Master Thesis

ANALYTICS IN ORGANIZATIONS: THE EFFECT OF ANALYTIC CAPABILITY DEPLOYMENT ON PERFORMANCE IN THE DUTCH FINTECH DOMAIN

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Preface

This master thesis is written as the final piece of the master program Business Administration with specialization Strategic Management at the Radboud University. The focal point of this research is examining a proposed relation between the deployment of the analytic capability and firm performance. During my internship at de Volksbank during my bachelor, and to a greater extent during the master program, my attention was attracted to the rapidly evolving world of data and data analytics. Especially in the financial services industry, data and information has acquired a more prominent role in everyday business and decision making processes. By conceptualizing a relatively ambiguous concept, analytic capability deployment, and researching its effect on firm performance, I was able to take a closer look at the importance, potential and origination of data analytics in a relatively new and innovative sector, the FinTech sector.

Writing this master thesis has been a long process during which I have learnt a lot about one of the sectors in which I would like to be active in the future. During this process I have encountered physical and mental struggles, but also learnt to overcome them. I have learnt a lot about conducting my own research and the things that I value during the research process. My gratitude goes out to Dr. ir. Gerrit-Willem Ziggers, who supervised my research process, for his support, patience and helpful feedback over the entire period of researching. Even in these difficult times (COVID19) in which social distancing is more important than ever, he found a way to provide me with feedback via online meetings, during which we discussed the progress and the overall research process. Furthermore, I would like to acknowledge Prof. dr. Nikolay A. Dentchev as the co-reader of this master thesis project. Moreover, I would like to specially thank all of the respondents and people who assisted in the process of data collection for their time and effort. They have been essential to finish this thesis. Lastly, I would like to thank all of my friends and family for all the support I have received over the previous period of time.

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Abstract

Ongoing developments in data collection and analytics have proven to be a source of performance enhancement. Especially in the financial services industry, specifically the FinTech sector, in which information is the basis of many products, these developments have gained increased attention. In order to optimally collect and analyze data, a well-developed analytic capability is important. However, what determines the maturity of a capability, and what the eventual effect of deploying that analytic capability on the firm performance is, is not clear. By researching the analytic capability, evaluating factors that determine the maturity level of that capability and study the effects on firm performance, this research tries to find a positive relation between the deployment level of the analytic capability and firm performance. Based on a multiple case study, with interviews as the main source of data collection, it was found that the deployment of the analytic capability has a positive effect on the firm performance, where the effect is stronger for firms that have a more mature analytic capability. It was also found that organizations with higher maturity level of the analytic capability deployment experience bigger effects on non-financial performance than firms with lower maturity levels.

Keywords: analytics, analytic capability, deployment of analytic capability, performance, FinTech

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1. Introduction

1.1. Background

The digital revolution that took place in the 90s was the cause of a major change in the world, in both social and business-related aspects. Individuals and businesses have experienced a transition towards an information technology (IT) basis of society (Gerlich, 2001). In the late 90s, 50% of the American people were in possession of a PC and were participating in the digitization age according to Microsoft Chairman Bill Gates (1999). He stated that individuals and businesses that would not embrace this change into technology were very likely to be left behind in an outdated, analog world.

In the years after, Gates' predictions were enforced by the first research results of IT positively influencing business performance (Barua et al, 2004). After this, strategy and management information systems literature have been researching the effect of IT on business performance. A significant, positive role of IT affecting business performance was found by Bharadwaj et al (2013). More specifically, IT has developed to form a crucial part of organizations, and as Gates (1999) stated, IT is essential for a firm to survive in a competitive environment (Arora & Rahman, 2016).

Recent developments (the digitization age) have opened doors to new ways of doing business, strategic and operational renewal (Berman, 2012). The digitization age has resulted in the emergence of analytics, which can be considered the application of advanced analytic techniques to data. Analytics can be used to effectively and efficiently process and use that data, which according to Eisenhardt (1999) can help making more effective strategic decisions that can potentially lead to improved performance (Schläfke, Möller, & Silvi, 2013). Analytics is not a technology, but rather a group of tools that are used to gain and analyze information in order to predict outcomes of problem solutions, which can in its turn be used to assist in strategic decision-making (Bose, 2009) and enhancing (financial and non-financial) performance. (Schläfke, Möller, & Silvi, 2013). For routine processes and decision, analytics can be leading. For wicked-problems, analytics can also be leading, but expert judgement should also be consulted in order to reach optimal effect (Hughes, 1996).

Increasingly, companies in almost every industry have started using advanced (also known as predictive) analytics to analyze their data (both structured and unstructured), combining and processing an overload of data of the past, present and even future information in the form of predictions (Bose, 2009).

In the past years, the emergence of analytics in organizations in all industries has been proven to play a successful role concerning business performance, where top-performing organizations use analytics five times more than low-performing organizations. Being innovative to achieve competitive differentiation and an overload of (ineffectively used) data formed the underlying pressure that encouraged firms to use analytics (LaValle et al, 2011; Carayannis & Sindakis, 2017). It is believed that the use of analyzing techniques (methods in analytics) could lead to a more effective and more efficient data generation and processing, which can result in more accurate and more efficient decision-making, therefore forming an opportunity for creating added value to firms, as well as a chance to differentiate and remain competitive (Bose, 2009; Carayannis & Sindakis, 2017). Therefore, the question is how exactly, an organization can use analytics to improve its performance.

La Valle et al (2011) state that the utilization and success of analytics depends on analytic capabilities, which can be defined as the ability to apply analytical techniques, and the extent to which these capabilities are actually deployed in an organization.

One of the industries in which analytics has emerged and gained attention rapidly, is the financial services industry (Flood et al, 2016). The financial services industry has been faced with, and still faces, a strong impact of digitization (PWC, 2016). One of the major reasons for this digitization is that financial products are almost exclusively based on information (Puschmann, 2017). The digitization of this information is not just leading to automation of processes, but also to a fundamental reorganization of the financial services value chain, i.e. an overload of data that is continuously gathered. The overarching term that reflects this digitization is ‘financial technology’, or short ‘FinTech’ (Puschmann, 2017). As the information stream in the FinTech domain is extremely high, the use of analytics in this sector is likely to grow over the upcoming decade(s). Furthermore, the Dutch FinTech domain is a rapidly growing sector ("Nederlands FinTech-landschap groeit flink in 2017", n.d.), with over 450 companies ("About us - Holland FinTech", n.d.), where continuous growth is expected.
The rise of analytics is therefore especially applicable to the developments in the FinTech sector with regard to performance as influenced by the enormous growth of the sector and the continuously changing landscape those FinTech companies operate in. However, the use of analytics depends, as LaValle et al (2011) stated, on the extent to which analytic capabilities are present within a firm. This is strengthened by a statement that Eisenhardt and Zbaracki (1992) made years earlier; the sources of advantage can be found in the organizational capabilities. Analytic capabilities can be defined as an organization’s ability to combine and

integrate resources that are necessary for the usage of analytics, to adapt to i.e. changes (O'Reilly & Tushman, 2008).

1.2. Problem formulation

Due to an overload of data that is continuously obtained, there is an increasing need for ways to process that data into information that can be used for i.e. performance enhancement (LaValle et al, 2011; Flood et al, 2016). As the attention for one of those ways, which is analytics, is increasing and more and more data is collected about the results of analytics in organizations, analytics is likely to play a major part in future developments in all industries, especially in technology driven industries, such as the financial services industry (Flood et al, 2016). Flood et al (2016) state that analytics can form a solid basis (analysis and documentation) for performance enhancement as analytics reduces risk from a conversion of complex, subjective and ambiguous information into a clear and objective ruling, and also accounts for the limitation of biases or problematic tendencies, as well as that it captures the analytic provenance of decisions. Flood et al (2016) however, do not research the specifics of the FinTech industry, but apply a rather general tone. Furthermore, the they do not address the fundamentals of the success of analytics; namely whether or not an organization possesses the analytic capabilities, nor its dependence on the extent of deployment of those capabilities as described by LaValle et al (2011). Moreover, according to LaValle et al (2011) and Eisenhardt & Zbaracki (1992), the organizational capability, in this case the analytic capability, is fundamental to create an advantage that could lead to better firm performance.

The lack of scientific research on the FinTech domain with regard to the presence and deployment of this analytic capability and its effect on performance, forms the aim of this study. General effects of the use of analytics are known, but little is known about the differences that arise from the extent to which analytic capabilities are actually deployed in organizations. Therefore, the focus lies specifically on the deployment of analytic capabilities. This leads to the corresponding research question:

> *How does the deployment of analytic capabilities influence the firm performance of FinTech organizations?*

In order to answer this research question, sub-questions[1] were formulated as guidance.

1. What is analytics?
2. What are analytic capabilities?
3. What is deployment of analytic capabilities?
4. What is performance?
5. What is the relation between analytic capabilities and performance?

The first one, "what is analytics?" should help to clarify the field of research and set a frame of reference for answering the second sub-question; "what are analytic capabilities?". The third sub-question aims to form a guidance for answering the first part of the research question by providing insights in the deployment of analytic capabilities and potential differences between firms or firm departments in this deployment. The fourth sub-question helps clarifying what is commonly considered as performance and therefore forms a benchmark for this research. The last sub-question leads to the final and actual goal of this research; answering the research question, by providing an initial answer to whether or not a relationship exists between analytic capabilities and performance.

The conceptual model that represents the research question is illustrated in Figure 1:

Figure 1: Conceptual model

1.3. Relevance

The following sections explain in what way this research will contribute to existing literature in the field of analytics and the FinTech domain. First, the academic relevance will be discussed, after which the practical relevance will also be illustrated.

1.3.1. Academic relevance

This research contributes to the scientific community in the field of strategic management, more specifically a capability (analytics) that can influence performance. Although the developments

[1] All sub-questions and conceptual model are related to research domain, namely the FinTech sector.

and effects of analytics on organizations have been researched before by i.e. Flood et al (2016) and LaValle et al (2011), the relation to strategy and performance in FinTech organizations, has not been researched yet. The definition of analytics for example, is very general, as mentioned earlier. In order to form a solid basis for research on analytics and the effect that it has on firm performance of organizations in the FinTech sector, concrete ideas about the practical use of analytics, i.e. different methods of analytics and the analytic capability itself, are to be identified.

Until now, the focus of research has been with the evaluation of (financial) performance of organizations (LaValle et al, 2011). The relation between analytics and firm performance has been found positive in other industries (Miles, 2017), but in the FinTech domain however, it has not been properly researched yet, which is most likely caused by the only recent rise of FinTech organizations (Puschmann, 2017; Alt, Beck & Smits, 2018). The findings of this research can create a clear visual of the Dutch FinTech domain and how firm performance in FinTech companies is or is not affected by the deployment of analytic capabilities. This will complement both research on analytics and literature on the financial sector, more specifically the Dutch FinTech domain.

1.3.2. Practical relevance

The digital transformation that has taken place, and still is, is changing the business environment. The digitization age in which we live today was created by an increasing combination of digital intensity, connectivity and big data, amplified by the growth of the Internet of Things (Diesveld, 2018). Products and services are increasingly purchased and sold with digital technologies and with that, new forms of business strategies are formed. With these developments, a lot of data is collected and in need of processing. An overload of data is already continuously generated and in order to effectively and efficiently process all this data, being able to implement analytics (and particular analytics' methods) could provide the solution to this ever-growing amount of data (LaValle et al, 2011). This analytic capability could form the basis for increasing firm performance, as it might provide firms the opportunity to assist in achieving their goals, i.e. differentiating or (re)gain competitive advantage (Bose, 2009; Carayannis & Sindakis, 2017).

1.4. Outline of the thesis

This chapter has introduced the topic of this research, defined the research objective and the research question. Furthermore, this chapter has discussed the academic and practical relevance of this study. In the remainder of this thesis, a theoretical framework is provided, serving as the basis for this research. In this theoretical framework chapter, the most important and relevant theories about analytics, the capabilities required for implementation of analytics, differences in deployment of analytic capabilities, and performance are discussed. But to start off, a description of the Dutch FinTech domain is provided. In the third chapter, the methodology of this research is described and elaborates on the context in which this study should be seen. Subsequently, the results of the study are shown in chapter 4, after which an interpretation of these results is provided in chapter 5, together with research implications (for both managers and academics) and limitations. Moreover, future research directions are discussed in chapter 5.

