-72.

Morris, H. (2003). The financial impact of business analytics: build vs. buy. *DM Rev*, 13(1), pp. 40-41.

Moses, J.W., & Knutsen, T.L. (2007). *Ways of knowing.* Palgrave Macmillan.

National institute of standards and technology (NIST). (2006). *Minimum Security Requirements for Federal Information and Information Systems.* FIPS Publication 200. https://nvlpubs.nist.gov/nistpubs/FIPS/NIST.FIPS.200.pdf

National institute of standards and technology. (2018). *NIST Big Data Interoperability Framework: Volume 1, Definitions. (Ver. 2).* NIST Special Publication 1500-1r. https://www.nist.gov/publications/nist-big-data-interoperability-framework-volume-1-definitions

Ogbeide, G.C.A. & Harrington, R.J. (2011). The relationship among participative management style, strategy implementation success, and financial performance in the foodservice industry. *International Journal of Contemporary Hospitality Management*, 23(6), pp. 719-738.

Pedhazur, E., & Schmelkin, L. (1991). *Measurement, Design and Analysis: An Integrated Approach* (1st ed.). Psychology Press.

Peng, M. (2001) The Resource-based View and International Business, *Journal of Management,* 27(6), 803-829.

Penrose, E.T. (1959). *The Theory of the Growth of the Firm.* John Wiley.

Perreault, W.D. (1975-1976). Controlling Order-Effect Bias. *The Public Opinion Quarterly,* 39(4), pp. 544-551.

Peteraf, M.A., & Barney, J.B. (2003). Unraveling the resource-based tangle. *Managerial and Decision Economics,* 24(4), pp. 309–323.

Pinsonneault, A., & Kraemer, K.L. (1993). Survey research methodology in management information systems: An assessment. *Journal of Management Information Systems,* 10(2), pp. 75-105.

Poole, M., & O'Farrell, P. (1971). The Assumptions of the Linear Regression Model. *Transactions of the Institute of British Geographers.* 52(3), pp. 145-158.

Popovič, A., Hackney, R., & Tassabehji, R. (2018). The impact of big data analytics on firms' high value business performance. *Information System Frontier,* 20(2), pp. 209–222.

Porter, M.E. (1985). *Competitive advantage. Creating and sustaining superior Performance.* Free Press.

Prescott, M.E. (2014). Big data and competitive advantage at Nielsen. *Management Decision*, 52(3), pp. 573-601.

Protogerou, A., Caloghirou, Y., & Lioukas, S. (2011). Dynamic capabilities and their indirect impact on firm performance. *Industrial and Corporate Change*, 21(3), pp. 615-647.

Ray, G., Muhanna, W.A., & Barney, J.B. (2005). Information technology and the performance of the customer service process: a resource-based analysis. *MIS Quarterly*, 29(4), pp. 625–652.

Ross, J.W., Beath, C.M., & Goodhue, D.L. (1996). Develop Long-term Competitiveness Through IT Assets. *Sloan Management Review,* 38(1), pp. 31-42.

Rouse, M.J., & Daellenbach, U,S. (2010). More thinking on research methods for Resource-based Perspective. Strategic management journal, 23(10), 963-967

