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ABSTRACT

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Abstract:

In the last decade, Information technology (IT) developments have been triggering markets to become more turbulent. Previous literature has suggested that business process agility (BPA) can help organizations to cope with such turbulence. This research reconsiders the commonly used measurement of BPA by separately measuring sensing and responding ability. Furthermore, this research quantitatively addresses the relationship between the frequency of use of Business analytics (BA), and BPA at a departmental level. Furthermore, two organizational factors are considered with regard to the relationship between BA and BPA: the presence of a data-driven environment and the extent of data-driven decision-making.

An analysis shows that BA tools can be categorized into two types. No significant effects of Type 1 BA on BPA are found. In contrast, Type 2 BA are found to directly and indirectly influence BPA positively. Type 2 BA has a direct positive impact on responding ability, and it has an indirect positive impact on sensing ability mediated by the existence of a data-driven environment. Furthermore, the extent of data-driven decision making is found to positively impact a department's responding ability. Speculative meanings are discussed for the two types of BA.

Key words	Business analytics, BA, Business process agility, BPA, Agility, Data driven environment, Data driven decision making
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ORGANIZING AGILITY THROUGH BUSINESS ANALYTICS:

A quantitative analysis of the impact of Business Analytics usage on Business Process Agility

Master thesis in Information Technology for Enterprise Management

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List of abbreviations

Abbreviation	*Full form*
AVE	Average variance extracted
BA	Business analytics
BD	Big data
BDA	Big data analytics
BI	Business intelligence
BPA	Business process agility
CI	Confidence interval
DDM	Data-driven decision-making
DDE	Data-driven environment
IT	Information technology
IS	Information system
KMO	Kaiser-Meyer-Olkin

1 INTRODUCTION

1.1 Problem

The ability of the organization to respond quickly to changes is a factor that has been increasingly relevant in order to become a high-performance organization (De Waal, 2007). A reason for this is that markets are experiencing a shift towards hyper-competition (D'aveni, 1994). This shift is illustrated by the digital transformations which many organizations are experiencing. These digital transformations are rapidly disrupting their competitive environments (Kettunen & Laanti, 2017). Examples of such disruptions initiated by organizations that have utilized digital technologies to outperform their competitors are ubiquitous. Most of these examples, however, involve younger organizations that are active in industries that already have been disrupted by digital innovations such as high-tech or music industry (Westerman & Bonnet, 2015).
For older companies that are active in traditional industries it might seem that adapting to digital transformation can wait. However, digital transformation and digitization are changing industries in a way that will cause most companies to have to become software companies (Chew, 2015; Kettunen & Laanti, 2017). This means that software will be used more and more in both new as well as existing business processes (Kettunen & Laanti, 2017). In order to be able to compete with disruptive newcomers, long-established business models have to be reconsidered. For traditional companies, this will result in changes in organizational structures, roles and competences (Kettunen & Laanti, 2017).

One digital transformation that is reshaping competitive environments can be found in the rise of business analytics (BA). A term used for describing a broad range of technologies as well as the organizational practices around them. Top performing organizations have adjusted their day-to-day operations in such a way that they base their decisions on data analysis at more than double the rate as compared to lower performing organizations (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

In increasingly turbulent industries characterized by digital transformations, the agility of organizations i.e. the capability of organizations to sense, and respond to, changes, has become essential in order to survive (Huang, Ouyang, Pan, & Chou, 2012). Agility has been a research topic for approximately twenty years and various perspectives have been considered when addressing agility. This research will address agility in business processes. This type of agility will be assessed as business processes are the key mechanisms through which organizations act (Raschke & David, 2005). Business processes therefore are essential for organizations to be able to sense, and respond to, changes. Furthermore, business process agility (BPA) forms an interesting combination with IT (Tallon, 2008). Chen et al.(2014), for example, showed that such BPA is mediating the relationship between an organization's IT capability and its performance. In a broader perspective on agility, an organization's IT capability is found to have direct and indirect effects, through digital options, on the agility of an organization (Overby, Bharadwaj, & Sambamurthy, 2006; Tallon, 2008). Scholars have also proposed that BA can be considered a salient information technology (IT) to enable the agility of an organization (Sambamurthy, Bharadwaj, & Grover, 2003). Organizations therefore might decide to invest in BA technology in order to benefit their BPA and their performance. However, the investment in the technology on its own will not guarantee such benefits. Lavalle et al. (2011) show that the biggest obstacles with regard to getting value from analytics are of organizational nature rather than of technological nature. These questions with regard to the organizational aspect of BA are also highlighted by Sharma et al. (2014). They argue that in order to understand the impact of analytics on organizations, research must focus on '*the roles of behavioural, organizational and strategic issues*' (Sharma et al., 2014, p. 434). Whereas previous literature has focused on discrete decisions and how these decisions can be improved, more attention should be given to '*the impact that business analytics can enable in conjunction with changes in organizational decision-making processes*' (Sharma et al., 2014, p. 434). This research will focus on finding and explaining possible relationships between the frequency of use of BA in business processes, BPA, and the organizational factors of BA.

1.1.1 Scientific relevance

The scientific gaps in the literature that this research will assess is threefold. First of all, it will re-assess the commonly used conceptualization and measurement of BPA as proposed by Tallon (2008). This conceptualization of the concept BPA is one that is not corresponding with the broader literature on agility. That is, most researchers refer to agility, as well as BPA (as a subtopic), as sensing of, and responding to, changes in the environment (e.g. X. Chen & Siau, 2011; Y. Chen et al., 2014; Gallagher & Worrell, 2008; Mathiassen & Pries-Heje, 2006). However, the commonly used definition and conceptualization of Tallon (2008) only reflects the capability of responding. The ability to sense threats in the market is not incorporated in this definition:

BPA is the ease and speed with which organizations can alter their business processes to respond to threats in the market (Tallon, 2008, p. 21). Chen et al.(2014) show that this capability to alter one's business processes with ease and speed is a significant indicator of organization performance.

Overby et al.(2006) conform with previous literature that agility is a combination of sensing and responding. Furthermore, they state that an organization is restricted to responding to only those changes that it senses. Therefore, Overby et al.(2006) argue that the proper construct for agility should include measurements for responding, sensing, and the alignment between sensing and responding. Such a construct can then be used to measure BPA as an independent variable. Additionally, they state that antecedents of agility should be measured separately, i.e. with sensing and responding as dependent variables. Overby et al.(2006) propose a strategy to create such a measurement. This research will build on the work of Overby et al. (2006) by measuring possible effects of BA separately on sensing and responding ability as well as by attempting to create a new measurement for BPA. This new measurement of BPA will not be used in this research, however it will serve as a starting point for further research to be conducted on BPA as an independent variable.

Second, this research will delve into the organizational factors that are part of an organization's BA capability. This scientific goal will be more of explorative nature, whereas some research has shown that there is a relationship between an organization's use of BA, and better insights and decisions (Cao, Duan, & Li, 2015), there is little research on the conditions under which such improvements are enabled. Cao et al.(2015) suggest that BA can only contribute to decision-making effectiveness in the case of a data-driven environment, which are strategies, policies and rules on the use of analytics. Furthermore a culture of data-driven decision-making is suggested to be an important factor in getting value from BA (Cao et al., 2015). This research will explore how these organizational factors are related to BA and BPA.

Third, this research will aim to categorize the usage of BA tools at the day-to-day business process level. This will be done in order to test whether the frequency of use of different tools yield different effects in BPA. Some categorizations exist (Cao et al., 2015; Mortenson, Doherty, & Robinson, 2015), however the categorization by Cao (2015) needs a broader empirical foundation, and the categorization by Mortenson et al.(2015) is difficult to use as the categories are not mutually exclusive.

1.1.2 Research questions

Building upon previous literature, the following research question is addressed:

"To what extent does the frequency of use of BA in day-to-day activities influence BPA and to what extent is this relationship moderated by a data-driven environment and data-driven decision-making?"

In order to answer this research question, first, this research will assess whether different categories of BA tools can be identified, i.e. which BA tools are used together at a business process level. Afterwards, the following sub questions will be assessed while taking into account possible categories of BA tools:

- To what extent does the frequency of use of BA influence BPA?
- To what extent does a data-driven environment moderate the relationship between the frequency of use of BA, and BPA?
- To what extent does data-driven decision-making moderate the relationship between the frequency of use of BA, and BPA?

1.1.3 Empirical approach

This research will be conducted in collaboration with the Dutch consultancy firm Quint Wellington Redwood. This organization consults clients who are aiming for a digital transformation. Rather than focusing on the technology in such digital transformations, they focus on organizational practices such as governance, strategy, and business processes. Their clients are mostly large organizations based in The Netherlands.

The unit of analysis will be at department-level. The reason for this is that one can not assume that the same BA tools are used to the same extent throughout the entire organization. This reason especially applies to large organizations, which will form a significant part of the sample. Similarly, individual respondents in large organizations might not be able to reliably make judgements about the entire organization regarding the other indicators used in this research.