2. Theoretical framework

This chapter forms the theoretical framework for the remainder of this research, in which the variables related to the research question are extensively explained in terms of background, relevance and recent developments.

2.1. FinTech industry

In order to illustrate the context of this research, the FinTech industry is described in terms of emergence and development, as well as the current situation in this industry.

2.1.1. Emergence and development of the FinTech industry

As mentioned in the introduction of this research, the overarching term that reflects this digitization in the financial sector is ‘financial technology’, or short ‘FinTech’ (Puschmann, 2017).

Considering the first part of the contraction; in general, the financial sector has grown enormously over the last centuries, with the first bank being established in 1472 and a large variety of other businesses (i.e. securities firms, insurance companies, etc.) following since (Alt & Puschmann, 2016). The financial sector is often referred to as service providers since they support firms in a primary market to conduct their business and have shaped a secondary market in which financial service providers act among each other, for example investment bankers, etc. (Alt, Beck & Smits, 2018). From this, an extensive network of interrelationships resulted (Zhu et al, 2004).

The second part, technology, has become key in handling financial processes (Alt, Beck & Smits, 2018). A technology is a way of organizing things, coordinating processes and performing tasks more easily (Bouwman et al, 2005). A technology therefore is not only considered digital, but also analog.

Previous research on the evolution of FinTech suggest that financial technologies have a longer legacy than the term FinTech (Alt, Beck & Smits, 2018). The history of FinTech has i.e. been linked to the diffusion of the internet (Lee & Shin, 2018) or even to the mid-nineteenth century (Arner et al, 2016). According to Alt, Beck and Smits (2018), the first application of technologies used by financial institutions relied on physical media containing information. Since transferring this information and values across distances was only feasible via physical modes of transportation, markets were primarily limited to a regional scope (Alt, Beck & Smits, 2018). This however, changed with the emergence of innovations in information and communication technology (short IT), starting with the appearance of the visual and later electrical telegraph (Alt, Beck & Smits, 2018; Malone et al, 1987). After 2008, the FinTech as known today, emerged, accompanied and arguably enabled by i.e. the increase of non-cash payments and stricter rules for the existing financial organizations (Alt, Beck & Smits, 2018). An overview of the development of FinTech is provided in appendix 1. The most important drivers that have led to this IT-induced transformation are the changing role of IT, the changing consumer behavior, changing ecosystems and the changing regulation (Puschmann, 2017).

Puschmann (2017) differentiates three areas that reflect the development of FinTech along five phases over the last decades. Next to a brief explanation of the phases, a table is also provided in appendix 2.

1. *Internal digitization (phase 1-3)*

   The first area of IT use focused on internal processes, i.e. payment transactions. In this first phase, financial organizations concentrated on the automation of financial services processes for efficiency gains. Focus lied on support and later back-office processes. Integration of IT was not or only partially existent and developed in the third phase where first multi-channel approaches were developed.

2. *Provider-oriented digitization (phase 4)*

   In this fourth phase, financial services providers focused on the integration of providers. For this, they standardized processes and application functions. The outsourcing of business processes started with support areas as IT and later also back-office areas were reached. The goal of this was to reduce in-house production.

3. *Customer-oriented digitalization (phase 5)*

   This area of FinTech application is centered around customers and their processes as redefine today's inside-out product-centered logic towards new ecosystems. Individual channels become obsolete with hybrid and overlapping forms of interaction-based customer processes as the center of financial products and services design. These services include the development of peer-to-peer business models as well as the evolution of non-financial service providers from outside the industry.

2.1.2. FinTech in the current situation

Today, FinTech is of high strategic importance for financial services companies (Puschmannm 2017). In banks, IT costs account for 15 to 20% of all costs and therefore are the second largest cost factor after labor costs (Gopalan et al, 2012). Moreover, banks traditionally have the highest IT investments compared to all other industries (Puschmann, 2017). The evolution of FinTech has shown that the focus has shifted from intra-organizational solutions to customer-oriented and provider-oriented inter-organizational approaches (Puschmann, 2017). Notable is that FinTech solutions differ regarding the providers and the interaction types (Chan & Lee, 2005), as well as regarding the banking and insurance processes they support (Haddad & Hornuf, 2016). Haddad & Hornuf (2016) illustrated that the maturity level of the various FinTech solutions differ regarding the process areas covered, for example, the most important sector of the emerging FinTech market is financing, followed by payment, cross-processes and investments. This shows that the evolution in the FinTech domain is very much affecting the financial industry. FinTech is even described as disruptive innovation in the context of the financial services industry, induced by IT developments (Puschmann, 2017). With the rapid innovations in IT and the more and more data driven society, adapting to these changes and using the available financial technology can be considered essential to avoid inertia (Gilbert, 2005).

Due to new regulation, the so-called Payment Service Directive 2 (PSD2), banks are forced to open up consumer payment accounts for appropriate licensed, innovative (bank and non-bank FinTech) service providers, providing FinTech players to capitalize on the emerging Application Programming Interfaces (API) landscape and to capture customer and developer mindshare as well as payment and non-payment revenues that were long taken for granted by incumbent financial institutions (Cortet, Rijks & Nijland, 2016). In the fintech landscape, an increasing number of service providers that focusses on improving specific parts of the traditional banking model by using innovative technology is present. When a firm possesses the capability to use analytics to adapt to and use this new regulation in its advantage, a shift in the financial services sector could be up hand. FinTech players namely, can outperform traditional banking in terms of costs, pace and quality, possibly because of using analytics. However, due to limited network effects; lack of reach, a lot of FinTech players do not manage to compete with banks yet (Cortet, Rijks & Nijland, 2016).

2.2. Analytics

This section answers the first sub-question; "what is analytics?". Analytics is, as mentioned in the introduction, the application of advanced analytic techniques to data, in order to enhance the decision-making process as well as find answers to problems that eventually can lead to improved firm performance (Bose, 2009). Over the past years, companies in almost every industry have increasingly started using analytics to process their (big) data (both structured and unstructured), combining information of the past, present and future (Bose, 2009). Initially, analytics was only a marketing feature, whereas over the past years, it has also been utilized for competitive analysis purposes (i.e. differentiation factors) (Xu, Frankwick & Ramirez, 2016). In general, analytics provides a wide field of possible application scenarios, i.e. the prediction of price trends and customer behavior (Pospiech & Felden, 2017; Miles, 2017).

The introduction of analytics was caused by an overload of data, based on the need for an effective and efficient processing of this information (LaValle et al, 2011). Therefore, analytics finds its basis in Business Intelligence (BI), which is considered the set of techniques, systems and tools that transform data into meaningful and useful information for business analysis purposes (Chen, Chiang, & Storey, 2012; Carayannis & Sindakis, 2017). Traditional Business Intelligence differs from big data analytics, as analytics is often referred to, in data storage, management, analysis and visualization technologies, mainly due to a service need for larger (exabytes instead of terabytes) and more complex (from sensor to social media data) applications that could not be served effectively with previous (BI) technologies (Herodotou, 2017). Industry leaders in the database system industry (i.e. SAP and Oracle) are adapting to this new status quo and develop more powerful and parallel hardware in combination with sophisticated parallelization techniques in the underlying data management software (Herodotou, 2017). The rise of analytics is thus not just a data storage issue, but also a processing technique(s) matter. Furthermore, the latest transition in the BI market, from traditional analytics to predictive analytics is crucial in understanding data and therefore also critical to business decision-making and performance management (Miles, 2017). Apart from the technological development, the rise of analytics also relates to a capability development. The development of the required capabilities is discussed in a later paragraph of this theoretical framework.

2.2.1. Types of analytics

Two types of analytics can be distinguished; traditional analytics and advanced analytics. Nowadays, advanced analytics is most commonly used (Xu, Frankwick & Ramirez, 2016). Traditional analytics focuses on improving key performance indicators (KPIs) for better insights regarding advertising, pricing, customer relationship management and new product development (Sathi, 2014).

Advanced analytics denotes the overall process of turning low-level data into high-level knowledge by extracting patterns or models from observed data (Bose, 2009). It consists of big data analytics (BDA), predictive analytics, mining of information from several sources (i.e. text) and is able to visualize and integrate data (Bose, 2009). Advanced analytics differs from traditional analytics in the four Vs of data: volume, velocity, variety and veracity (Xu, Frankwick & Ramirez, 2016). That means that advanced analytics can process more information, that is retrieved from various sources, on a higher pace. More concrete, this means that advanced analytics is able to process both structured, semi structured and unstructured data, through multiple technologies and techniques in order to come to a higher quality outcome in the form of decision value (Bose, 2009), which is visually presented in Figure 2.

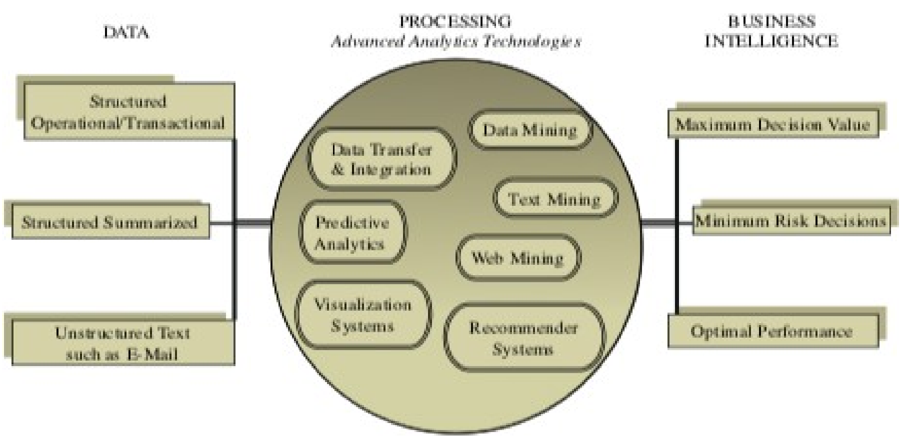

Figure 2: Visual representation of advanced analytics (Bose, 2009)

Within those technologies, information can be analyzed through multiple analytical techniques, dependent on the goal of the analyst. For data mining for example, goals can consist of prediction, (multivariate) regression, classification, clustering, link analysis, model visualization and exploratory data analysis (Bose, 2009; Chen, Chiang, & Storey, 2012). As presented, many different analytic techniques are available. The ability to effectively use one or more of these techniques provide organizations a manner to potentially increase their performance, but also forming a possible basis for differentiation between firms (Schläfke, Möller, & Silvi, 2013).

2.2.2. Capabilities required for (advanced) analytics

In this research, a capability is defined as an organization's ability to combine and integrate resources to adapt to i.e. changes (O'Reilly & Tushman, 2008). In order to understand what a capability is, it is useful to understand what the difference between an ability and a capability is. An ability is the skill or intelligence to do something, whereas a capability is the ability or power to actually use a skill (Cambridge, n.d.). In this research, the ability or the skill is analytics or the analytic techniques, whereas the capability is the ability to actually use that skill.

The basis for this paragraph is formed by competence-based theories, which accentuate the role that resources and capabilities play in the creation and capturing of value within a firm. Profitability and performance of an organization is the result of effectively utilizing the resources and capabilities that an organization possesses (Diesveld, 2018). One of the most popular perspectives for firm profitability, and the base theory for the creation of value through capabilities is the resource-based view of the firm (RBV) as developed by Barney (1991). This theory states that a firm's resources are the focal point in obtaining a sustainable competitive advantage. The knowledge-based view (KBV), that states that knowledge is the crucial resource of obtaining a sustainable competitive advantage (Grant, 1996), is an extension of the RBV.