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students* (5th ed.). Pearson.
Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal,* 35(2), pp. 179-203.
Schreyögg, G., & Kliesch-Eberl, M. (2007). How dynamic can organizational capabilties be? Toward a dual-process model of capability dynamization. *Strategic Management Journal*, 28(9), pp. 913-933.
Schryen, G. (2013). Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. *European Journal of Information Systems,* 22(2), pp. 139-169.
Sirmon, D.G., & Hitt, M.A. (2009). Contingencies within dynamic managerial capabilities: interdependent effects of resource investment and deployment on firm performance. *Strategic Management Journal,* 30(13), pp. 1375–1394.
Sotarauta, M. (2005). Shared Leadership and Dynamic Capabilities in Regional Development. In I, Sagan., & H, Halkier (Eds.), *Regionalism Contested: Institution, Society and Governance. Urban and Regional Planning and Development Series,* (pp. 53-72). Ashgate.
Spanos, Y.E., & Lioukas, S. (2001). An examination into the causal logic of rent generation: Contrasting Porter's competitive strategy framework and the resource based perspective. *Strategic Management Journal,* 22(10), pp. 907-934.
Srivastava, R., Fahey, L., & Christensen, K. (2001). The Resource-based View and Marketing: The Role of Market-based Assets in Gaining Competitive Advantage. *Journal of Management,* 27(6), pp. 777-802.
Steven, A. (2008). Defining information systems as work systems: implications for the IS field. European journal of information systems, 17(5), pp. 448-469.
Straub D., Boudreau M.C., & Gefen D. (2014). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems*, 13, pp. 380-427
Strome, T.L (2013). *Healthcare Analytics for quality and performance improvements* (1st ed.). John Wiley & Sons, Incorporated.
Tambe, P. (2014). Big Data Investment, Skills, and Firm Value. *Management Science,* 60(6), pp. 1351-1616.
Teece, D.J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), pp. 1319 -1350.
Teece, D.J, & Pisano, G. (1994). The dynamic capabilities of firms: an introduction. *Industrial and Corporate Change,* 3(3), pp. 537-556.
Teece, D.J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal,* 18(7), pp. 509-533.
Tepper, B.J., Dimotakis, N., Lambert, L.S., Koopman, J., Matta, F.K., Park, H.M., & Goo, W. (2018). Examining followers responses to transformational leadership from a dynamic, person-environment fit perspective. *Academy of management journal,* 61(4), pp. 1343-1368.
Thomas, A., & Chopra, M. (2020). On how big data revolutionizes knowledge management. *Digital Transformation in Business and Society*. Palgrave Macmillan.
Titah, R., & Ortiz A.G. (2015). Strategic use of IT. *Management Information Systems,* 7.

Tranmer, M., Murphy, J., Elliot, M., & Pampaka, M. (2020) *Multiple Linear Regression* (2nd ed.). Cathie Marsh Institute Working Paper.

Tweney, D. (2013, June 10). *Walmart scoops up Inkiru to bolster its 'Big Data' Capabilities Online*. VentureBeat. Retrieved 2022, February 12, from: https://venturebeat.com/2013/06/10/walmart-scoops-up-inkiru-to-bolster-its-big-data-capabilities-online/

Tyagi, S. (2002). Using data analytics for greater profits. *Journal of Business Strategy,* 24(3), pp. 12-14.

Vidgen, R., Shaw, S., & Grant, D.B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research.* 261(2), pp. 626-639.

Ward, D.G. (2014). A guide to the strategic use of big data. *Information Management Journal,* 48(6), pp. 45.

Wentland, E.L., (1993). *Survey responses: An evaluation of their validity.* (1st ed). Academic Press.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal,* 5(2), pp. 171-180.

Wilden, R., & Gudergan, S.P. (2015). The impact of dynamic capabilities on operational marketing and technological capabilities: Investigating the role of environmental turbulence. *Journal of the Academy of Marketing Science*, 43(2), pp. 181-199.

Wills, M.J. (2014). Decisions through data: Analytics in healthcare. *Journal of Healthcare Management*, 59(4), pp. 254-262.

Winter, S.G. (2012). Capabilities: Their origins and ancestry. *Journal of Management Studies*, 49(8), pp. 1402-1406.

Wixom, B.H., Yen, B., & Relich, M. (2013). Maximizing value from Business Analytics. *MIS Quarterly Executive,* 12(2), pp. 111-123.

Wooldridge, J.M. (2009) *Introductory Econometrics: A Modern Approach.* (4th ed.). Cengage Learning.

Wright, P.M., McMahan, G.C., & McWilliams, A. (1994). Human Resources and Sustained Competitive Advantage: a Resource-based Perspective. *International Journal of Human Resource Management*, 5(2), pp. 301-26.

Zaheer, A., & Zaheer, S. (1997). Catching the Wave: Alertness, Responsiveness, and Market Influence in Global Electronic Networks. *Management Science,* 43(11), pp. 1493-1509.

Zhang, C., Zheng, C., Song, P. & Yu, X. (2018). Data analytics and firm performance: An empirical study in an online B2C platform. *Information & Management.* 55(5). pp. 633-642.