1.1.4 Thesis outline

The theoretical background of this thesis will focus on introducing BA: what tools exist, and how they can be used. Subsequently, it will assess the current literature on BA capability, this is valuable for the research as it focuses on what an organization should do in order to get value from BA. The next part of the theoretical background will be devoted to analysing the literature on agility. The concept will be clarified by analysing previous literature. Furthermore, agility will be alienated from several similar research topics in order to create a better understanding of agility. Additionally, showing that agility is a separate research topic will aid the understanding of why this research is relevant. The theoretical part will then shed light upon the two main concepts of agility: sensing and responding. Afterwards, in order to place BA into a larger field of research (i.e. IT), the theoretical part will delve into research that has combined agility and IT.

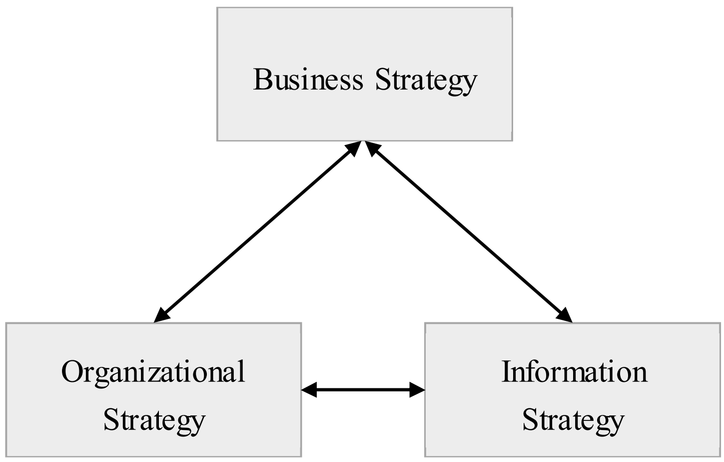
Finally, hypotheses will be proposed by combining the literature on BA and agility. The methods section will show how the questionnaire was created, and which statistical tools were used to analyse the data. The data analysis and results chapter will describe the data, assess the validity and reliability of the constructs, and provide analysis of the data that will be used to answer the research questions. To conclude, the results will be discussed and limitations as well as future research avenues will be touched upon.

2 THEORY

2.1 Information systems strategy triangle

The focus of this research can be illustrated using the information systems strategy triangle as developed by Pearlson and Saunders (2010). This framework, as shown in figure 1, captures the impact of information systems on organizations by relating to business strategy, Information systems (IS) strategy, and organizational strategy. The business strategy is presented as the top of the triangle as successful organizations have a predominant business strategy which is the driver for the organization's organizational strategy as well as the organization's IS strategy. However, it is not simply a case of one strategy following the other. Organizations have to consider interdependencies between the three strategies to keep a balance in the organization (Pearlson & Saunders, 2010). An organization might for example decide to focus on using IS to gain strategic advantage, forcing this organization to continuously innovate its IS. This will result in a need to constantly adjust the organizational as well as the business strategy in order to align with the IS strategy. In another case, an organization's business needs might drive the organization to change its IS. Yet, such changes can have unintended organizational implications which, if disregarded, might have adverse effects with regard to the business strategy. This research is situated in the interaction between information strategy and organizational strategy. A business strategy of achieving agility might drive the use of BA, this however might unintendedly change the organizational strategy of this organization.

Figure 1 Information systems triangle adapted from (Pearlson & Saunders, 2010)



2.2 Business analytics

Davenport and Harris (2007) state that the definition for BA that is most commonly used is: “the extensive use of data, statistical and quantitative analysis, exploratory and predictive models, and fact-based management to drive decisions and actions” (Davenport & Harris, 2007, p. 9) . Watson (2009) defines BA as “a broad category of applications, technologies, and processes for gathering, storing, accessing, and analysing data to help business users make better decisions” (Watson, 2009, p. 491).

Whereas there are multiple definitions for the concept which in this research is referred to as BA, there also seem to be multiple other names referring to the same concept. This is noted by Bayrak (2015) as well as Sircar (2009), who state that the terms BA, business intelligence (BI), and big data (BD) have been used interchangeably over the last years. However, the IT community tends to use the term BI whereas the business community tends to use the term BA. In contrast to this statement of interchangeability of names, Laursen and Thorlund (2016) claim that there is a difference between BI and BA. They argue that analytics go beyond simple technical reporting tools which are often associated with BI. An example of this is that in the past 10 years, analytical models have started to use artificial intelligence to make decisions in the operational process (Laursen & Thorlund, 2016).

The commonly used definitions of BA given at the start of this paragraph focus primarily on the technologies and processes that are implemented to use data in decisions. This however is not the only perspective on defining BA. Laursen and Thorlund, for example, define BA as “delivering the right decision support to the right people and digital processes at the right time” (Laursen & Thorlund, 2016, p. XVII). Building on a similar thought, Sharda et al.(2006, p. 19) define analytics as “the process of developing actionable decisions or recommendations for actions based upon insights generated from historical data.” Rather than focussing primarily on the technologies used in BA, these definitions put the emphasis on the decision rather than on the technology. More specifically, Laursen & Thorlund (2016) look at BA as an information system consisting of three elements: First, the *technological element* typically comprised of IT. Second, the *human competencies element,* employees who are able to deliver information as well as people who make and are affected by decisions. Third, the specific business processes that use the information.

2.2.1 History of BI/BA

The field of BI tools and research is rooted in the developments in decision support systems that were made as early as the 1970's (Sprague & Watson, 1975; Watson, 2009). Such tools were initially also called executive information systems. When they started to include additional visualization, alerts, and performance measurement capabilities the term BI started to come into use. (Sharda et al., 2006). Around 2005 business intelligence started to include artificial intelligence capabilities (Laursen & Thorlund, 2016). Important changes have been made in the field. Many of which have been caused by the rise of the internet which altered the way in which information is shared and delivered. Furthermore, techniques in data visualization have allowed information to be presented and analysed in different ways. Most of these changes have been of technological nature (Watson, 2009). In 2006 Sharda et al. stated that the term BI had been replaced by BA by many practitioners and academics.

2.2.2 Types of BA technology

From a technology perspective, some effort has been done to taxonomize the types of BA. In a factor analysis Cao et al. (2015) find three types of business analytics technologies. (1) Commonly used BA, (2) Model based BA, and (3) Web-oriented BA. This distinction provides a convenient and wide categorization of technologies. Such a categorization based on a factor analysis however, shows which technologies tend to coexist within firms, and therefore not necessarily which BA technologies fall into the same functional category.

Another taxonomy is that of descriptive, predictive, and prescriptive analytics (Mortenson et al., 2015). This is a taxonomy popularly used by practitioners. The technologies are taxonomized by looking at which questions they help answering.

Descriptive analytics answer questions such as "what is currently happening", and "what has happened" (Mortenson et al., 2015). These tools summarize data and transform it into information such that it can be more easily investigated. Examples of this might be dashboard applications or tracking of KPI's. Predictive analytics answer questions such as "what is going to happen next" and "why is this going to happen". Prescriptive analytics answer questions such as "what should we do next". This taxonomy however, is also problematic as the categories are not mutually exclusive (Mortenson et al., 2015), i.e. a BA technology might fall into multiple categories. Additionally, these categories of BA technologies build on top of each other in such a way that descriptive analytics are used to predict what will happen, and consecutively what should be done. The categorization however provides a set of easily understandable categories.

2.3 Business analytics capabilities

In order for BA insights to lead to actions in the organization, these insights have to be closely linked to the business strategy, easily understandable for end users, and embedded into organizational processes (LaValle et al., 2011). Lavalle et al. (2011) propose three levels of analytics capability: (1) aspirational organizations: these organizations focus on reducing costs in existing business processes. (2) Experienced organizations: these organizations have moved through the aspirational phase and are looking to optimize their organization through revenue growth rather than cost efficiency. (3) Transformed organizations: these organizations are efficiently organizing people, processes and tools in order to optimize and differentiate. The biggest obstacle in moving towards a BA capability is not the data itself. Rather, it are managerial and cultural barriers that are blocking the way (LaValle et al., 2011).

In an effort to create an integrated typology on big data analytics capabilities, Akter et al. (2016) combined literature on big data analytics (BDA), advanced analytics, and BA and identified three main building blocks of BDA. (1) Management capability, (2) Technology capability, and (3) Talent capability. These building blocks are consistent with the main elements of BA as defined by Laursen and Thorlund (2016).

The technology capability of BDA is concerned with the flexibility of the system as shown by three characteristics. First of all, its connectivity, or the ability to connect with different sources of data. Second, its compatibility which allows information to flow through systems in order to allow for real time decisions. Third, modularity of the system enables easy addition, modification, or removal of features.

The talent capability of BDA is concerned with the knowledge regarding tasks in the data environment. The analysts that work with the system should be competent in technical knowledge (e.g. programming languages), technology management knowledge (e.g. knowledge on how to visualize data to benefit decision-making), business knowledge (e.g. understanding what the issues are in the business environment), and relational knowledge (i.e. the ability of analysts to collaborate with employees from other business functions).