Apart from possessing the initial capability that can create and capture competitive advantage, a firm needs to be able to adapt to rapidly changing environments and situations (Bose, 2009; Carayannis & Sindakis, 2017; Teece, Pisano & Shuen, 1997). A theory that provides an answer is the dynamic capability theory (DC). Dynamic capabilities are generally defined as "the firm's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments" (Diesveld, 2018, p. 9; Teece et al, 1997, p. 516). This means that firms can obtain competitive advantage by adapting to (environmental) changes, through firm-specific resources, assets and capabilities.

In general, Leonard (1995) distinguishes three types of capabilities: core capabilities, enabling capabilities and supplemental capabilities. Core capabilities are the capabilities that have developed over time and cannot be easily imitated, therefore resulting in competitive advantage for a firm (Leonard, 1995). These capabilities relate to the RBV, KBV and DC theories in the sense that they form the centrum for the firm's competitive advantage. Second, the enabling capabilities are those that are necessary in support of the regular operations as a minimum basis for competition in the industry, but convey no particular competitive advantage themselves (as they are i.e. easy to imitate or developed quickly). Last, the supplemental capabilities are the capabilities that are, as Leonard (1995) states, nice to have, but not essential.

In order to effectively and efficiently implement analytics in an organization, that organization should have certain capabilities that enables this. The capability that enables the use of analytics is the ability to apply analytic techniques, i.e. data mining, to their gathered data (Davenport, Harris, De Long and Jacobson, 2001). This is the capability that enables (enabling capability) analytics in the first place. Furthermore, a firm needs to be able to process the information acquired via analytics into information that eventually leads to a strategic decision. Both capabilities exist of the following three building blocks (abilities) that are the basis of any capability: people, processes and tools (La Valle et al, 2011). The resources that are required for the use of analytics, and therefore together form the analytic capability are:

1. *People*: knowledge about the utilized software, hardware and analyzing techniques is required (Bose, 2009; Chen, Chiang, & Storey, 2012; Xu, Frankwick & Ramirez, 2016). This is often managed by hiring analysis experts that have followed a significant amount of training in order to use the relevant tools. These experts together form the main part of the building block people.
2. *Tools*: in order to effectively use analytics, certain software and hardware is required (Bose, 2009: La Valle et al, 2011). Regarding the use of analytics, up-to-date technology is needed in order to effectively use it (Herodotou, 2017; Miles, 2017). Furthermore, end-users of the analysis outcomes have a need for simple-to-use tools that effectively and efficiently solve their business problems (Bose, 2009; La Valle et al, 2011).
3. *Processes*: according to La Valle et al (2011), data does not form the most important adoption barrier for organizations. They state that managerial and cultural related aspects are more important barriers. However, the leading obstacle to analytics

adoption is the lack of understanding of how to use information coming from the use of analytics to improve business, which enforces the statement by Bose (2009) and La Valle et al (2011), that end-user friendly tools enhance the effectivity of analytics and its introduction. In order to deal with these issues, predetermined and well-defined implementation and adaptation processes are to be developed (La Valle et al, 2011). These processes mainly consist of standardized tools and procedures that employees can follow easily, resulting in an increased pace of data processing into information that management can use to make strategic decisions

When these resources / building blocks are acquired, organizations still need to have the ability to combine and integrate those resources (building blocks) in order to form a capability, i.e. use analytics (Leonard, 1995: LaValle et al, 2011).

Overall, an organization needs to possess two capabilities, that can be considered the analytic capabilities:

1. The ability to apply analytic techniques to their gathered data.
2. The ability to process the outcomes of the used analytic techniques into useful and understandable information that form the basis for a (strategic) decision, which can be done via i.e. standardized processes.

After the organization possesses the capability of implementing the analytic capabilities that form the basis of analytics usage, it should generally follow three stages that are required for deployment of (advanced) analytics (Bose, 2009). For a successful implementation, an organization must be able to responsibly (in terms of finance) implement and use analytics, based on the three building blocks as described by LaValle et al (2011). Moreover, analytics must be used on a regular basis in order to solve business problems in order to be successful in the long run (Bose, 2009). According to Bose (2009), using analytics on a regular basis increases the expertise level (can be considered the capability level), which results in more effective and efficient usage. In terms of deployment level, regular use of analytics improves the expertise level, therefore potentially increasing the knowledge of how to deploy the analytic capability, which can lead to a firm achieving a higher level of analytic capability deployment. This process can also be described as the organizational learning cycle as illustrated by King (2009). In his book, King explained how a firms' performance can improve through evolution of knowledge or skill within a firm, via i.e. better understanding of how to use knowledge or skills to achieve goals as a result of organizational learning (e.g. experience).

The levels of deployment are discussed below. Last, full exploitation of analytics technology is needed within the organization, in order to enable the most effective on-demand use of analysis based on individual needs (Bose, 2009). Full exploitation is considered to be the most mature level (transformed level) in deploying the analytic capability, which is discussed in the next paragraph.

La Valle et al (2011) even depict this three-stage theory further in terms of the level of maturity of the capability and the effect that it has on the extent to which analytics is implemented in an organization. La Valle et al (2011) distinguish three different levels of presence of the analytic capability with regard to the adoption of analytics. Organizations that find themselves in the **aspirational level** are the furthest from achieving their desired analytical goals. Those organizations use analytics to justify their actions and focus on efficiency or automation of existing processes in order to cut costs. Firms in this level lack the basic building blocks as depicted by La Valle et al (2011) to collect, understand, incorporate or act on analytical insights. The lacking of resources or at least quality of the resources, means that the capabilities required for the use of analytics, which were mentioned earlier, are not fully present. For example, the organization hired data analysts that are not considered experts in their field. The aspiration to use analytics is there, but the organization is still hesitant with regard to hiring (expensive) experts. This indicates that the analytics cannot be utilized up to its full potential.

Organizations that find themselves in the **experienced level** have gained some analytical experiences, most likely with efficiencies at the aspirational phase. The goal of these firms goes beyond cost reduction. Next to efficiency goals, organizations at this phase also use analytics for growth objectives. The main motive for using analytics that firms at this level have is to guide their organizations' actions. Organizations that are in this level are developing better ways to collect, incorporate and act on analytics effectively in order to optimize their organizations (La Valle et al, 2011). This means that those organizations have invested in the required resources that form the analytic capabilities. Taking the previous example, the organization at this level hired a data expert, who has full knowledge of all required techniques. However, he is still alone and the business is not yet centered around him. Therefore, the level of resources present is still not optimal for utilization of analytics.

The last level of the adoption process is the **transformed phase**. Organizations that are at this level of analytics adoption have substantial experience using analytics across a broad range of functions. Organizations at this level use analytics to prescribe actions that are related to efficiency goals, growth objectives and complex business challenges. Within these organizations, analytics is used as a competitive differentiator enabling them to adapt at organizing people, processes and tools to optimize and differentiate. Firms in this phase are relatively even less focused on cost management than organizations that are at one of the above two mentioned stages, and are most likely to have automated their operations through effective use of (by analytics) gained insights. This is mainly because the organizations' motive for using analytics goes far beyond helping to achieve financial objectives. Firms at this level have optimized the allocation of the required resources for the use of analytics. Using the same example of the data analysts; the organizations at this level have hired one or more data experts, and have centered their business around this expert(s) and therefore this has become the main source of competitive advantage for the firm. Firms that find themselves at this stage of the analytics adoption have indicated that they substantially outperform their industry peers (La Valle et al, 2011).

So overall a firm can go through three stages of analytic capability deployment, which can also be regarded as phases of maturity of the capability. The aspirational phase is the most basic phase, and the transformed phase represents the phase in which the analytic capability is most mature. This maturity is based on the presence and allocation of the three resources as described earlier.

Besides, the analytic capability can also be considered a dynamic capability as organizations that use or aspire to use analytics find themselves in a continuously changing environment in terms of regulatory changes, increasing competition and a still increasing amount of data that gains more and more importance within firms (Bose, 2009; Carayannis & Sindakis, 2017; Teece, Pisano & Shuen, 1997; Puschmann, 2017). In order for an organization to reach a higher deployment stage and also remain at that stage, the capability requires continuous improvement (La Valle et al, 2011). This continuous development of the capability can be done by investing in the three building blocks of a capability as described by La Valle et al (2011).

2.3. Firm Performance

Performance has been an important concept in strategic management research and practices for many years, despite the long time lacking of an unambiguous definition (Santos & Brito, 2012). For a firm to maintain viable and survivable, achieving a certain minimum level of firm performance is crucial (Richard et al, 2009). Not achieving that firm specific minimum level, in other words poor firm performance, can lead to negative consequences for the firm, even bankruptcy.

In an effort to define the domain of performance, Venkatraman and Ramanujam (1986) distinguished firm performance from the broader concept of organizational effectiveness. They came up with a visualization as shown in figure 3.

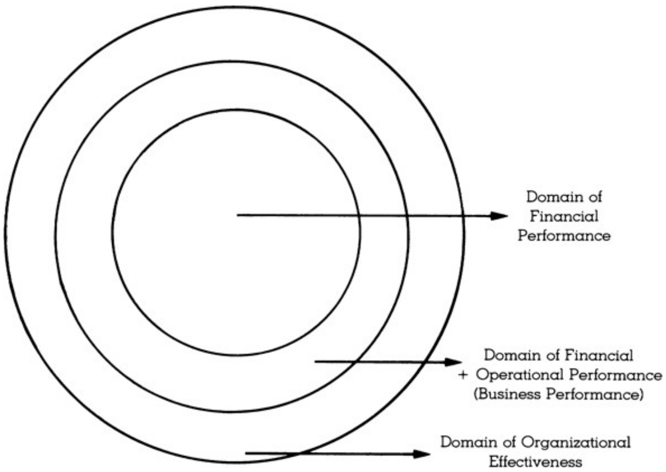

Figure 3: Visualization of the domain of organizational effectiveness.

As becomes clear from this visualization, organizational effectiveness, consists of two domains: the domain of financial and operational performance, and the economically focused financial performance domain, which together form a third domain; operational effectiveness.

Over the years, a transition has taken place, from a solely financial view of performance towards a view in which financial performance and stakeholder theory are combined (Harrison & Wicks, 2013; Santos & Brito, 2012). In their view on business performance, Venkatraman and Ramanujam (1986) suggest a conceptual model with two second-order dimensions, the financial performance domain and the strategic or operational performance domain, which is also known as non-financial performance. This model is represented in figure 4. As this model does not only consists of objective financial performance, but also contains subjective elements (strategic or operational performance), performance can be considered an objective and subjective concept.

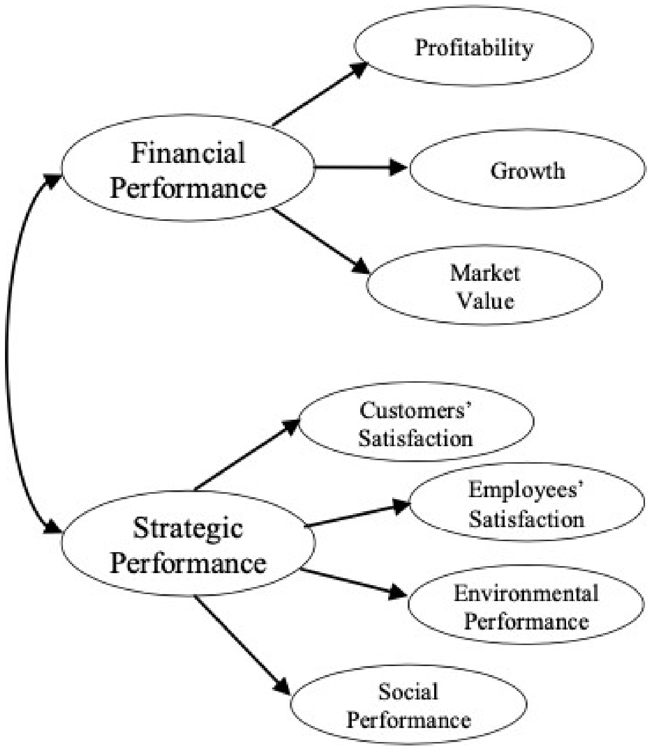

Figure 4: The conceptual model of business performance (Venkatraman & Ramanujam, 1986).