Zikmund, W.G. (2000). *Business research methods* (6th ed.). Harcourt College Publishers.

8. Appendix

Appendix 1: The VRIO-Framework

Valuable	Does the resource the company to explore an environmental opportunity and/or neutralize a threat?
Rarity	Is this resource currently controlled by a small number of competitors?
Imitability	Do companies without the resource face a cost disadvantage to get it or return it?
Organization	Are other policies and procedures of the company organized to support the exploration of its resources which are valuable, scarce and costly to imitate?

Source: (Barney, 1991)

Appendix 2: LinkedIn Post and Company E-mail Text

”Hi there!

We are two students from the Stockholm School of Economics and are currently writing our master's thesis about the relationship between organization's data analytics practices and their financial- and market performance.

If you are working at a firm that have used data analytics for at least three years, we would very much appreciate if you could take 3 minutes to answer this survey! Your response will be completely anonymous and for every response we will donate 2 SEK to UNHCR in support of the children in Ukraine.

Survey link: https://lnkd.in/esM2jF6b

Thank you in advance and do not hesitate to reach out if you have any questions!”

Appendix 3: Survey

Section 1: Introduction and GDPR consent

Handelshögskolan i Stockholm

Hi,

We are two students from the Stockholm School of Economics and are currently writing our master's thesis about the relationship between organization's data analytics practices and their financial- and market performance. In the context of this study, data analytics is referred to as a "*set of techniques that focus on gaining actionable insight to make smart decisions from a massive amount of data*" (Duan L., Da Xu L,. 2021).

If you have any questions about the survey, do not hesitate to contact us.

Thank you in advance,
Maria (24127@student.hhs.se) & Beverly (41831@student.hhs.se)

Handelshögskolan i Stockholm

The student project. As an integral part of the educational program at the Stockholm School of Economics, enrolled students complete an individual thesis. This work is sometimes based upon surveys and interviews connected to the subject. Participation is naturally entirely voluntary, and this text is intended to provide you with necessary information about that may concern your participation in the study. You can at any time withdraw your consent and your data will thereafter be permanently erased.
Confidentiality. Anything you say or state in the survey will be held strictly confidential and will only be made available to supervisors, tutors and the course management team.
Secured storage of data. All data will be stored and processed safely by the SSE and will be permanently deleted when the projected is completed. No personal data will be published. The thesis written by the students will not contain any information that may identify you as participant to the survey or interview subject.
Your rights under GDPR. You are welcome to visit https://www.hhs.se/en/about-us/data-protection/ in order read more and obtain information on your rights related to personal data.

I have taken part of the information provided above and consent to take part in this study:

- ◯ Yes, I DO consent
- ◯ No, I do NOT consent

Handelshögskolan i Stockholm

The organisation I work at uses data analytics and have done so for at least 3 years

- Yes
- No

Handelshögskolan i Stockholm

You are working at an organization adopting data analytics. When taking this survey, think of yourself at your respective organization and answer as truly to your everyday experiences as possible.

Section 2: Indicators for independent variables

Handelshögskolan i Stockholm

The organization enforces adequate plans for the utilization of data analytics

1 (disagree)	2	3	4	5	Click to write Choice 6	7 (fully agree)
○	○	○	○	○	○	○

In our organization, data analysts and employees from various departments regularly attend cross-functional meetings

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Workstreams involving data analytics are monitored regularly

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Handelshögskolan i Stockholm

Decisions are based on data rather than on instinct

1 (disagree)	2	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○	○

Employees are regularly encouraged to draw knowledge and make decisions based on data

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

All personnel know which role data analytics play in the firm's business strategy

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Handelshögskolan i Stockholm

There are no identifiable communications bottlenecks within our organization for sharing analytics insights

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

All personnel are willing to override own intuition when data contradicts their viewpoints

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Our managers are able to understand where to apply data analytics

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Handelshögskolan i Stockholm

Our organization performs data analytics planning processes in systematic ways

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Our leadership are able to understand the business need of managers and customers to determine opportunities that data analytics might bring to our business

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Personnel are regularly educated in technological trends, new technologies, or data analytics