The management capability of BDA is fundamental to making sure that solid business decisions are made. This capability is comprised of BDA planning, investment, coordination, and control. During the planning process the organization determines what are the opportunities for the business with regard to BDA and how it can benefit the organization's performance. BDA investment reflects decisions regarding cost-benefit analyses. BDA coordination structures cross-functional analytics activities in organizations. BDA control refers to ensuring commitment and utilization of resources to analytics. While, at first glance, the management capability might look as if it addresses the interaction between technology and organization. This management capability of

BDA as proposed by Akter et al.(2016) mostly reflects the management of the technology itself rather than managing the interdependencies between the technology and the organization, the latter of which will be described in the following paragraph.

2.3.1 Data-driven environment and decision-making

When analysing the literature on organizational factors related to the use of BA, one might notice two types of organizational practices. On the one hand, those that are initiated at the top of the organization, e.g. the data-driven environment as described by Cao et al.(2015) or the alignment between business strategy and analytics by Akter et al. (2016). On the other hand, those organizational practices which are performed throughout the organization, e.g. data-driven decision-making by Cao et al.(2015), or analytics culture by LaValle et al. (2011) or Kiron et al. (2014).

In order to build on top of existing literature, this research will refrain from introducing more concepts, and use the concepts as proposed by Cao et al. (2015).

Cao et al. (2015, p. 5) define this data-driven environment as "*the organizational practices reflected by developing explicit strategy and policy to guide analytic activities, and designing structure and processes to enable and facilitate BA activities*". Examining this definition shows that these practices are characterized by their top down approach. I.e. strategies, policies, structures, and processes are usually created or structured at higher levels in the organization.

Data-driven decision-making is defined as *"the extent to which an organization is open to new ideas that challenge current practice based on data-driven insight; has the data to make decisions; and depends on data-based insight for decision-making and the creation of new services or products."* This definition refers to factors that are existing throughout the organization as opposed to shaped in a top down manner.

The distinction between organizational factors shaped at the top, and organizational factors existing throughout the organization is followed throughout this research in order to assess the relationship between BA and BPA.

2.4 Agility

Many organizational environments can be considered hypercompetitive (D'aveni, 1994). Organizations in such industries are faced by complexities caused by turmoil and discontinuity. The term 'agile' is being used increasingly to write about organizations which can adapt, and perform well in such an environment (Overby et al., 2006). The concept has been receiving attention from researchers as well as business, yet a clear definition remains to be found. Sambamurthy et al. (2003, p. 238) define BPA as “the ability to detect and seize market opportunities with speed and surprise.” Chen et al. (2014, p. 329) define agility as providing “organizations with the ability to respond quickly to customer demands, market dynamics, and emerging technology options”. Overby et al.(2006, p. 121) define Enterprise agility as “the ability of organizations to sense environmental change and respond readily”. Even though there is debate and uncertainty around the exact definition of agility, four characteristics of agility are clear in the literature (Roberts & Grover, 2012): Agility should be regarded as a capability, i.e. a set of organizational routines and processes that produces a particular output (Dove, 2002). Second, agility consists of two capabilities: sensing and responding (Roberts & Grover, 2012). These are two capabilities that complement each other. Third, the importance of agility is dependent on the dynamism and speed of the environment. Fourth, agility is domain-specific, one’s ability to sense and respond might be valid in one industry where it might be slow in another.

Agility is a field of research that builds on, and is similar to, other fields of research regarding organization success in dynamic environments. Examples of such theories are dynamic capabilities (Teece, Pisano, & Shuen, 1997), strategic flexibility (Hitt, Keats, & DeMarie, 1998), absorptive capacity (Zahra & George, 2002), and adaptive capacity (Staber & Sydow, 2002). Yet, agility can be considered as a distinct field of research within these theories. In the following paragraphs, agility will be alienated from other theories to show how agility is a relevant concept rather than just old wine in new bottles.

2.4.1 Resource based view of the organization and Dynamic capabilities

A major contribution to research on factors that characterize high performing organizations has come in the form of the resource based view of the organization as well as the dynamic capabilities literature (De Waal, 2012). The resource based view of the organization assumes that organizations exist of bundles of resources which are heterogeneously dispersed over organizations and that these resources differ over time (Wernerfelt, 1984). The theory states that when organizations have resources that are valuable, rare, inimitable, and non-substitutable, they enable sustainable competitive advantage (Wernerfelt, 1984). A downside of the resource based view of the organization is that it does not lend itself well for explaining organizations that are active in environments characterized by rapid and unpredictable change (Teece et al., 1997). This might be a problem as digital disruptions are causing “*rapid and even disruptive change in a majority of companies and future competitive environments*” (Kettunen & Laanti, 2017, p. 15).

An enhancement of the resource base view of the organization to match unpredictable markets comes in the form of dynamic capabilities (Eisenhardt & Martin, 2000; Teece et al., 1997). Eisenhardt & Martin (2000, p. 1107) define dynamic capabilities as *”the organization’s processes that use resources, specifically the processes to integrate, reconfigure, gain and release resources, to match and even create market change. Dynamic capabilities thus are the organizational and strategic routines by which organizations achieve new resource configurations as markets emerge, collide, split, evolve, and die.”* Helfat et al. (2007) define dynamic capabilities as: “*the capacity of an organization to purposefully create, extend, or modify its resource base*”. These resources, among others, might include human, technological, knowledge-based, and tangible-based capital (Easterby-Smith, Lyles, & Peteraf, 2009). Dynamic capabilities are considered to be at the foundation of competitive advantage in environments characterized by rapid (technological) change (Teece, 2007). Not only do dynamic capabilities allow an organization to respond to environmental change (Teece et al., 1997), they can also be the source of disruptive change (Eisenhardt & Martin, 2000).

There are similarities between the concepts of agility and dynamic capabilities, as they both try to find answers on how to perform well within a dynamic environment. However, dynamic capabilities is a concept that can be considered broader as opposed to agility. Agility can be considered a part of dynamic capabilities as it reflects only the sensing and responding to dynamics in the environment, whereas dynamic capabilities can be applied to all types of business processes (Overby et al., 2006). Additionally, agility describes which capabilities are necessary to be able to sense, and respond to, environmental change.

2.4.2 Adaptive capacity and adaptation

Another field of research addressing organizations in turbulent environments can be found in adaptive capacity and adaptation. Staber & Sydow (2002) discuss two different strategic reactions to environments of high turbulence. The conventional reaction, they argue, is to take an adaptionist approach. The adaptionist approach tends to focus on core competencies, streamlining routines and tightening resource belts (Staber & Sydow, 2002). Adaptionist organizations tend to seek fit with their environment in a reactive manner, not uncommonly by following a set of best practices (Staber & Sydow, 2002). The counterpart of the adaptionist approach comes in the form of adaptive capacity. Rather than seeking a static optimal fit to environmental contingencies as is the adaptionist strategy, adaptive capacity is a way of continuously developing and applying new knowledge. Whereas adaption tries to maximize fit with the existing conditions, the focus of adaptive capacity is to be able to manage future circumstances. Staber & Sydow

(2002) focus their research around the management of knowledge. This knowledge focus of adaptive capacity is shared by the theory on absorptive capacity. Absorptive capacity is referred to as processes and routines to acquire, assimilate, transform, and exploit knowledge to create the capability to be dynamic. These four activities do resemble the sensing and responding activities of agility. Acquiring and assimilating knowledge is similar to sensing, and transforming and exploiting is similar to responding. However, the focus of the theories is different as adaptive- as well as absorptive capacity focus on managing knowledge, whereas agility focusses on managing change.

2.4.3 Strategic flexibility

Another field of research that resembles agility is strategic flexibility which is the capacity of proactively or reactively responding to market threats and opportunities to manage economic and political risks (Grewal & Tansuhaj, 2001). Such strategic flexibility is usually achieved by having pools of resources that can be assigned to managing 'surprises'. This theory however, solely refers to issues that are of a strategic nature. To contrast this, agility focusses both on issues of strategic nature as well as issues of operational nature (Overby et al., 2006). The scope of this research will be more narrow as it will delve into the BPA of an organization.

2.4.4 Sensing

As described before, the common idea of agility is the ability to sense changes and respond to those changes. Overby et al.(2006) created an agile enterprise framework proposing the types of changes in the environment which an organization must be able to sense, and the types of responses that an organization can utilize. The forces of environmental change that are described by Overby et al.(2006) are competitors' actions, consumer preference changes, economic shifts, regulatory and legal changes, and technological advancements. Examples of capabilities to enable a sensing capability are market intelligence, government relations, legal, research and development, and IT. The importance of each of these capabilities might be dependent on which industry the organization is acting in. However, all of them are likely to be important.

The sensing of environmental change refers to the ability of the organization to detect, anticipate, or, sense, competitive market opportunities, evolving conditions, and environmental changes (Overby et al., 2006). A capability that is similar to information processing capability as described by Cao (2015). This information processing capability is defined as "*the gathering, interpreting, and synthesis of information in the context of* *organizational decision-making"* (Cao et al., 2015, p. 4). Interpreting both concepts suggests that the sensing capability is a subset of the information processing capability. I.e. sensing capability is an information processing capability dedicated to change and opportunities.