2.3.1. Performance and Analytics

In order to understand the link between the deployment of analytic capabilities and firm performance, the role of analytics in determining performance must be clarified. As mentioned earlier, analytics is considered to be the application of advanced analytic techniques to data, in order to enhance the decision-making process as well as find answers to problems that eventually can lead to improved firm performance (Bose, 2009). Shortly, analytics is a tool or skill that can assist in improving performance. Naturally, analytics is dependent on data and consists of metric and analytic data analysis. In essence, that is where the main source of difference is between financial and non-financial performance evaluation or analysis. Financial performance is often quantified or quantifiable and therefore easier to analyze or measure (Venkatraman and Ramanujam, 1986), whereas non-financial performance is harder to measure (Venkatraman and Ramanujam, 1986; Chatterji & Levine, 2006. As i.e. LaValle et al (2011) showed, analytics has a positive effect on performance. Besides their insights in the general performance effects, LaValle et al (2011) also illustrated for what functions analytics was used in the three different stages of analytic capability deployment. They found that organizations that were in a more mature phase, also used analytics for non-financial purposes, whereas organizations in less mature phases only used analytics for financial purposes. LaValle et al (2011) state that typically organizations start with efficiency purposes. Unfortunately, LaValle et al (2011) do not illustrate the effects on these two types of performance but rather see performance as one, financial and non-financial performance combined.

2.4. The deployment of analytic capabilities and firm performance

In previous literature, a link between analytics and performance has been described. However, in previous literature, concerning the link between analytics and firm performance, focus has been with whether or not firms use analytics at all, rather than the differences between firms in using analytics. Previous literature has not focused on the capabilities that are required for effective use of analytics, more specifically differences between organizations that arise from differences in the possession of those analytic capabilities, relative to firm performance in the FinTech sector.

What has become clear from the theoretical framework is that analytics consists of two types (traditional and advanced) and requires enabling capabilities that are dependent on the combination and integration of resources (people, processes and tools), which differ in certain stages of implementation. Furthermore, deployment of analytics can go through three levels (aspirational, experienced and transformed), which reflect to what extent an organization uses analytics, but also shows what capabilities are already present, based on the yet acquired resources. As shown in the previous paragraphs, there are two analytic capabilities that are required for a firm to successfully implement analytics in their business: the ability to use analytic techniques and the ability to process the data that is obtained from application of those analytic techniques. Simplified, a firm needs the ability to use analytic techniques to analyze data, and a firm needs the ability to translate the outcomes of the data analyses into information that is useable for performance increasing purposes. The main difference between the two types of analytics (traditional and advanced) and the stages of the analytic capability deployment is that the stages illustrate to what extent the capability is present and used, whereas the type of analytics indicates the type of analysis techniques and data collection methods that are used. To illustrate: the type of analytics can say something about the capability level (i.e. using advanced analytics means more data can be processed than when a firm uses traditional analytics in the same frequency), but is not the only factor that influences the capability level. The type of analytics used does, for example, net necessarily indicate that processes are less or more designed to use analytics.

Based on the earlier discussed theories, it can be proposed that the performance of FinTech organizations is positively influenced by the level of deployment of the two most important capabilities (that together form the analytic capability) that are required for implementation of analytics in an organization. The influence of the analytic capabilities on the firm performance is more positive (better performance) for organizations that find themselves in the transformed phase, in contrast to organizations that are in the aspirational phase.

The literature study provides a solid basis for this research, the following proposition is suggested:

Proposition 1: Firms that have a more mature level of (deploying) the analytic capability experience a bigger positive effect on firm performance than firms with a lower maturity level.

This first proposition implies that firms that deploy their analytic capability increase their firm performance, where a more mature capability leads to a bigger positive effect on firm performance. However, literature pointed out that performance can be either financial or strategic. Based on the purpose of (advanced) analytics as depicted by Bose (2009); to stimulate accurate, timely and effective decision at all levels, extended by the theory of LaValle et (2011) who stated, firms typically start using analytics for efficiency purposes and pursue other goals when reaching higher capability levels, it is proposed that firms with a higher maturity level of the analytic capability deployment experience bigger strategic performance development effects than firms with a lower maturity level. La Valle et al (2011) namely, already found that more mature firms, in terms of analytic capability deployment, also use analytics for non-financial purposes, whereas less mature firms do this less. From these theoretical theories, it the following can be proposed:

Proposition 2: Firms with a higher maturity level of the analytic capability deployment experience bigger strategic performance development effects than firms with a lower maturity level.

2.5. Conceptual model

In the previously discussed paragraphs, the deployment of the analytic capabilities is discussed, as well as the direct effect of the deployment of the analytic capabilities on firm performance. In figure 5, the conceptual model for the deployment of analytic capabilities (proposition 1) is presented. The model is a visual representation of the theoretical framework and forms the basis for this research. The conceptual model shows what deployment of analytic capabilities consists of, as well as the proposed positive relationship between the deployment of analytic capabilities and firm performance. The multiple plusses in the conceptual model indicate the strength of the effect, e.g. firms that have a more mature analytic capability find themselves in a higher level of deployment, which leads to a stronger positive effect on firm performance than firms that have a less mature analytic capability (and thus find themselves in a lower deployment level). Figure 6 shows the conceptual model for proposition 2. It is the very same model, but the dependent variable has changed.

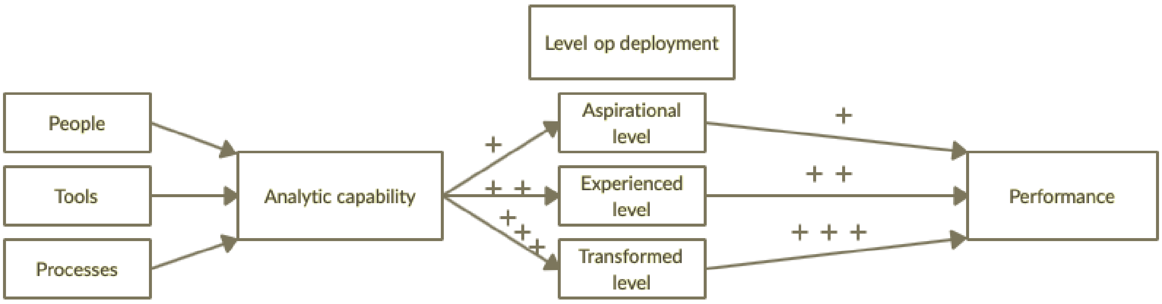

Figure 5: Conceptual Model (Proposition 1)

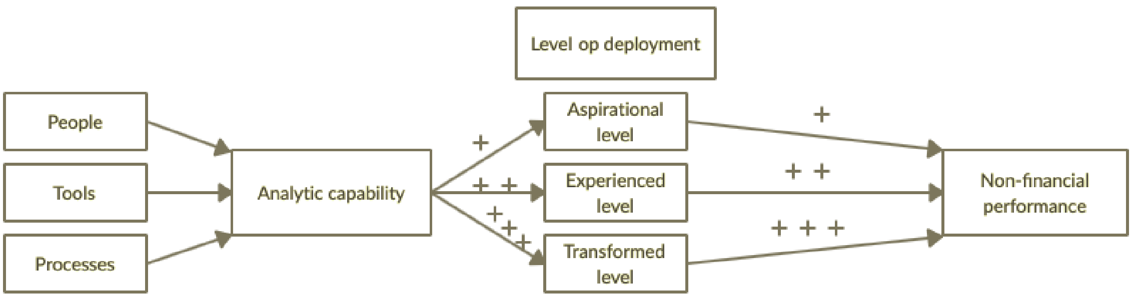

Figure 6: Conceptual Model (Proposition 2)

3. Methodology

In this chapter, the research design and method are described. Furthermore, the context of this research and the sample are explained.

3.1. Research design and method

In general, research can be either exploratory or conclusive, where exploratory research focuses on providing insights about a phenomenon and conclusive research focuses on testing hypotheses and/or examine relationships (Malhotra et al, 2013). This research contains both elements, but can be mainly described as an exploratory research, as a proposed relationship is researched, but the focus is with finding insights about a phenomenon, namely the deployment of the analytic capability and its effect on firm performance.

This research is conducted to provide insights on the use of analytics and presence of analytic capabilities in the FinTech domain with regard to performance, which is a topic that needs to be addressed more clearly. Producing new insights about a phenomenon is what characterizes qualitative research as was stated by Yin (2011).

Furthermore, this research has a deductive approach, as this research is based on a solid theoretical framework, from which propositions were formulated as an expectation of the potential empirical study results. However, contradictory to traditional deductive research, in which one tests preset hypotheses, this study does not aim to accept or falsify an existing theory, but rather tries to create or extent knowledge about a phenomenon, based on concepts and theories from existing literature. The existence of relevant literature helps to establish concepts that guide the research, which is what helps the qualitative research in this case (Yin, 2011). In this case, a mix between an inductive and deductive approach was used.

This research consists of a comparing multiple case study with the aim of comparing different firms and their analytic capability deployment and the effect that this has on the firm performance (Bleijenbergh, 2015). Furthermore, a literature review on analytics, FinTech and firm performance is done, which will be complemented by interviews that are held at different firms.

3.2. Context and Sample

This research will be conducted in the Netherlands, with the objective of generating new knowledge about the Dutch FinTech domain and the involvement of analytics in firm performance, more specifically the presence and deployment of analytic capabilities with regard to firm performance. This study focuses on the FinTech domain, meaning that the Dutch financial services sector is the focal point of this research. In order to acquire reliable and valid results, 8 interviews were conducted, in the same amount of firms. The number of respondents is 9. The respondents were chosen in accordance with the following criteria: the respondent must be (1) active in the FinTech sector and (2) has knowledge about the topic of research, so analytics, the analytic capability and the firm's performance. As Dutch FinTech sector is rather small, respondents could be active in a wide variety of organizations (i.e. banks, software developers and consultancy), as long as the firm operates in the Dutch FinTech sector. The interviews are semi-structured, meaning a list of interview questions (Appendix 3) was made beforehand, which served as a guiding line through the interviews, but could be expanded by on the spot questions that result from obtained information. Contact for the interviews was made via channels like LinkedIn, email or phone calls. Also the Holland FinTech network was used to contact respondents.

3.3. Reliability and validity

In order to hedge reliability and / or validity issues, several precautions are taken. First, the internal validity of the research might be affected by the semi-structured interviews, as the preset questions guide the interview into a certain direction, potentially leaving out important information (Bleijenbergh, 2015). This potential problem might be solved by using triangulation of both, sources and methods (Bleijenbergh, 2015). Triangulation of sources can be done by comparing the interviews with each other, whereas method triangulation can be done by comparing the interview results to company documents, i.e. annual reports. In this research, source triangulation and self-reflection are the main method of internal validity assurance. Furthermore, using a semi-structured interview enhances the validity of the research since the respondents will be asked the same questions for the larger part. In terms of external validity, the comparing multiple case study foresees potential issues. By comparing multiple organizations from the same industry, patterns that are found can be considered generalizable for that particular industry (Bleijenbergh, 2015).

The reliability of this research is assured by the use of transcripts of the interviews. This means that all questions and answers that lead to a final conclusion are available to each person that tracks back the origination of the research results.

3.4. Operationalization

In the previous chapter, the central concepts of this research were defined and the propositions that arose from the literature review were discussed. In order to research those propositions, the central concepts that have been determined in chapter 2, need to be converted into variables that can be measured or at least be more easily interpreted. Therefore the main concepts of this research, analytic capability deployment and firm performance are operationalized in this section. As this research has a deductive character, the operationalization is based on existing literature.