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Handelshögskolan i Stockholm

Data analytics plans are frequently adjusted to better adapt to changing conditions

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Information is shared across our organization, regardless of the location

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Clear performance criteria are set regarding workstreams involving data analytics

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Handelshögskolan i Stockholm

Our managers frequently examine innovative opportunities for the strategic use of data analytics

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

The organization ensures that personnel have the required knowledge about the business environment and customer needs

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

In our organization, different responsibilities regarding analytics development are well-defined and assigned

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Choose option "5"

1 (disagree)	2	3	4	5	6	7 (fully agree)
○	○	○	○	○	○	○

Section 3: Indicators for dependent variables

Handelshögskolan i Stockholm

Using data analytics improved ____ during the last 3 years relative to competitors

	1 (not at all)	2	3	4	5	6	7 (significantly)
Acquisition of new customers/users more quickly	○	○	○	○	○	○	○
Customer retention	○	○	○	○	○	○	○
Customer satisfaction	○	○	○	○	○	○	○
Market share	○	○	○	○	○	○	○
Introduction of new products or services to the market faster	○	○	○	○	○	○	○
The success rate of our new products or services	○	○	○	○	○	○	○

Handelshögskolan i Stockholm

Using data analytics improved ____ during the last 3 years relative to competitors:

	1 (not at all)	2	3	4	5	6	7 (significantly)
Sales Growth	○	○	○	○	○	○	○
Profitability	○	○	○	○	○	○	○
Return on investment	○	○	○	○	○	○	○
Overall financial performance	○	○	○	○	○	○	○

Section 4: Control variables and quality questions

Handelshögskolan i Stockholm

Industry

Position in your company

- C-suite
- Vice President
- Director
- Manager
- Individual contributor (e.g. consultant, associate, analyst, representative)
- Other

Gender

- Female
- Male
- Other

This survey focused on organizational practices related to:

- IT processes
- Data analytics
- Digital transformations

Section 5: End

Handelshögskolan i Stockholm

We thank you for your time spent taking this survey!

Your response has been recorded.

Please, feel free to share the link to this survey with professionals in your network!

Appendix 4: UNHCR Donation

Sverige för
UNHCR
FN:s flyktingorgan

Hej!

Varmt tack för att du hjälper barn och familjer i Ukraina. Din gåva skyddar människor som just nu tvingas fly. Du räddar liv.

Vi hörs snart igen,

Carina Pettersson
Givarservice, Sverige för UNHCR

Här kan du läsa mer om situationen i Ukraina och hur din gåva hjälper de människor som tvingas på flykt för att söka säkerhet
www.sverigeforunhcr.se/ukraina

Undrar du något? Hör gärna av dig till mig på telefon 08-121 491 00 eller mejla till info@sverigeforunhcr.se

Psst. Gilla oss gärna på Facebook:
https://www.facebook.com/sverigeforunhcr

Inskickade uppgifter:

- Datum: 15/05/2022 18:49
- Belopp: 500 kr
- Betalsätt: Swish Godkänn i appen
- Transaktionsnummer: 14209012039

Appendix 5: ANOVA overview

Model		Sum of Squares	df	Mean Square	F	Sig.
Firm performance without control variables	**Regression**	137.884	6	22.981	68.817	<0.001
	Residual	68.099	198	0.344		
	Total	205.983	204			
Firm performance with control variables	**Regression**	141.338	20	7.067	20.115	<0.001
	Residual	64.645	184	0.351		
	Total	205.983	204			
Non-financial performance without control variables	**Regression**	164.866	6	27.478	54.565	<0.001
	Residual	99.709	198	0.504		
	Total	264.575	204			
Non-financial performance with control variables	**Regression**	168.314	20	8.416	16.086	<0.001
	Residual	96.261	184	0.523		
	Total	264.575	204			
Financial performance without control variables	**Regression**	114.273	6	19.045	30.490	<0.001
	Residual	123.680	198	0.625		
	Total	237.953	204			
Financial performance with control variables	**Regression**	126.288	20	6.314	10.405	<0.001
	Residual	111.665	184	0.607		
	Total	237.953	204			