2.4.5 Responding

The ability to respond is referred to as the physical ability to respond efficiently and effectively (Overby et al., 2006). After sensing a change in the environment, an organization might take 3 types of responses: (1) a complex move which might involve embarking on a new venture. (2) a simple move which might involve adjusting an existing venture by for example changing the price of a product or changing the features of a product. (3) no move, if this is a calculated decision, a no-move can also be considered a response to environmental change rather than a failure to sense the change (Overby et al., 2006). At the business process level, such responses might for example involve customizing a product for an individual customer or, reacting to new pricing schedules. In order to measure an organization's response ability at the business process level this research will use Tallon's (2008) concept of BPA. Even though the term refers to 'agility', the definition as well as the conceptualization only reflect the responding part of agility as can be seen in table 1.

Examining the indicators shows that this construct measures whether the organization is able to respond to a change, e.g. by customizing a product or service to suit an individual customer. This however does not paint the complete picture of agility. An organization might be able to customize a product easily and effectively, however, in order to do so it will have to sense the individual preferences of this customer. Continuing this example, the process of sensing these preferences is a different one from responding to them by altering the product. Therefore, both sensing and responding should be measured separately.

Table 1 Definition and indicators of BPA (Tallon, 2008)

Business process agility: BPA is the ease and speed with which organizations can alter their business processes to respond to threats in the market (Tallon, 2008, p. 21)	
Indicators:	*To what extent do you agree that your organization can easily and quickly perform the following business actions:* - Respond to changes in aggregate consumer demand. - Customize a product or service to suit an individual customer. - React to new product or service launches by competitors. - Introduce new pricing schedules in response to changes in competitors' prices. - Expand into new regional or international markets. - Change the variety of products/services available for sale. - Adopt new technologies to produce better, faster and cheaper products and services. - Switch suppliers to avail of lower costs, better quality, or improved delivery times.

2.5 Agility and performance

Research on the antecedents of organizational performance is broad. Unsurprisingly researchers of organizational agility have not skipped the subject. Dynamic capabilities, one of which is agility, are found to be necessary and a predictor of organizational performance (Kim, Shin, Kim, & Lee, 2011; Teece, 2007). More specific to this research, Chen et al. (2014) find that BPA has a positive impact on organizational financial performance. Chen et al. (2014) however, use Tallon's (2008) conceptualization of BPA. As argued in the previous paragraph, this conceptualization refers to the responding part of BPA only. A more in depth research on the relationship between BPA and organizational performance should reflect a construct of BPA that includes sensing, responding, and the alignment of sensing and responding as suggested by Overby et al.

(2006). Even though Chen et al. (2014) focus on agility as only responding, as opposed to sensing and responding, the logic that is used to support the empirical findings are still valid. Being able to sense, and respond to, opportunities and threats in an organizational environment will allow this organization to achieve financial benefits from those opportunities and mitigate the financial disadvantages from the threats.

2.6 IT and agility

IT can be considered an enabler of the sensing and responding capabilities of organizations. This happens in two ways, directly, and indirectly through digital options. Delving in to the direct relationship between IT and agility, Tallon (2008) notes that BPA can be achieved with an IT capability by enabling rapid business process operations, facilitating flexible business processes, and enabling business process innovation. Overby et al. (2006) state that in order to sense relevant changes, organizations must have an adequate level of IT capability. Research has also found that there is an indirect effect from IT towards agility through an organization's digital options (Sambamurthy et al., 2003). Digital options are referred to as "*a set of IT-enabled capabilities in the form of digitized enterprise work processes and knowledge systems"* (Sambamurthy et al., 2003, p. 247). These digital options can vary in their reach and richness. They argue that IT has a positive influence on the reach and richness of an organization's knowledge and its processes.

Knowledge reach is referred to as "*comprehensiveness and accessibility of codified knowledge in the organization*" (Overby et al., 2006, p. 126). Rich knowledge, is "*high-quality information which is timely, accurate, descriptive, and customized to the recipient*" (Overby et al., 2006, p. 126). These improvements in reach and richness enable an organization to sense and respond more effectively (Sambamurthy et al., 2003). High reach and richness of an organization's knowledge have a positive impact on the organization's ability to sense as managers are provided with information on the changes in the organization's environment.

Additional to IT's impact on *knowledge* reach and richness, IT impacts *process* reach and richness. Processes with a high reach are those "*processes that tie activity and information flows across departmental units, functional units, geographical regions and value network partners"* (Sambamurthy et al., 2003, p. 248). Process richness is defined by Sambamurthy et al. (2003, p. 248) as the "*quality of information collected about transactions in the process, transparency of that information to other processes and systems that are linked to it, and the ability to use that information to reengineer the process"*. Both process richness as well as process reach are argued to be having a positive influence on the responding ability of the organization (Overby et al., 2006).

Sambamurthy (2003) describes that some information technologies are more adapt at enhancing knowledge, whereas others are more adapt at enhancing process reach and richness. Overby et al. (2006) conclude that by having in place both process and knowledge reach and richness, an organization creates a digital options platform of which it can perform agile moves. A lack of either process- or knowledge-oriented IT will lead to a situation in which it is more complicated to perform agile moves. In short, three mechanisms of how IT influences agility can be derived from literature:

Mechanism 1: IT can positively influence BPA, and an adequate level of IT is required in order to sense relevant changes.
Mechanism 2: IT can positively influence an organization's knowledge reach and richness, which in turn lead to a better ability to sense and respond.
Mechanism 3: IT can positively influence an organization's process reach and richness, which in turn lead to better responding ability.

Conforming with the indirect relationship between IT and agility, a case study by Huang et al.(2012) on operational agility, shows that successfully leveraging IT helps the organization to gather, synthesize and disseminate information, which in turn leads to efficiency and effectiveness in information processing. This has a direct effect on operational agility, a term identical to BPA (Huang et al., 2012). Huang et al.(2012) also suggest that the IT capability is particularly important in turbulent environments as the ability to process information reduces the uncertainty which is a characteristic of such environments. This is in line with the findings of Chen et al. (2014) who find that IT capabilities lead to a higher level of BPA in more complex environments, therefore IT can be used as a means to increase process agility to cope with complex environments.

2.7 Business analytics and agility

The relationship between BA and BPA is suggested in the literature (e.g. Isik, Jones, & Sidorova, 2011; Sambamurthy et al., 2003), however empirical evidence remains to be delivered. Overby et al. (2006) state that it is important to measure agility by measuring both sensing and responding as opposed to measuring the concept agility itself. This advice will be used in developing the measurements and hypotheses for this research. Therefore, the following paragraphs will delve into the relationship between BA and BPA by examining the individual relationships of BA on sensing and responding.

2.7.1 Business analytics and sensing

As explained in the chapter on BA, descriptive analytics tools help organizations to answer the general questions: ’what is currently happening’ and ’what has happened’ (Mortenson et al., 2015). These descriptive analytics tools such as visualization technology might help organizational members to convert data into meaningful information. One can argue that having information on what is going on in the environment will benefit one to sense changes in this environment. Building on descriptive analytics, predictive analytics use machine learning technology to answer the general question ’what will happen next?’ (Mortenson et al., 2015). Logic suggests that knowing what will happen next, will have a positive effect on one's ability to sense change, threats, and opportunities in the environment. A similar proposition is made by Isik et al.(2011), they reason that BA will enhance sensing ability by improving accuracy, consistency, and timeliness of information in organizations (Isik et al., 2011).

The research of Sambamurthy (2003) on digital options might also be a way of explaining the relationship between BA and agility. BA tools can enhance knowledge reach, as they combine data from different sources and make it comprehendible for individuals. Furthermore, these tools can contribute to knowledge richness in an organization, as BA tools are designed to provide accurate data to the right people (Sharda et al., 2006). Following the reasoning in this paragraph, hypothesis 1 is created:

H1: Greater use of BA in business processes has a positive influence on sensing ability.

This relationship, however, might be more complex as described above. Cao et al.(2015) combine multiple organizational factors with the use of BA. They argue that the usage of BA leads to a data-driven-environment (i.e. data related organizational practices initiated at the top), which in turn enhances information processing capability (or sensing) of an organization. In this research by Cao (2015), a strong assumption is made that when an organization implements BA this will lead to an organization adjusting its internal environment to fit this implementation of BA, i.e. into a data-driven environment. However, such an adaptation of the internal environment into becoming more data-driven might not come naturally. This is illustrated by LaValle (2011) who finds that the bigger impediments towards getting value from data are of organizational and managerial nature. Put differently, these organizations, which are experiencing managerial impediments, have the proper technology in place, yet they are blocked from getting value from that technology by managerial obstacles. Implying that a proper managerial approach towards BA is a prerequisite for allowing an organization to benefit from BA technologies. Furthermore, it is a prerequisite that does not always follow the implementation of BA technology as is suggested by Cao (2015). Following this, one might argue that the data-driven environment is an enabling factor which allows organizations to achieve a better ability to sense opportunities and threats by using BA. In other words, the benefits of BA tools are conditional upon having in place a data-driven environment. Consequently, the following hypothesis is created:

H2: The effect of BA on sensing is positively moderated by a data-driven environment.