3.4.1. Operationalization: analytic capability deployment

As discussed in chapter 2, the analytic capability deployment can also be considered a maturity estimate for the analytic capability in a firm. As based on the theory of (La Valle et al, 2011), three levels of maturity can be distinguished, of which each has its own characteristics. However, the exact characters of each level are not explicitly defined, which means that this is open definitions that are obtained via empirical evidence from the interviews. For that reason, it is hard to operationalize this concept. However, as theory provides a basis, this basis forms the core of the operationalization of the concept analytic capability deployment. This basis consists of the core resources of any capability as discussed in chapter 2: people, tools and processes. The operationalized concept is shown in figure 7. In this figure, the concept of analytic capability deployment is operationalized as the level of maturity of the analytic capability, along with dimensions and indicators that determine this level of maturity. The level of maturity can be interpreted as the extent to which the dimensions and indicators are present and used, where simply said ‘more is better’. In general, the more or more mature the resources an organizations possesses, the better. The quantity of resources is rather simple to measure, either via hard evidence (i.e. reports) or obtained information from interviews. The maturity of the resources however, is harder to measure. In general, maturity can refer to experience or skill level. I.e. the higher skilled people are, the more mature the resource people is. For the resource people, the quality of this resource was evaluated by i.e. asking about the skill level of the people that were present and / or deployed. For the resource tools, firms were asked to assess their tooling and compare it to their competitors. That way, the maturity of the resource tool could be evaluated without needing measurable indicators. For the last resource, processes, it was asked whether or not the processes in the organization were suitable for a data driven approach. Based on expert judgment (the interviewees), the maturity of this resource could be evaluated. Overall, some simple indicators are provided on a theoretical basis. However, the actual and practical definition of maturity is likely to be obtained from the interviews. These interviews form the basis for evaluating the proposition.

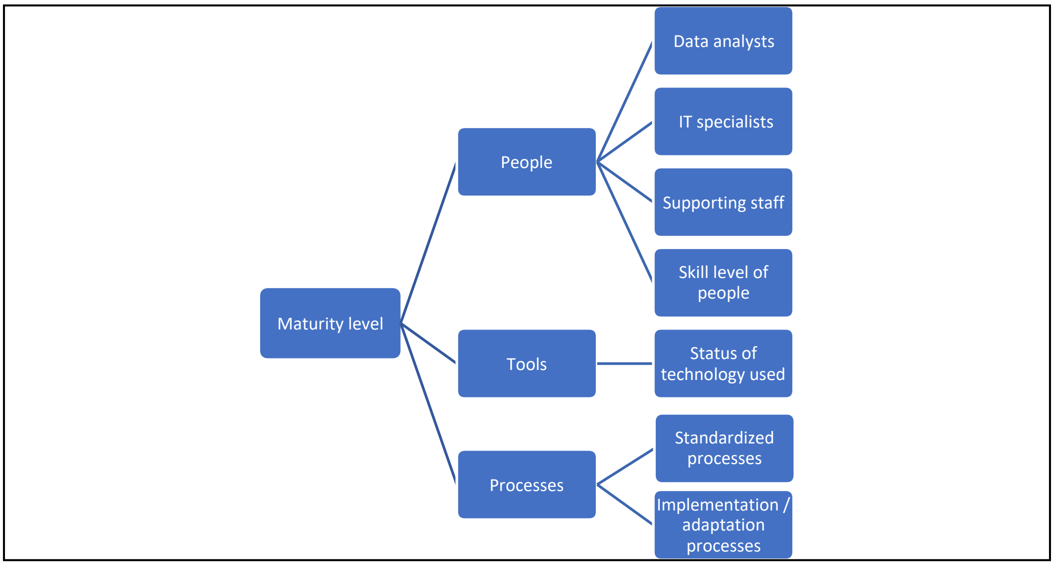

Figure 7: Operationalization of Analytic Capability Deployment

3.4.2. Operationalization: firm performance

In the literature review, it was argued that firm performance contains both objective and subjective measurements. Financial performance often is characterized by objective measurements, whereas strategic performance measurements can be either objective or subjective. Furthermore, it has become clear that performance is a multi-dimensional construct, which means that a lot of dimensions can be taken into account and measured. For this matter, the definition of performance will not be specifically defined in the interviews. As firms can use multiple indicators to evaluate their performance, the interviewees in this research can describe their view on performance based on the view of their firm. After all, the main goal of qualitative research is to obtain a detailed view of a phenomenon by i.e. gathering a wide variety of information (Bleijenbergh, 2015).

However, in order to check whether the information obtained via interviews is adequate and in accordance with the actual figures, a questionnaire (appendix 4) about their firm performance is filled out by each interviewee. This is done via a subjective measure. A subjective measurement complies, taking into account the objective of this research; establishing a relationship between analytic capability deployment and firm performance, as this research is conducted with several firms, each having different performance figures. Reliability of a subjective performance measurement is not an issue as literature established significant correlations between objective performance measures and the corresponding subjective measures (Venkatraman & Ramanujam, 1987). This means that subjective measurements can be considered reliable for measuring firm performance, let alone for the control purpose for which it is used in this research.

The respondents are asked to assess the firms performance on a 7-point rating scale as used by Zhou et al (2005), ranging from 'much worse' (1) to 'much better' (7). Although the subjective measurement is obtained via interviews that are meant to be open, the 7-point scale is used for interpretation and comparison purposes. Respondents are asked whether after the period in which the analytic capability has been deployed, the firm performance has become worse, better or equal to their performance compared to the period before. The respondents are asked the same question, with an addition of a comparison to other firms in the industry, as the items that are assessed also reflect competitive advantage (Wiklund & Shepherd, 2003). The items that respondents are asked to assess are based on the research of Zhou et al (2005): sales growth, profit level, return on investment and market share. However, as is stated before, firm performance does not only consist of financial indicators, non-financial measures of firm performance are included as well. The basis for these non-financial indicators lies in previous studies (i.e. Freeman, 1984; Harrison & Wicks, 2013; Slaper et Hall, 2011) and is centered around the stakeholder view on firm performance. Stakeholder theory as described by i.e. Freeman (1984) is about the essence of satisfying stakeholder needs in order to optimize firm performance. Two non-financial performance measures that can be applied to the FinTech sector are customer value and corporate social responsibility (hereafter CSR).

In total, the respondents are asked to assess 6 performance measures, after which 2 extra items are included, namely overall firm performance and comparison to competitors (competitive position). Those two extra performance items are added to check for adequacy of the other 6 performance measures. It is expected that overall firm performance is similar to the average of the other 6 performance measures. The same goes for the competitive position. If not, relevant performance measures might be missing, meaning this study is not representative for the respondent.

Overall, the interviews provide the more detailed information about the performance of the researched firms, where the questionnaire checks the adequacy and accordance of the via interviews obtained information. The interviews are therefore leading in this research.

3.5. Data analysis

Information that was obtained from the literature formed the basis for conducting several expert interviews. However, the goal of this research is to find a theory by means of doing a qualitative study, therefore theoretical concepts were only used as a basis for the interview. The interviews function as the source of data collection in this research. The interviews are transcribed (Appendix 6) and coded. As the aim of this research is to establish a certain pattern and to provide insights on what influences a potential pattern, an inductive coding approach is used (Bleijenbergh, 2015). With this method of coding, the interviews form the basis for the analysis of the data, where the central constructs that were acquired from literature form a back-up, making sure the analysis keeps close to the initial research question. With this type of coding, the information that is obtained via interviews takes a central role the data analysis, rather than the analysis being based on literature. Besides, for a deductive coding method, two other criteria are to be met; clear indicators need to be present (1) and dimensions must be exhausting and exclusive (2) (Bleijenbergh, 2016). Both criteria cannot be fully met in this research as the theoretic basis for this interview is limited and dimensions (partially) overlap (i.e. analytics and analytic capability). However, some clear indicators could be distinguished from the literature review and some of the coding could have been done deductively, but as there is not enough ground for deductive coding, an inductive approach was chosen.

For coding the interviews the program Atlas.ti was used, which is a software that assists in qualitative data analysis (Hwang, 2008). In Atlas, the ‘open coding’ was done after which a code list was exported to Excel. ‘Open coding’ means that fragments of the transcribed interviews are labelled with codes that describe that particular fragment (Bleijenbergh, 2015). The code lists of each interview can be found in Appendix 7. Comparing the codes provided insights into particular patterns that form the basis for the result of this research.

The information that is obtained via the questionnaire is not specifically processed by means of a quantitative research, but rather forms a check-up for the information that was gathered in the interviews. Due to the argumentative and suggestive nature of the subject, not all participants returned a filled out questionnaire. The other results can be found in Appendix 4.

3.6. Research ethics

When conducting a qualitative research, or any other academic research, certain research ethics must be safeguarded (Yin, 2011). In his book, Yin states several ethics codes which were obtained from multiple academic ethics associations. These codes state that certain behavior is desirable when conducting a (qualitative) research, i.e. the guarantee of anonymity, transparency, discreetness, truthfulness in handling data and personal information that are obtained. Therefore, in this research, all the collected data in this research is handled in accordance with these ethics codes and with the highest care with respect to all involved parties. The researcher has signed a research integrity form concerning the code of conduct with respect to academic integrity, as requested by the Nijmegen School of Management (2018).

The obtained information is not shared with other parties. Also for i.e. privacy reasons, permission for recording the interviews was asked in advance and recording was only done after permission was granted by the participant. Furthermore, respondents were informed about the topic of the research, including the common thread of the questions, beforehand, and were also informed about the expected duration of the interview. Besides, anonymity was assured for all parties that requested to be anonymized in this research. Last, the respondents was offered the opportunity to obtain the research results.

To safeguard academic integrity, the researcher follows the APA rules for referencing, delivers his own and original work and guarantees transparency in the processing of obtained research data, as well as the presentation of that data and the results (Nijmegen School of Management, 2018).

4. Results

This section contain the results of the data analyses. The data analyses can be found in appendix 6 (interview transcripts) and 7 (code lists). Furthermore, appendix 8 contains an overview of the most important codes, the selective codes. In this section, the results of the data analyses are presented, structured accordingly with the two variables of the research question: analytic capability deployment (1) and performance (2). Furthermore, the patterns that were found during the data analyses are discussed. By means of inductive coding several patterns, also known as selective codes, were found. 7 Selective codes were distinguished (appendix 8) that form the basis for answering the research question.

4.1.Deployment of the Analytic capability

In order to determine the maturity of the analytic capability deployment of each researched firm, four pattern codes were used: background information (1), data collection (2), analytics (3) and analytic capability (4). Based on the obtained data (interviews and questionnaires), theoretical considerations from the literature review, and between company comparison the firms were plotted in a graph (figure 8) which represents the maturity level of the analytic capability deployment per firm.

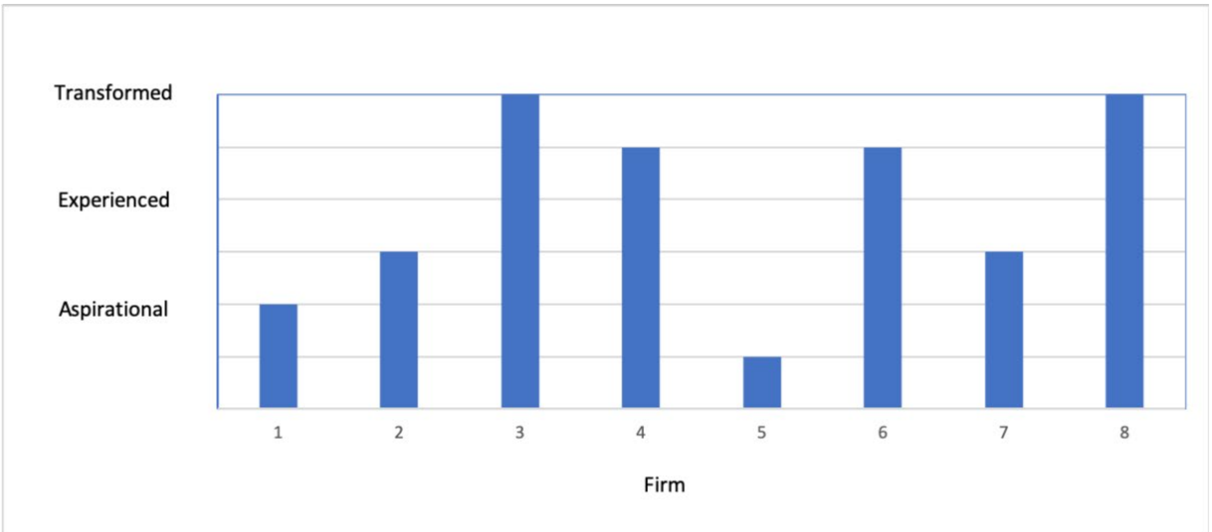

Figure 8: Overview of analytic capability deployment for the interviewed firms

Based on the analyzed data and some theoretical considerations, an overview (table 1) was created that shows the most important findings for each of the seven pattern codes with regard to the three maturity levels of analytic capability deployment. In the remainder of this chapter, the findings considering the analytic capability deployment are presented as well as the researcher explains the considerations for the plotting of the firms on the graph as presented in figure 8.

4.1.1. Background information

To be able to generalize the results of this research and understand the origins of differences in the deployment of analytic capabilities between firms, every interview started with questions that helped shaping a context. By means of a simple open question, "can you tell something about the company you work for?", a wide variety of context shaping answers was collected.

Generally, three important background information indicators were extracted from the interviews: company size, company type, and market type (table 1).

Concerning the size of the organization, firms 1, 2 and 5 were relatively small compared to firms 3, 4 and 6. Not only was their employee count a lot smaller, also the revenue, profit and / or balance sheet total was smaller. An overview of size indicators is presented in appendix 10. The differences between the interviewed organizations were big; *"The company is about 100 man large, with about 26 / 27 million revenue"* (interviewee 1); "*Firm 6 is the 4th retail bank of the Netherlands, balance sheet total of about 65 billion and an annual profit of around 268 million last year"* (interviewee 7).

The second important indicator for the selective code 'background information' is 'company type'. In general, the data analysis of the interview transcripts has shown that within the FinTech sector two main types of businesses were to be found: Business to Business (B2B) and Business to Consumer (B2C). An interesting finding of this research is that the smaller sized companies more often can be classified as B2B, whereas the larger sized companies can regularly be classified as B2C (table 1).

Regarding the third indicator, market type, it was found that in this research two main types of markets could be identified: relational market and transactional market. Similar to the type of company, the market type was found to have a strong link with the size of the company. Generally, smaller organizations described the markets that they operate in as relational rather than transactional, whereas for the larger organizations this is the exact opposite.

One thing that these indicators have in common, is that the data analyses have shown that they strongly affect the use of analytics as well as the maturity level of the analytic capability within an organization. As is presented in table 1, organizations that find themselves in the aspirational phase of analytic capability deployment are mostly smaller companies. On the contrary, organizations that find themselves in the experienced or transformed phase are generally the larger companies. The size of a company however, has as mentioned earlier, a strong link with the type of company (B2B or B2C) and the type of market (relational or transactional) in which it is active.

B2B companies show less interest in using analytics, because those firms have fewer relevant data to analyze; "*We do not conduct extensive analyses on customers because it is not a great amount of clients. We do not have thousands of customers that we need to manage"* (Interviewee 2). Interviewee 2 clearly stated "I think that we are too much B2B for it to make meaningful contributions", showing that the B2B companies lack urgency or interest in order to invest in the development of the analytic capability, let alone deployment. Contradictory, B2C companies collectively recognize the importance of data analytics and the required capability; *"in order to successfully invest, as I mentioned earlier, data analytics is just very important to make good investment decision. So yes, it is crucial."* (interviewee 3).

So apart from the size or type of company, also the type of market plays a very important role in the urgency and interest to invest and deploy in the analytic capability. Interviewee 6 for example stated that *"No, it will always be an assisting tool. Otherwise we give it too much honor. I would really want to determine what to do, purely on a data driven basis, but it is just too much of a people's job at this moment."*. Interviewee 8 also emphasizes the strength of the network as a focal point of business; *"We do a lot of thing on the network of the people that we know… sometimes you close a deal focusing mostly on the relation".* Typical for a transactional market is a large amount of customers. As interviewee 7 states *"I do not want to say it is essential, but it helps a lot to serve your customers better"*, showing that organizations that are more focused on a transactional market evaluate the role of analytics and the deployment of the analytic capability as much more important. For interviewee 9, this went even a step further, as he stated that *"Data becomes essential in the sense that as we do not speak to clients a lot anymore, we still want to objectify and take good decision, so therefore we want to use the right data to make good decisions"*.

Generally, the background or context of a company tells a lot about the importance of analytics in the organizations and therefore also about the importance of developing and deploying the analytic capability. Therefore, the background or context of a firm is an important factor in determining the maturity level of the analytic capability within the organization.

4.1.2. Data collection

As a start for evaluating the maturity level of analytics and the analytic capability in an organization, every interviewee was asked what role data collection plays in their companies. By asking this question, the researcher acquired a clear view of how data was collected, how much data was collected and arguably most importantly, why data was collected. As is commonly known, data collection forms the basis for data analytics.

From analyzing the qualitative data it was found that firms at the aspirational level only use rather simple and less sophisticated data collection methods and collect data on an occasional basis. Interviewee 1 for example, stated that "*When it comes to data, a lot is incidental"*, showing the lack of consistency in both the data itself and the collection.

Interviewee 6 even stated that his company was new to data collection; *"What we are going to try with this fund, but this is in its early stages so we are not very far yet, is collecting data"*, perfectly illustrating the maturity phase in which firms in the aspirational level find themselves.

Companies that are in the experienced phase show to be a step further concerning data collection. In this research, a combination of the analytic results of firm 2 and 4 are regarded as representation for the experienced level, by lack of organizations that are exactly at the experienced level. Firm 2 for example, has implemented 2 systems that are able to collect data, showing the aspiration to become more data driven. Interviewee 2 said: *"Like many companies, we have a CRM system"* but also *"Apart from the customer system, we also have a marketing system for a more output oriented focus"*, which also illustrates the purpose of data collection for firm 2. Apart from these two systems no other data was collected, showing that firms that have almost reached the experienced level collect more data and collect it on a more frequent basis, but leave a lot of room for improvement. Firm 4, which can considered to be just past the experienced level, already has standardized data collection processes in place; *"we have loads of data that we receive on a standard basis, without active actions"* (interviewee 5), showing the improvement in data collection from the experienced maturity level towards the transformed level.

Firms that find themselves at the transformed level of the analytic capability deployment have showed to collect data on a frequent basis, via various sources, in high quantities, with a critical view on the quality of their data. As interviewee 3 said: *"Data is super, super important"* and *"Data collection is the basis of what our investors do, via personal contacts, reading newspaper or buying huge databases".* Firms at the transformed level mainly stress the importance of data collection for their companies. Interviewee 7 for example, stated that data collection was essential for his organization; *"What role it plays? An essential role!".* Moreover, these organizations also recognize the importance of data quality; *"Data quality, when that is top, the analysis improves as well. You can analyze loads of data, but when the data is crap, the analysis is useless."* (interviewee 7), as an important factor in data collection and processing.

The role of data collection in a firm tells something about the importance of data in an organization. What is found from analyzing the answers of the interviewees about what role data collection plays in their organizations, is that data collection plays a far more important role in companies that find themselves in the transformed phase, whereas that role is smaller in companies in the aspirational or experienced phase. This however, is a logical finding as organizations with analytic capability deployment in the transformed phase consider data to be the basis for conducting business and decision making; *"Within the investment process I think that data, and the next step; data analytics, forms the corner stone of what we do"* (interviewee 3). This finding however, is logical and in accordance with theoretical considerations, but helps to evaluate the maturity level of the deployment of the analytic capability in organizations.

4.1.3. Analytics

Considering the use and importance of analytics in organizations, no shocking results were found. However, asking the interviewees about the role that analytics plays in their organizations assisted in determining the level of maturity of the analytic capability deployment for the interviewed firms.

Firms 1, 2 and 5 stated that analytics was not or only occasionally used in their organizations. Interviewee 1 for example, stated; "*We look at historical measures"* and *"We look at the annual cycle and try to anticipate on it", "But I think we are too much B2B to make analytics meaningful"*. Additional to the limited use of analytics or analytic techniques, these organizations do not recognize the importance of extensive use of analytics for their firms, despite the statements that these firms do see the potential of analytics and do not exclude it from future developments in the organization. Interviewee 2 for example said: *"I am sure that if we grow, it can become of greater importance"*. Also interviewee 6 (firm 5), recognized the potential and possible increasing importance of analytics for his firm; *"For us, it will become important"; "It cannot be dependent on one person. If someone leaves… there must be a methodical way to structure your decisions and governance structure"*.

Organizations in the experienced phase use more advanced analytic techniques such as machine learning or regressions, but still do not fully use the potential of analytics. Although this research does not contain firms that find themselves in the experienced phase, an estimation of used analytic techniques and utilization of the potential could be done by comparing transformed and aspirational firms. After comparison, it could be stated that companies in the experienced phase use multiple advanced analytic techniques, i.e. regressions and machine learning, but are not able to optimally use the potential that analytics provides. Improvements can be realized in the sophistication of the analytic techniques, the variety of techniques used, the frequency of usage and role it plays in the firm (central or supportive).

Organizations in the transformed phase use a wide variety of advanced and sophisticated analytic techniques that play a central role in the organization. Interviewee 3 for example stated that firm 3 uses techniques *"like regression techniques, machine learning…random forests,* *null networks… natural language processing, automatic processing of textual sources",* illustrating the wide variety of advanced techniques that are used. Additional to using a wide variety of techniques, firms in the transformed phase also integrate analytics in i.e. their visions. Interviewee 5 for example illustrated that *"The importance is acknowledged… and currently integrated in the entire vision of the firm"*. Organizations in this phase also acknowledge analytics being essential for modern business models, as interviewee 9 stated: *"For every modern business model, data analytics is fundamental in order to be distinctive and successful"*.

The role that analytics plays in an organization helps understanding the deployment level of the analytic capability. It shows the usage of analytics as well as the importance within the organization, which indicate the level of maturity of the analytic capability. Generally and in accordance with theory, it was found that firms in the aspirational phase only use simple analytics and only see the potential of it rather than act upon it, whereas transformed firms use a wide variety of sophisticated techniques that play a central role in the firm. The firms at the experienced level find themselves somewhere in between; the importance and potential of analytics is recognized and acted upon, but not all available and advanced techniques are used.

4.1.4. Analytic capability

In addition to the conceptual model that was created after reviewing literature, next to the three main building blocks of the analytic capability (people, tools, processes), a fourth building block appeared from the data analysis; infrastructure. The infrastructure is considered the foundation for tooling, people and processes to work. Interviewee 7 for example, stated *"You need a foundation for your data systems, that is the data architecture."*, where interviewee 3 also mentioned that the infrastructure is needed to optimally use analytics; *"we have built the infrastructure to do all this, but it must always be more and better"*, which directly shows the importance of a proper infrastructure.

Considering the presence and maturity of the analytic capability within a firm, it can be stated that there are big differences in the tooling that is available and used in the interviewed organizations. Organizations in the aspirational phase only use simple tooling for data analysis, for instance Excel, that do not have as many options as advanced tools. Interviewee 3 (transformed phase) pointed out that Excel only has limited options; *"but at a certain time you will reach the limit of what you can do in Excel"*. The lack of sophistication of the used tools in the aspirational level is illustrated perfectly by interviewee 1; *"people that know the process and that are good at Excel, but those are not data analysts, no"*, implicating that Excel is not the most specialist tool available. Organizations in the transformed phase use far more sophisticated and advanced tooling like *"Python, Sequel (SQL)"* (interviewee 3), *"data visualization tools"* (interviewee 7), or *"process mining tools"* (interviewee 4). Organizations in the experienced and transformed phase also show the possession of bigger capacity data storage and even firm specific data servers; *"Firm 3 still has its own data server"* (interviewee 3). Logically, the more tooling and the more sophisticated and advanced of the tooling that is present and also used, the higher the deployment level of the analytic capability.