Some empirical evidence for this hypothesis has already been found by Akter et al.(2016). They find that the relationship between an organization's BDA capability and its performance is moderated by the alignment between data analytics and strategy. This analytics capability business alignment is defined as "the extent to which BDA capabilities are aligned with the overall strategy of the organization"(Akter et al., 2016, p. 120). Such alignment is considered to be a part of a data-driven environment as it is a process that is initiated at the top of the organization.

2.7.2 Business analytics and responding

Using data does not only help in identifying changes. Data also helps to respond in an efficient way by making decision-making rely more on facts as opposed to intuition (Provost & Fawcett, 2013). Types of prescriptive analytics might for example help by indicating what is the most efficient way of responding. Furthermore, types of predictive analytics can help predict how customers might react to a certain response. Işik et al. (2011) propose that BA will help enhance response ability of an organization by allowing the organization to quickly introduce new products. In a more specific examination of this relationship, Sambamurthy (2003) proposes that decision support technologies as well as analytics can help an organization increase its process richness. Such process richness is achieved by improving the quality and transparency of information about the process. Sambamurthy (2003) theorizes that process richness leads to a better responding ability. Following this line of reasoning, hypothesis 3 is created.

H3: Greater use of BA at the business process level has a positive influence on responding ability.

However, in a similar way as a data-driven environment enables the positive impact of BA on sensing ability, an organization's responding ability is dependent on its organizational surroundings. The main reason for BA having a positive impact on responding ability of the organization is that decisions are made on the basis of facts rather than on the basis of intuition (Provost & Fawcett, 2013). Assuming that the BA tools function as they should, they will provide the organization, with facts. However, only having these facts somewhere in the organization will not automatically lead to better ability to respond. LaValle (2011) finds that the main impediment to getting value from data lays within the organizational culture. This impediment is one that frequently occurs in organizations. This is affirmed by McAfee and Brynjolfsson (2012) who state that decisionmakers throughout the organization tend to have the culture of relying on intuition rather than on data for making their decision. Following these arguments, a proposition is formed that organizations need to make data the main driver for decisions in order to translate BA into the ability to respond. Therefore, the extent to which BA positively influence responding ability is dependent on the extent to which decision-making is driven by data. Following this line of reasoning hypothesis 4 is constructed.

H4: The positive effect of BA on responding ability is positively moderated by the extent to which decision-making is data-driven.

3 METHOD

This research is done as an explanatory quantitative study. The method for doing this quantitative study is a survey. It will build upon previous research by better explaining the mechanisms through which BPA is achieved. Such previous literature focused for example on the relationships between BPA and performance (Y. Chen et al., 2014), IT and BPA (Tallon, 2008), BA and decision-making effectiveness (Cao et al., 2015), and agility and digital options (Sambamurthy et al., 2003). Furthermore, this research answers the call of Overby et al. (2006) to create a measure that better explains the concept of agility.

3.1 Research design

In order to research the relationships among the use of business analytics, agility, and organizational factors, this research collects data from a range of organizations using a questionnaire. The study is a cross-sectional one as all the data is collected at one point in time using an internet-based questionnaire. This questionnaire will be distributed in the network of Quint. The organizations that are in this network are active in various industries, however, the majority is active in banking, healthcare or, the government. Most of Quints projects are conducted from an IT perspective, therefore, a significant part of the population consists of IT professionals. The 'key informant approach' to collecting data is used (Bagozzi, Yi, & Phillips, 1991). This means that the choice of informants is based on characteristics such as specialized knowledge or position in the organization. In this research, the respondents are selected primarily on availability as it is limited to the network of Quint. Secondary, the respondents are selected on their position in the organization. The questionnaire is distributed among employees in management functions and employees with IT related functions as these employees are likely to be knowledgeable on the researched concepts.

When doing a statistical analysis, one has to take sample size into consideration, as this impacts the generalizability of the results. (McAfee et al., 2012). In order to identify the minimum number of observations multiple rules of thumb exist. When doing a multiple regression analysis, the ratio of observations to independent variables has to be at least 5, however following a more conservative rule would suggest one to find at least 10 observations per independent variable (Kotrlik & Higgins, 2001). In total, this research uses 5 independent variables (including control variables), therefore the number of observations should be at least 25. However, following the more conservative, optimal, rule of 10 to 1 would lead to needing at least 50 observations. Tabachnick & Fidell (2007, p. 123) suggest using a sample size of $N > 50 + 8m$ in which m represents the number of independent variables. This would suggest a sample of at least 90 respondents. In addition to this minimum number of observations, one should take into account the statistical power of the analysis when determining the optimal response rate (Swanson & Holton, 2005). Following Maxwell (2000), in the case of a regression analysis with 5 predictors, one should have a sample size of 419 to achieve a power equal to .80.

Considering the size of the network of Quint (6.679), this research would need a response rate of 1.13% in order to reach 90 respondents. In order to reach a power of .80, this research would need a response rate of This would imply a response rate of 6.3 percent.

3.2 Instrument design

In the process of developing the questionnaire, where possible, existing constructs were extracted from scientific literature in order to increase the validity and reliability of the constructs. These constructs occasionally had to be rephrased in order to create a logical structure and cohesion in the questionnaire.

All variables, with exception of some control variables, were measured using a Likert-scale. As described by Krosnick (2018), there is little conclusive evidence for choosing a certain number of answering options on a Likert scale. Reliability and validity of scales are highest when using a scale with a moderate amount of points (i.e. 5, 7, 9, or 11). The indicators in this research are measured on a 5-point or 11-point Likert scale. A 5-point scale was used for the constructs business analytics, data-driven decision-making, and data-driven environment. A 5-point Likert-scale is considered a proper instrument as it provides a balance between having more variation in the answers as opposed to a dichotomous scale and having slightly better reliability as opposed to larger scales. An 11-point scale was used for the constructs sensing, responding, and agility alignment. The reason for this can be found in the article by Overby et al. (2006) who propose that measures for sensing, responding, and agility alignment should range from 0 to 1. This will allow the researcher to calculate the agility level of the firm using a formula that will be explained later in this chapter. An 11-point Likert scale is easily translated into levels 0, 0.1, 0.2 – 1. The individual constructs will be discussed below. The constructs with its respective indicators are presented in appendix 1, the codebook is presented in appendix 2.

3.2.1 Business analytics

The construct for the usage of BA by an organization is a validated measure which was created by Cao et al. (2015). It measures the frequency at which a BA technique is used. By doing a factor analysis, they suggest that BA is a higher-order component consisting of three lower-order components, which they refer to as: commonly used BA, model-based BA, and web-oriented BA. This categorization is based on usage throughout the entire organization. In contrast, this research focuses on the usage of BA during day-to-day business processes. BA is considered a formative multidimensional construct (Cao et al., 2015). A factor analysis will be conducted to create one or more variables for BA that can be measured reflectively. The questioning was slightly adjusted such that it reflects how frequently BA is used in day-to-day business processes as opposed to how often it is used in the entire organization. The possibilities on the 5-point Likert scale ranged from *Never* to *Continuously*.

3.2.2 Data-driven environment

The construct for data-driven environment of an organization has been validated in research by Cao (2015). It measures the extent to which an organization has strategy, policies and rules, and an organizational structure which guide and enable BA activities. Furthermore, it measures the extent to which the organization prioritizes BA investments according to its expected impact on business performance.

3.2.3 Data-driven decision-making

The construct for data-driven decision-making of an organization has been validated in research by Cao (2015). It measures the extent to which organizations use data-based insight for creating new products and making decisions. Furthermore, it measures the extent to which an organization has data to make decisions and whether the organization is open to challenging current practices based on data-driven insights.

3.2.4 Responding

As argued in previous chapters, the commonly used concept of BPA only reflects an organization's responding capability. This however is an incomplete illustration of BPA as in previous agility literature, the common understanding is that agility consists of sensing and responding (Roberts & Grover, 2012). This research is built on the assumption that this combination of sensing and responding does not only apply to the agility of the entire organization, but also to its subsets, one of which is BPA. This research will therefore use Tallon's (2008) measure of BPA to assess an organization's responding ability at the business process level.

3.2.5 Sensing

As of yet, no conceptualization of an organization's sensing ability has been created. However, as argued in the theoretical background, the concept of sensing strongly resembles the concept of information processing capability. In order to create the concept of sensing for BPA, the information processing capability measurement by Cao (2015) was scoped to measure changes and opportunities. Furthermore, the question was adapted in such a way that it measured changes and opportunities at the business process level.