Concerning the building block 'people', it was found that organizations in the transformed phase have analytically skilled and highly educated people present in the firm that often form the basis of data analytics or data science teams, which are the foundation of the company. Interviewee 3 for example, said "3 years ago we were not that far, but now we have the people with the required skills". An interesting finding was that interviewee 3 *"You need a quite big team for that"* stated that the quantity of data experts and data analysts was necessary for optimal use of analytics, whereas interviewee 7 *"Quantity does not really matter. In the future, if you do it well, you could possibly do it with less people"* illustrates the vision that it is not the quantity that matters, but rather the quality of the available people. However, as interviewee 4 stated *"the more data you can analyze, the more value can be delivered",* indicating that the bigger the capacity (quantity of people), supports the ability to analyze more data. Typical for organizations at the transformed level is that data analysts or the knowledge and skills of the data analysts are shared throughout the entire organization. Interviewee 4 for example, stated that *"It is our future vision that we need to have something like a hub-spoke model, where all knowledge comes together and all complex cases are executed",* showing the firm wide integration of the analytic capability. However, this directly shows the reason that firm 4 is not yet fully transformed, but rather finds itself between the experienced and transformed phase. Companies at the lower levels, for example the aspirational level, do not necessarily lack qualified or specialized people, but mainly miss firm wide deployment. Although interviewee 6 pointed out that his firm does not hire data analysts *"We do have business analysts, or interns, there is some continuity there, but that is not data yet"*, other firms at the aspirational level stated that their data experts are just not used within their own firm, but act as data expert in the name of the clients *"Actually our main business is data, but we mostly do that for our clients"* (interviewee 2). So generally, the main finding for the building block 'people' were that organizations at the higher maturity levels have more specialized and skilled people available, which share their knowledge by i.e. means of training other colleagues; *"We try to assist people*" (interviewee 7), or special knowledge sharing models (hub-spoke model as visualized by firm 4), whereas organizations at the lower analytic capability maturity levels simply do not have the people present, or do not use the available people for their own data analysis (consultants are given data assignments at clients).

The third building block, processes, were less mentioned in the interviews. However, it was found that organizations at the aspirational level do not have the processes (i.e. decision making processes) in place to use analytics, whereas for firms at the transformed level the companies have set up standardized processes; *"We have a lot of data that is standardly delivered, without active action"* (interviewee 5), that are fully data driven, from data collection to valuable insight creation. This however, is rather logical as firms that only use limited data collection are less likely to adapt their processes to become data driven, let alone standardize them for only a small amount of clients.

The last building block, which was found after analyzing the interview data, is 'infrastructure'. The infrastructure can be considered the foundation for the usage of analytics. It is the foundation which allows the people, tools and processes to render in organizations where analytics and the analytic capability are deployed. This directly leads to the main finding concerning this building block, the organizations that extensively use analytics and do have the analytic capability almost fully deployed have an infrastructure in place that allows them to optimally use analytics. Interviewee 3 for example, said *"We use a public cloud platform… on which we can install a lot of calculation power, machines and tooling… an open source infrastructure than is accessible for all of us"*, where interviewee 7 confirmed the importance of a solid foundation *"You need a foundation for your data systems".* Organizations at the aspirational level generally do not recognize the importance of a solid infrastructure, mainly due to the fact that only limited analytics is used and these simple techniques do not require an extensively developed infrastructure, as well as that processes are not designed to be data driven.

What was generally found for the dimension of the analytic capability is that organizations at the transformed level have more and more developed each of the building blocks is present in an organization than organizations at the aspirational, which is logical. The companies in the experienced phase are characterized by having mediately developed building blocks present in their firm. Notable is that the analytic capability is generally considered to be a dynamic capability as interviewee 8 for example stated: *"it is an iterative process"* where *"feedback loops are important"*.

4.1.5. Analytic capability deployment

Based on the above discussed selective codes, some summarized findings can be presented concerning the deployment of the analytic capability. In terms of analytic capability deployment, as mentioned, 4 factors are important. First, the background information provides the context and mostly shows the intent or reason of why an analytic capability is present in an organization or not. The second factor, data collection, provides an extended explanation of why deployment of the analytic capability is important. It was found that firms in which data collection plays a bigger role have more importance in developing and deploying the analytic capability, therefore resulting in higher maturity levels of the analytic capability deployment, as presented in table 1 and figure 8. Regarding the use of analytics, it was found that firms in the aspirational phase use significantly less analytic techniques than organizations that find themselves in the transformed phase. Next to the quantity differences, transformed firms also used more sophisticated and advanced techniques with more options, than aspirational firms. The most important finding for the fourth factor, the analytic capability, is that firms in the aspirational phase are in not in possession of as far developed building blocks / resources that allow analytics to be performed, as the transformed firms possess.

4.2. Performance

In this section, the results of the data analyses considering the performance and performance evaluation of the interviewed firms are presented. This is done by extracting the 3 selective codes that represented the variable performance: performance (1), analytics and performance (2) and the analytic capability and performance (3).

4.2.1. Performance

In order to properly evaluate the effects of analytic capability deployment, it was necessary to know what the interviewed firms considered to be performance. As was pointed out in the literature review, organizations at the aspirational level are more likely to only use analytics for financial purposes rather than non-financial purposes. As a starting point, it was therefore interesting to know how organizations define performance and what their view on performance is.

It was found that organizations at the aspirational level generally have financial performance as the primary focus; *"The rate of return is the most important"* (interviewee 6), and only pay very limited attention to non-financial performance *"We have an employee survey, but that is not as extensive as I have seen in other companies. It is done by our HR department, but the financial dominates"* ; *"This is a quite extreme Anglo-Saxon private equity culture"* (interviewee 1). Organizations that find themselves at the transformed level depict the non-financial performance as *"also super important"* (interviewee 3), where interviewee 7 states *" For every stakeholder group; client, employee, society and shareholder, we have sets of performance indicators in place to measure how well we do for all stakeholders and for the bank as a whole."*, illustrating the importance of both the financial and non-financial performance for the firms at the transformed level (or almost at the transformed level).

4.2.2. Analytics and performance

In the interviews, participants were asked what the role of analytics was in determining the performance and whether or not the performance of the firm changed after the implementation of analytics. This was asked because understanding the firms view on the impact of analytics on performance as well as the purposes for which analytics was used, provides insights in the importance that firms give to analytics and therefore the analytic capability.

Organizations in the aspirational phase mainly use analytics for financial performance improvement if analytics influences the performance at all. Interviewee 7 said *"the impact is fairly small for us"*, showing the rather small effect of analytics on performance for firms at the aspirational level. Firms at this level also find it hard to define the role of analytics in performance; *"It is difficult to say. I think that it mainly provides insights in how we do. It is, I think, especially useful to guide people in the decision making process, etc."* (interviewee 2). For the firms at the transformed level, the importance of analytics in relation to performance is defined as crucial; *"In order to invest well, as mentioned earlier, data analytics is super important to make good investment decisions. So, yes it is crucial."* (interviewee 3), indicating that the effect of analytics on performance is big for transformed organizations. Interviewee 7 stated; *"Especially for performance indicators, data and data analysis is very important."*, stressing the importance of analytics and the effect of it on performance, both financial and non-financial. Most firms did also see a change in performance since the adoption of analytics, but whether or not that change was caused by that adoption remains unclear as more factors can influence the performance; *"I read the quarterly report two weeks ago and I saw the NPS had increased, but I think that we have not been the only radar in that change."* (interviewee 4) stated. However, most of the respondents state that although it is hard to quantitatively measure the impact, it can be argumentized; *"I do not know if the performance has changed, but I think you can bring more focus to your work and that can have a positive impact… So I do not know. But you could argumentize it."* (interviewee 7).

4.2.3. Analytic capability and performance

The main finding after analyzing the data is that in general, there is a positive effect of analytic capability deployment on performance. However, all interviewed firms pointed out that an exact effect is difficult to measure; *"this is very, very difficult to measure"*, *"In many occasions it is nearly impossible I think"* (interviewee 3), because there are more factors that influence the performance than just the deployment of the analytic capability; *"but I think that we have not been the only radar in that change."* (interviewee 4). But as interviewee 7 stated; *"Only if already it leads to less mistakes in the chain, it already is an advantage as you do not have operational risk anymore, or less operational risk, no repetition of work. So already if it only causes you to make less mistakes, it would be worth it. Let alone the fact that can also do positive things with it.",* the positive effect of the analytical capability deployment on performance is recognized, no matter how small or large the effect is for each firm.

By analyzing the interviews, it was found that firms at the aspirational level do not recognize large effects of deploying the analytic capability on performance. This is inherent to the role that analytics plays in the organization. As mentioned in the previous paragraph, firms in the aspirational phase of analytic capability deployment find it hard to define the role of analytics and also the analytic capability in determining performance, as the role as limited. However, as interviewee 6 mentioned *"we are investors, so if we think that we need to invest in i.e. a data analyst, there must be a significant positive effect on the performance"*, so generally it is thought that investing in the analytic capability must be creating value, otherwise the investment will not be done. As the importance of analytics is rather limited for firms in the aspirational phase, *"the impact is fairly small for us"* (interviewee 7), those firms only limitedly invest in the analytic capability and the deployment of that capability, leading to only a small positive effect on performance. Moreover, as those firms do not or only very little allocate their limited analytic capability deployment to non-financial goals, only very small positive effects are experienced in this matter.

For firms in the experienced phase, the analytic capability is seen as an important capability for conducting business, but is not yet considered the core capability. Therefore firms feel the urgency to invest in the capability as a factor to improve performance; *"Maybe we do not use analytics a lot, and we do not have all available tools… the things that we do, positively contribute to our performance I think."* (interviewee 2), but are not yet in possession of the building blocks that together make a firm reach the transformed phase.

Firms in the transformed phase however, recognize the importance of investing in and deploying the analytic capability as a means of improving the performance. For those firms, the deployment of the analytic capability, and therefore optimal use of the potential that analytics has, is essential for the performance of the firm; *"In order to optimally do that, we need the capability, so the people, the tools and the support within the organization."* (interviewee 3). Interviewee 4 agreed with the positive effect of the analytic capability deployment on performance; *"I think it is reflected in our performance. What we often do is a cost-benefit analysis, if the costs are higher than the benefits, the project has no value"*, *"In general I think that the more data you can analyze, the more value creation you can help to deliver"*. This goes for both financial and non-financial performance. The experienced positive effects on non-financial performance is therefore also bigger than for firms at the aspirational level.

4.3. Main findings

A summary of the main findings is presented below (table 1).

	Maturity level		
Selective Codes	**Aspirational**	**Experienced**	**Transformed**
Analytic Capability	Simple tooling (i.e. Excel)	Tooling is good, but can improve	Tooling sophisticated (i.e. Python, data visualization tooling)
	People with specialized skill absent	Skilled people present, but only in small specialized teams	Highly skilled people form basis of special data (analytics and science) teams
	Processes not adapted to using analytics	Processes are in transition to become data driven	Processes are standardized and data driven
	Infrastructure not designed for analytics	Infrastructure shows steps towards full implementation of analytics, but is not yet implemented firm wide	Infrastructure is equiped and designed for firm wide deployment of analytics
Analytic Capability and Performance	Investing in capability only for financial purposes	Organizations recognize the importance of possessing the analytic capability for performance improvement	The analytic capability is essential for firm performance
	Effect on performance is limited	Analytic capability is not yet one of the core capabilites of a firm, but performance can experience its impact	Organization invests a lot in acquiring and developing the analytic capability as it is essential to performance
Analytics	Little analytic techniques used	More advanced analytic techniques are used (i.e. machine learning or regressioins)	Wide variety of analytic techniques used, that form the basis of conducting business
	Potential of analytics is recognized but not acted upon	Potential of analytics is not fully used (i.e. more analyses can be done)	Potential of analytics (almost) fully used
Analytics and Performance	Data analysis for financial purposes	Data analytics is used mainly for financial purposes, but non-financial purposes attract increasing attention	Data analytics can help increasing both financial and non-fnancial performance
Background information	Small size companies	Mid size to large size companies	Large size companies
	Often B2B companies	Often B2C companies	Mostly B2C companies
	Often relational markets with a lot of personal contact	Transactional markets with little relational characteristics	Mostly active in transactional markets
Data collection	Basic data collection (i.e. web traffic, simple client data)	Large amounts of data collected, not always quantifiable	Large amounts of standardized data collection and quality checks that form the basis for the business
Performance	Financial performance is all that matters	Financial performance most important, non-financial performance gains increasing attention	Good performance is performance for all relevant stakeholders

Table 1: Overview of maturity levels and important findings in accordance with the selective code

5. Conclusion and discussion

The aim of this chapter is to evaluate the findings in terms of formulating a conclusion. In this chapter, the research question and propositions are discussed, after which the results are interpreted and assessed in accordance with the existing academic literature. Furthermore, the practical implications of this research are evaluated. The closing of the chapter exists of a critical reflection on the research process and limitations of the research, after which potential directions for further research are addressed.