3.2.6 Agility alignment

The indicators for agility alignment are created for this research based on Overby et al.(2006). They proposed that agility alignment should measure whether an organization senses opportunities in only those areas where it has the capability to respond, or whether those sensed opportunities go beyond the range of its responding capabilities (Overby et al., 2006). Overby et al. (2006) identify two types of misalignment. (1) The organization senses more opportunities than it can respond to, (2) the organization senses opportunities in areas in which it can not respond. Both lead to a waste of sensing ability. The level of alignment should be measured on a continuous scale rather than a binary (aligned, non-aligned) scale.

3.2.7 Business process agility

As discussed in the introduction, this research will propose a new measurement for BPA. By doing this, it will answer the call of Overby et al. (2006), who state that agility scores should be calculated by combining an organizations sensing, responding, and alignment scores. The method Overby et al. (2006) propose for calculating this score is discussed here.

For a firm that is aligned with regard to its sensing and responding abilities, the BPA score can be calculated by taking the minimum of the sensing and responding scores. The logic behind this is that whenever an organization's sensing and responding abilities are in synch its agility is restricted only when it runs out of either sensed opportunities or threats, or the capacity to respond to these opportunities or threats.

$$BPA\ score^{aligned} = \min(Sensing\ score, Responding\ score)$$

The BPA score for non-aligned firms is calculated differently as those opportunities that an organization senses and those to which it can respond do not always match. This limits the number of opportunities which the organization can take advantage of. This misalignment is addressed by multiplying the sensing score with the responding score. The rationale behind this is given by Overby et al. (2006). In a misaligned situation, the extent to which an organization can respond to sensed changes is dependent on both the ability to sense relevant changes and the ability to respond to relevant changes. Even though an organization might be able to sense an X amount of changes, it can only respond to a fraction of these. The size of that fraction is dependent on the ability to respond to changes. The BPA score for non-aligned firms is calculated as follows:

$$BPA\ score^{non-aligned} = Sensing\ score\ \times\ Responding\ score$$

These two BPA scores represent the range in which the actual BPA score of an organization will be placed. A completely aligned firm will get the score calculated in $BPA\ score^{aligned}$. A completely non-aligned firm will get the score calculated in $BPA\ score^{non\text{-}aligned}$. Alignment however is calculated as a continuous measure rather than as a binary one, therefore the actual BPA score will fall somewhere between the aligned and non-aligned score. The reasoning is presented in the following formula:

$$\begin{aligned} BPA\ score^{actual} \\ &= BPA\ score^{non-aligned} + Alignment\ score \times (BPA\ score^{aligned} \\ &- BPA\ score^{non-aligned}) \end{aligned}$$

In order to clarify the measure, an example is provided here: an organization has a sensing score of 0.7, a responding score of 0.6 and an alignment score of 0.4. Following the provided formulas, this results in a $BPA\ score^{aligned}$ of 0.6 and a $BPA\ score^{non\text{-}aligned}$ of 0.42. The BPA score can now be calculated:

$$BPA\ score^{actual} = 0.42 + 0.4\ \times (0.6 - 0.42) =\ 0.472$$

3.2.8 Additional variables

This research includes several additional variables. Some variables will provide contextual information, other variables will serve as control variables to increase the reliability of this research. As contextual variables, organizational size, department size, core business, and department type. The number of employees is used as a proxy for the size of the organization as well as the size of the department. Both are measured using close-ended questions, the answer possibilities can be found in the codebook (appendix 2). The core business of the organization was asked with answer possibilities (Banking/finance, Telecom, Retail, Manufacturing, Trading, IT, Services, Government, Healthcare, Other). Next to this, the respondent was asked to indicate the department in which he or she is active, the answer options were IT operations, Finance, HR, Marketing & sales, Logistics, Procurement, R&D, and Other.

As control variables the age of the organization and the dynamism of the environment were measured. The age of the organization is determined by asking the number of years ago that the organization was founded. The construct for environmental dynamism was derived from Chen et al.(2014) who find that environmental complexity is a strong predictor for business process agility. Furthermore, Chen et al. (2014) find that additional to a direct effect of environmental complexity on BPA, environmental complexity positively moderates the effect of an IT capability on BPA. In other words, in a complex environment, a high IT capability leads to more BPA as opposed to in a simple environment. This interaction effect of the environment however is out of scope for this research.

3.2.9 Statistical tests used

The gathered data is analysed using several statistical tests. These tests are done in IBM SPSS statistics 21. Factor analyses are done to check the reliability and validity of the scales. Furthermore, a factor analysis will be used to assess the possibility to categorize the BA construct. Subsequently, a MANOVA will be used to assess whether different department types statistically differ on the measured constructs. The hypotheses will be tested using multiple regression analyses.

4 DATA ANALYSIS AND RESULTS

4.1 Data preparation

Before starting the analysis, the data was first checked for errors. That is, the data was checked primarily for values that did not fall within the range of possible scores. As most questions are measured with a closed, multiple choice question type, it is impossible to fill in values that do not match the scale. The exception to this is the variable measuring organizational age. As the oldest running organization in the world was formed 1313 years ago (Baer, 2014), all values over 1313 are considered as out-of-range and changed to missing. As a result, 4 cases were changed. In further analyses, missing cases will be excluded pair-wise as prescribed by Pallant (2013), this allows for maximum use of data as opposed to using list-wise exclusion. Furthermore, the items ALI1 and ALI2, measuring alignment, were reversed, such that a higher score indicates a higher level of alignment. Construct scores were calculated by taking the mean score of its individual indicators.

4.2 Sample description

4.2.1 Response and participation rate

As presented in chapter 3, the sample consists of organizations in the network of Quint that could be contacted via email. 6679 persons opened the email that was sent in the network. In the 2 weeks that the survey was opened, the link to the survey was clicked 277, and 144 responses were recorded. Of those 144 responses, the survey was fully completed 83 times. Following the rule-of-thumb calculations recommended by Swanson & Holton (2005) for having at least 50+8m responses was not satisfied, however not all independent variables are entered into a single regression, i.e. only 4 independent variables are used per regression. Therefore, albeit that the sample size is small, the sample size is considered acceptable. In order to have a power value of .8, a recommended sample size of 419 is needed (Maxwell, 2000). This minimum sample size was not satisfied.

4.2.2 Description respondents

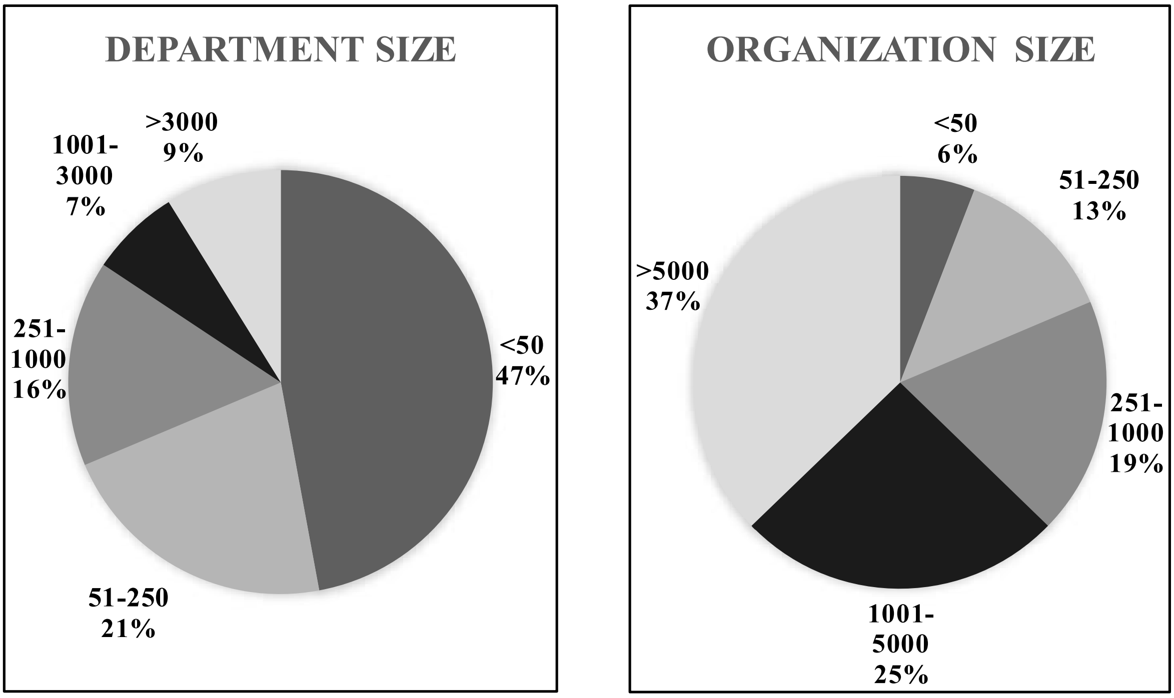
The respondents were obtained from different industries. The frequency of industry types of the responding organizations is shown in table 2. The organizations that responded with 'other industry type' are active in agriculture, pharmaceutics, education, and libraries. The observed types of departments in which the respondents are active are shown in table 2. Clearly, most respondents are active in IT departments (59.8%) with other notably frequent department types being Marketing & Sales (10.8%), and Operations (8.8%). The respondents who described their department as 'other' responded with varying answers, e.g. Risk, Facility management, and Construction. Additionally, organizational, and departmental size were observed by measuring their number of employees. Both size frequencies can be seen in figure 2. The responding organizations showed differences in size, as expected the organizations were mostly large organizations. With 62,7 percent being larger than 1000 employees. The sizes of the departments had a tendency towards smaller sizes. 47.1% of the departments had less than 50 employees and 15.7% of the departments had over 1000 employees active in them. The age of the observed organizations ranged from 1 to 450 years. The average age of the organizations is 66.01, however it is noteworthy that this variable has a median of 36 and a skewness of 2.769, showing that this average organizational age is influenced by some extreme values. About 10 % of the organizations recorded an age over 100 years.