5.1. Conclusion

The objective of this research how the deployment of analytic capabilities influences the firm performance of organizations that are active in the FinTech sector. The corresponding research question was: How does the deployment of analytic capabilities influence the firm performance of FinTech organizations? In order to find an answer to this question, first literature was reviewed, after which a multiple case study was needed to obtain relevant data.

This qualitative study consisted of an extensive literature study on the context, analytics, the analytic capability and performance, followed by 6 expert interviews. The objective of the literature review was to form a solid theoretical basis for the interviews, in which the most important data was to be collected. In this research, the theoretical framework functioned as a basis for the interview questions and structure, but by lack of theoretical support for some of the central concepts, the expert interviews formed the focal point of this research. The relevant theoretical concepts and theories were discussed in chapter 2 of this research. The study of LaValle et al (2011) proved to be most suitable to serve as the basis for this study, since it evaluated the path that data covers from big data, to analytics, to insight and eventually the results; the value creation. This study provided the three levels of deployment or maturity which in this study were linked to the analytic capability.

With those theoretical concepts and theories as a starting point, the interviews were conducted. The research took place within the financial sector, more specifically the financial technology (FinTech) sector, since this sector has to deal with an increasing amount and importance of data (Flood et al, 2016). The interviewed organizations were all established profit organizations, delivering a wide variety of services and products. The total amount of organizations involved in de data collection is six, whereas the total amount of involved respondents is 7.

Analysis of the gathered interview data, it became clear that a clear division occurred regarding the deployment level of the analytic capability between firms, and that all firms deal differently with data, analytics and performance. The analysis on itself, was based on the 7 selective codes or pattern codes that were extracted from the inductive coding process, which was done due to a lack of theoretical foundation for a deductive approach. This however, offers an holistic view of the studied phenomenon, as well as it provides in depth knowledge. After rearranging the pattern codes, as was done in chapter 4, the remainder of this paragraph discusses the main findings per variable as well as it provides implications for answering the research question.

Concerning the independent variable, deployment of the analytic capability, it was found that the maturity of the analytic capability is dependent on four factors; background information (1), data collection (2), analytics (3) and analytic capability (4). These factors needed to be evaluated in order to understand exactly why differences in maturity of the analytic capability exist. First, the background information functioned as an important context provider and mostly showed the intent or reason of why an analytic capability is present in an organization or not. The factor data collection provided an extended explanation of why deployment of the analytic capability is important. It was found that firms in which data collection plays a bigger role have more importance in developing and deploying the analytic capability, therefore resulting in higher maturity levels of the analytic capability deployment. Regarding the use of analytics, it was found that firms in the aspirational phase use significantly less analytic techniques than organizations that find themselves in the transformed phase. Next to the quantity differences, transformed firms also used more sophisticated and advanced techniques with more options, than aspirational firms. The most important finding for the fourth factor, the analytic capability, is that firms in the aspirational phase are in not in possession of as far developed resources that allow analytics to be performed, as the transformed firms possess. Overall, the deployment of the analytic capability is mainly based on the importance of data and data analytics within a firm, as this importance is the starting point for investments in the capability.

Concerning the variable 'firm performance', it became clear that two main findings stood out that together evaluate both the pre-formulated propositions. The first important finding of this research is that all interviewed organizations experience a positive effect of the deployment of the analytic capability on their firm performance. Moreover, arguably an even more important addition to this finding is that organizations that find themselves in the transformed experience larger effects on their performance than firms at the aspirational level. This is caused by the further developed capability itself, but also by the central role that data plays in these transformed organizations. This central role of data makes the use of analytics, and therefore the presence and deployment of the analytic capability essential for the firms daily operations and decision making processes. A stronger effect on the firm performance can therefore be logically clarified. The first proposition, which also reflects the research question: "*Firms that have a more mature level of (deploying) the analytic capability experience a bigger positive effect on firm performance than firms with a lower maturity level."* can therefore be evaluated as correct. The second important finding is that firms at the aspirational level tend to have a central focus around purely financial performance, whereas experienced and, to an even greater extent, transformed firms value the non-financial performance as well. This is therefore also represented in the corresponding performance. This is in accordance with the study of LaValle et al (2011), who already stated that transformed firms use analytics for both financial and non-financial purposes, whereas aspirational firms solely used analytics for financial gain. After analyzing the conducted interviews, a small nuance is to be placed here as this research found that firms at the aspirational level were aware and valued the non-financial performance and corresponding indicators. However, the big difference is that firms at the aspirational level do not actually use analytics to evaluate or improve the non-financial performance. With this finding, the second proposition "*Firms with a higher maturity level of the analytic capability deployment experience bigger strategic performance development effects than firms with a lower maturity level."* can be evaluated as correct. Although these differences were not specifically mentioned in the interviews, it was possible to come to a valid evaluation for this proposition, as it could be derived from the views of the interviewed organizations towards firm performance.

5.2. Discussion

In this section, the academic contribution, practical implications, research limitations and directions for further research are discussed.

5.2.1. Academic contributions

As stated in the problem formulation, scholars from (strategic) management literature recognize the increasing amounts of data and the need for ways to process that data into valuable insights (LaValle et al, 2011; Flood et al, 2016), i.e. in the financial services industry. It is generally believed that analytics can form the basis for performance enhancement as it reduces the risk from a conversion of complex, subjective and ambiguous information into clear and objective management directions (Flood et al, 2016). Moreover, according to LaValle et al (2011) and Eisenhardt & Zbaracki (1992), the analytic capability is fundamental to create an advantage that could lead to better firm performance. However, how this is exactly relevant to and done within the financial sector, more specifically the FinTech sector, had not yet been researched. By researching the relation between the deployment of the analytic capability and performance in the Dutch FinTech sector, this research tries to fill that gap in academic literature. Although the study of LaValle et al (2011) provided a usable theoretical basis for this research, detailed theoretical considerations that should form the basis for an extensive operationalization lacked. Therefore, this study followed an inductive data analysis method, that formed the basis for answering the research question. The conclusion that organizations in the transformed phase of analytic capability deployment experience larger positive effects on their firm performance than organizations that find themselves in the aspirational and experienced phase, is in line with and complementary to the existing literature. It is in line with the study of LaValle et al (2011) in the sense of the more mature the analytic capability, the better the performance. This research complements the study of LaValle et al (2011) in the sense that it adds a very important analytics adoption barrier for organizations; the actual relevance of data in firms and therefore the (lack of) urgency to deploy or develop the analytic capability. Furthermore, it confirms the finding of LaValle et al (2011), that firms at the aspirational level mainly use analytics for financial performance purposes, whereas transformed firms use analytics for improving both, financial and non-financial performance. In this study however, it was formulated slightly different, which resulted in the following complementary conclusion: the level of maturity causes differences in the development of financial and non-financial performance indicators. Apart from confirming academic theories and complementing existing theories (i.e. Flood et al,2016; La Valle et al, 2011; Bose, 2009), this research also contributes to the literature concerning the Dutch financial sector, specifically the FinTech sector, by researching what motivates firms in this specific sector to use analytics and invest in the analytic capability.

5.2.2. Practical implications

Firms and managers should generally always be aware of the changing environments and the implications that these changes might have for those firms. The financial services industry has faced and is still facing a strong digitization impact (PWC, 2016). Accompanied with this digitization comes the emergence of huge amounts of data that needs to be collected and analyzed. Especially in the financial services industry this plays a very important role as financial products are almost exclusively based on information (Puschmann, 2017). Therefore, this industry is one that is faced with a rapid emergence or analytics, which also gains a lot of attention in a quick tempo (Flood et al, 2016). Being able to optimally use analytics can therefore quickly become very important for firms operating in the financial sector, more specifically the FinTech sector. The analytic capability will then play a very important role in determining firm performance. As this research pointed out, a more mature and deployed analytic capability leads to bigger positive effects on firm performance than when a company has a less mature and deployed analytic capability. Furthermore, this research also illustrated that transformed organizations experience bigger positive effects on both, financial and non-financial performance, where aspirational firms mainly experience small positive financial performance effects. Therefore, this research shows the potential of analytics and the important role that the analytic capability can play in achieving a greater performance.

5.2.3. Research limitations

As arguably every research, this study has some limitations. The first limitation is of a theoretical basis. Although thorough literature research was done, it is possible that not all relevant aspects of the analytic capability, analytics or performance were found. Most of the theory is derived from multiple academic studies and completed by expert interviews. Nevertheless, there is a possibility that other important factors that are of interest for this research were not included in this study. Potentially, the discussed variables and according indicators can be expanded.

A second limitation of this study is regards the data collection procedure. As the Dutch FinTech sector is relatively small, respondents were mainly contacted via the same platform, the Dutch FinTech Network. Furthermore, respondents were acquired by means of personal contacts. This type of data collection may be subject to a form of selection, since firms can consider cooperation a personal favor or specifically choose to respond (more often) to similar requests.

Thirdly, a limitation of this research is the lack of quantification of the researched effect. As respondents pointed out, there are more factors that influence the firm performance, which makes the exact effect of the analytic capability deployment on performance difficult to measure and determine. The respondents also stated that measurement of this effect is nearly impossible, due to that presence of multiple other factors. Therefore, the exact impact of the proposed relation remains, to some degree, subject to interpretation and may be considered suggestive.

Another limitation is the lack of generalization of this study. The amount of conducted interviews is relatively small and the sample was too specific in terms of sector, in order to be generalized to a larger group. Furthermore, analytics is as presented in the coding schemes, a very broad concept which can be interpreted in many ways. This may lead to deviating interpretations of questions and related concepts, and therefore deviating answers during the interviews.

5.2.4. Directions for future research

Future research can build upon this study and try to overcome the mentioned limitations of this research. Some of the suggestions follow directly from the limitations of this study. First, an important contribution of future research is the quantification of the impact that the deployment of the analytic capability has on firm performance. As mentioned in the limitations section, even the current experts in the field do not know how to quantify such a relation. A quantification of the relation could however, provide valuable insights in how important the analytic capability truly is in determining the firm performance, and in addition to that, what quantitative differences can be found between financial and non-financial performance.

Furthermore, future research can extent the used theoretical framework and potentially find new additions that might be relevant to the study. Also, the current lack of academic literature concerning the Dutch FinTech sector provides a reason for future research, that can contribute both to the existing literature and this research.

Methodologically, future research can increase the external validity of the research by increasing the amount of organizations analyzed. Moreover, increasing the amount of respondents will benefit future research as this provides opportunities for a more extensive collection of perspectives, that in its turn can increase the internal validity. Addition of perspectives can always lead to new insights and therefore make relevant contributions to the academic literature.

A last direction of future research is concerns the sector of the studied phenomenon. In order to compare whether or not the same results are found in other sectors, the same research can be conducted in multiple other sectors. This can be done domestically, so for one country, as was the case in this research, or international. This provides the opportunity to compare the maturity of the analytic capability and the effect that it has on performance between industries and countries.

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