Table 2 Industry type and department type frequencies

Industry type	*Frequency*	*Percent*
Banking/Finance	26	25.5
IT	16	15.7
Services	16	15.7
Government	13	12.7
Healthcare	9	8.8
Manufacturing	8	7.8
Telecom	4	3.9
Retail	1	1.0
Logistics	3	2.9
Trading	1	1.0
Other	5	4.9

Department Type	*Frequency*	*Percent*
IT	61	59.8
Marketing & Sales	11	10.8
Operations	9	8.8
Finance	4	3.9
HR	4	3.9
R&D	4	3.9
Logistics	5	4.9
Other	4	3.9

Figure 2 Department size and organization size frequencies



4.3 Reliability and validity of scales

Even though previously constructed and validated scales were used in this research, it is important to check the reliability and validity of these scales. The reason for this is that the reliability and validity of a scale can vary per sample (Pallant, 2013). Furthermore, a newly developed construct for agility alignment is tested.

4.3.1 Validity

The construct validity of the scales is measured by assessing the convergent validity and the discriminant validity of the constructs. Convergent validity tests show whether the theoretically related indicators are actually related in reality (Pallant, 2013). Cronbach's alpha is a measure that is used for this, additionally, a factor analysis is done. Alpha should be above 0.8 and average variance extracted (AVE) should be above 0.5 (Fornell & Larcker, 1981). The Alpha, and AVE scores are shown in Table 3, the Cronbach's alpha scores are found to be satisfactory considering the conditions set by Fornell & Larcker (1981). Except for data-driven decision-making all AVE's are above .5. This indicates that the convergent validity of data-driven decision-making falls slightly short of the AVE rule of thumb for convergent validity. Some cross loadings are found, and the construct of BA is divided into two variables.

To assess the discriminant validity of the scales, the loadings and cross loadings of the factor analysis are observed. More specifically, the square roots of the AVE values were compared to the correlations between constructs. According to Fornell & Larcker (1981), the square root of AVE should be higher than the inter-construct correlations, this requirement is met, suggesting discriminant validity. Refer to table 6 to compare correlations and the square roots of AVE scores.

Table 3 Cronbach's Alpha scores for variables

Variable	*Abbreviation*	*Cronbach's alpha*	*AVE*
Use of business analytics	BA1	.878	.571
	BA2	.862	.559
Data driven environment	DDE	.914	.574
Data driven decision making	DDM	.869	.460
Sensing	SEN	.958	.799
Responding	RES	.949	.549
Agility alignment	ALI	.959	-
Environmental Dynamism	DYN	.901	.787

4.3.1.1 Factor analysis

The factor analysis was done using an oblique rotational approach as in this research it is reasonable to assume that the factor solutions might corelate to some extent. More specifically, the direct oblimin rotation is used. Two principle component factor analyses were done. First a factor analysis to explore whether the construct BA should be divided into multiple indicators. This is important because this indicator, as developed by Cao (2015) can be considered a formative construct (Cao et al., 2015; Petter, Straub, & Rai, 2007). The second factor analysis covers the discriminant validity of all indicators in the questionnaire.

4.3.1.1.1 Factor analysis 1

The first factor analysis explores whether the indicators of BA can be summarized into a smaller set of components. To determine whether the data is suitable for such a factor analysis. The factorability is assessed using Bartlett's test of sphericity, and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. Both are satisfactory as KMO is greater than .6 (.854) (Tabachnick & Fidell, 2007), and Bartlett's test of sphericity is significant ($p = .000$). The eigenvalues were assessed using Monte Carlo PCA for parallel analysis, this resulted in the extraction of two components. This two-component solution explained 64 % percent of the variance, with the first component explaining 48.5%, and the second 15.5%. Because the components extracted with an oblimin rotation are correlated (r = .381) the varimax rotation was not used.

The results from the factor analysis are shown in table 4. The factor loadings lower than .4 are not shown in this table. The discriminant validity is not completely satisfactory because of Optimisation, Predictive modelling, simulation, and data-and-text mining cross loadings that do not have a higher difference than 0.2 from the main loading.

These results can be compared to the findings of Cao (2015)ca. The first observation in this comparison is that the indicators that do not discriminate on a satisfying level in the current research are actually forming a third component in Cao (2015) (i.e. Optimisation, Predictive modelling, simulation, and data-and-text mining). Furthermore, in Cao (2015) statistical analysis, forecasting, query and analysis, and Business reporting/KPI's are referred to as 'commonly used BA'.

The two components are used as two constructs in the remaining part of the analysis in order to respect the formative nature of BA. BA1 will be computed as the mean of the indicators in component 1. BA2 will be computed as the mean of the indicators in component 2.

Table 4 Factor analysis 1

	Component 1	*Component 2*
Statistical analysis	**.865**	
Forecasting	**.786**	.43
Query and analysis	**.874**	
Business reporting/KPI's	**.716**	
Model management	**.763**	.517
Optimisation	**.532**	.379
Predictive modelling	.600	**.614**
Simulation	.579	**.681**
Data and text mining	.534	**.677**
Web analytics		**.819**
Social media analytics		**.862**
Text-audio-video analytics	.329	**.836**

4.3.1.1.2 Factor analysis 2

The second factor analysis is done to assess discriminant validity of all constructs used in the regression analyses. This was done using a PCA. The assumptions for PCA were met, KMO>.6 (.865) and Bartlett's test of sphericity significant (p = .000). Following Kaiser's criterion, the number of factors was determined by examining the eigenvalues (Pallant, 2013). The factor analysis was used to extract 8 components. This was done as following the theory the predicted number of variables would be 7, however following the previous factor analysis BA would be split up into two factors. Furthermore, 8 components could be extracted while remaining an eigenvalue above 1.

Table 5 shows the factor loadings using Oblimin rotation. As expected, some correlations between the components are found and therefore no orthogonal rotation was attempted. To keep the table shorter, the item labels are used in the first column. Appendix 1 shows the item labels with its corresponding indicators. In contrast to the previous factor analysis, the indicators for BA are now spread out over three components as opposed to two components. Also, three indicators for BA show cross loadings with a difference of below 0.2 suggesting low discriminant validity for these indicators. As the previous factor analysis showed that dividing BA into three components as opposed to two components would improve the eigenvalue of BA any better than a random set of data. Therefore, it was decided to keep the division of BA into two components. Furthermore, the indicators for agility alignment (ALI1r and ALI2r) do not load on a single component, the discriminant validity of agility alignment is therefore not satisfactory.

4.3.2 Reliability

Two commonly used tests for measuring the reliability of a scale are test-retest and internal consistency (Pallant, 2013). The test-retest method was not used for this research as it is difficult to expect respondents to fill in the same questionnaire twice. This absence, however, is considered acceptable as the scales had already been found to be reliable in previous research.

The internal consistency of the constructs was tested using the Cronbach's Alpha coefficient. As a rule of thumb, ideally a scale should have a Cronbach's alpha above .7, however a Cronbach's alpha above .8 is preferable (DeVellis, 2016). This indicates that the items of a scale 'hang together', i.e. they measure the same underlying construct.

The Cronbach's alpha values can be observed in table 3. All constructs have a Cronbach's alpha higher than the threshold of .8 which is set as a rule of thumb. This suggests good internal consistency reliability of the constructs. No indicators were found with a higher Alpha-if-item-deleted score, also suggesting good internal consistency reliability.

Table 5 Item loadings and cross-loadings

	BA1	*BA2*	*BA3*	*DDE*	*DDM*	*SEN*	*RES*	*DYN*
SA1	**.783**							
FC1	**.694**							
QA1	**.830**							
KPI1	**.837**							
MM1	**.525**	.340						
OPT1	.371	**.440**						
PM1		**.610**						
SIM1		**.631**						
DTM1			**-.481**					
WA1			**-.929**					
SM1			**-.903**					
TAV1		-.499	-**.547**					
DDE1				**-.835**				
DDE2				**-.781**				
DDE3				**-.633**				
DDE4				**-.767**				
DDM1					**.599**			
DDM2					**.725**			
DDM3					**.729**			
DDM4					**.651**			
SEN1						**-.943**		
SEN2						**-.948**		
SEN3						**-.894**		
SEN4						**-.780**		
RES1							**.589**	
RES2							**.718**	
RES3							**.644**	
RES4							**.891**	
RES5							**.746**	
RES6							**.928**	
RES7							**.690**	
RES8							**.651**	
ALI1r				.353			-.588	
ALI2r				.423			-.546	
DYN1								**.940**
DYN2								**.886**

4.4 Descriptive statistics and Correlations

The correlations and square roots of AVE scores of the variables used in the regression are presented in table 6. The descriptive statistics of the variables that are used in the regression analyses are presented in table 7. Multiple significant correlations are found in table 6. However, no conclusions can be made from these statistics.

Table 6 Correlations and AVE scores of variables used in the regression

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
1 AGE	-	-	-	-	-	-	-	-	
2 BA1	.126	**.756**	-	-	-	-	-	-	
3 BA2	.167	.583**	**.748**	**-**	-	-	-	-	
4 DDE	.107	.495**	.536**	**.757**	-	-	-	-	
5 DDM	-.052	.447**	.370**	.551**	**.678**	-	-	-	
6 SEN	.011	.384**	.469**	.524**	.668**	**.894**	-	-	
7 RES	-.089	.358**	.414**	.447**	.539**	.642**	**.740**	-	
8 DYN	-.186	.278*	.253*	.238*	.343**	.380**	.498**	**.887**	
9 ALI	.057	-.342**	-.397**	-.562	-.491**	-.528**	-.654**	-.326**	**-**
10 BPA	-.085	.390**	.436**	.537**	.660**	.850**	.864**	.524**	-.589**

Square roots of AVE scores expressed in bold

Examining the skewness score of the variables, table 7 shows that organizational age is highly skewed to the left of the mean, BA1 is moderately skewed to the right of the mean, BPA is moderately skewed left of the mean. The other variables are found to be approximately symmetric. The kurtosis score shows the peakedness of the variable, a positive score shows that the distribution is peaked with little values in the extremes. Scores below 0 show that the distribution is more equally distributed among scores.

Table 7 Descriptive statistics of variables used in the regression

Variable	*M*	*SD*	*N*	*Min.*	*Max.*	*Skewness* Statistic	*SE*	*Kurtosis* Statistic	*SE*
AGE	66.01	84.53	98	0	450	2.769	.244	8.664	.483
BA1	3.38	0.87	102	1.0	5.0	-.491	.239	-.126	.474
BA2	2.61	0.91	102	1.0	5.0	.213	.239	-.114	.474
DDE	2.76	1.09	96	1.0	5.0	.030	.246	-.868	.488
DDM	3.00	1.01	93	1.0	5.0	-.144	.250	-.570	.495
SEN	4.48	2.55	89	0.0	10.0	.094	.255	-.541	.506
RES	3.77	2.67	84	0.0	8.38	.131	.263	-.923	.520
ALI	2.79	1.23	83	1.0	5.0	.314	.263	-.896	.520
DYN	3.46	0.99	83	1.0	5.0	.121	.264	-.927	.523
BPA	2.713	1.90	84	.00	8.1	.603	.263	-.179	.520

*** Correlation is significant at the 0.01 level (2-tailed) *Correlation is significant at the 0.05 level (2-tailed), AVE scores are expressed in bold*

4.5 MANOVA on department types

As the unit of analysis is at the departmental level it is important to test whether the observed scores of the measured constructs statistically differed between department types. This is done with two multivariate analyses of variance (MANOVA). This test will indicate whether differences between groups are likely to have occurred by chance. The first test will compare BA1, BA2, data-driven decision-making (DDM), and data-driven environment (DDE) regarding department types. The second test will compare SEN and RES regarding department types. The assumptions for MANOVA were tested before conducting the analyses, these include: outliers, linearity, multicollinearity, normality, and homogeneity of variance-covariance matrices. Because of the relatively small sample size, Pillai's Trace will be used for the multivariate test of significance. The reason for this is that even though the sample size is sufficient, a larger one would be preferable. Pillai's Trace is considered more robust than the more commonly reported Wilk's Lambda in the case of small sample sizes or violated assumptions (Pallant, 2013).

4.5.1 MANOVA assumption tests

Outliers were checked using Mahalanobis distances, no cases exceeding the critical value were found, therefore the assumption was not violated. Linearity was checked by generating a matrix of scatterplots, these do not show violations of the assumption.

Correlations can be checked in table 6, the variables do not violate the assumption for multicollinearity. Considering the kurtosis statistics suggests that the normality assumption is violated for DDE, DDM, SEN, and RES. However, MANOVA is generally robust to violations of normality if they are not due to outliers (Pallant, 2013), and therefore it is not considered necessary to change the statistical test. The homogeneity of variance-covariance matrices is tested using Box's M test of equality of covariance matrices and shows no violations of the assumption.

4.5.2 MANOVA results

The first MANOVA includes dependent variables BA1, BA2, DDE, and DDM. No statistical difference was found between department types were found on the combined dependent variables: Pillai's Trace .330 (p = .346).

The second MANOVA includes the dependent variables SEN and RES. The test showed no statistical difference between department types on these variables: Pillai's Trace .138 (p = .665).

These results show that no evidence is found that the groups of department types differ with regard to the variables that will be tested in the regression models. Therefore, these regression analyses will be done without accounting for department type.

4.6 Regression models

To test the hypotheses two hierarchical multiple regression models are conducted. Multiple regression analysis makes assumptions about the input data. These assumptions are related to sample size, multicollinearity, outliers, and the distribution of scores. The results of the assumption tests are given before presenting the results of the regression models. The results of the regression models will be presented as follows: First, the regression model with dependent variable sensing ability will be presented. Second, the regression model with dependent variable responding ability will be presented.

4.6.1 Multiple regression assumptions test

The sample size is assessed with the commonly used rule of thumb of Tabachnick and Fidell (2007). This rule of thumb suggests that one should have a sample size of $N > 50+8m$ in which N is the number of cases and m is the number of independent variables. The regression models include at most 2 control variables and 2 independent variables, leading to a minimum N of 82. The number of respondents that completed the entire questionnaire is 83, therefore the sample size is satisfactory.

Multicollinearity occurs when multiple independent variables are highly correlated. This does not occur. For an overview of all correlations one can refer to table 6. Additionally, Variance inflation factors are checked, and no violations are found. Outliers are checked using Mahalanobis distances and are not encountered.

Furthermore, multiple regression analysis can be influenced by skewed distributions of scores. This is the case for the control variable Age (Skewness = 2.769). An investigation of the histogram plot shows that the scores are highly clustered to the left of the mean. Following this shape of the histogram plot and the work by (Pallant, 2013), it is decided to transform the variable such that it can be included in the analysis without violation of the assumptions. The transformed variable is computed as following: AgeT=LG10(AGE).

4.6.2 Multiple regression results

The hypotheses that were constructed as a result of a theoretical analysis are statistically tested using multiple regression. Hypothesis 2 and 3 are focused on sensing ability, BA, and a data-driven environment, whereas hypothesis 4 and 5 are focused on responding ability, BA, and data-driven decision-making. Two hierarchical multiple regression analyses are conducted, the first assesses hypotheses 2 and 3, and the second assesses hypotheses 4 and 5.

4.6.2.1 Multiple regression results on sensing ability

Table 8 shows the outcomes of the hierarchical regression analysis with sensing ability as the dependent variable. In model 1, only the control variables are entered. Only environmental dynamism has a significant effect on the dependent variable sensing ability. Examining the F score shows that the control model predicts the dependent variable significantly better as opposed to the null model ($F=6.359$, $p<.01$).

The independent variables BA1 and BA2, presenting the frequency with which the departments use BA, are entered into the regression. This leads to a significant change in explained variance ($\Delta F = 8.363$, $p < .01$). BA1 does not have a significant effect on sensing ability. However, as predicted in H2, the frequency of use of BA2 has a positive influence on sensing ability ($B = .968$ $p < .01$).

Table 8 Hierarchical regression analysis predicting scores of Sensing ability

Variable	*Model 1* B	*Model 2* B	*Model 3* B	*Model 4* B	*Model 5* B
Dynamism	.800** (.225)	.497* (.220)	.435* (.209)	.448* (.211)	.442* (.210)
Age	.148 (.564)	-.461 (.538)	-.549 (.510)	-.536 (.513)	-.587 (.517)
BA1		.396 (.362)	.138 (.353)	-.266 (.712)	.130 (.355)
BA2		.968** (.339)	.618 (.341)	.603 (.343)	1.052 (.811)
DDE			.819** (.267)	.242 (.923)	1.192 (.687)
BA1xDDE				.167 (.256)	
BA2xDDE					-.153 (.259)
R^2	.145	.309	.388	.392	.391
Adjusted R^2	.122	.271	.346	.341	.340
F	6.359**	8.144**	9.147**	7.633**	7.611**
ΔF	6.359**	8.636**	9.405**	.426	.348
ΔR^2	.145	.164	.08	.004	.003
N	89	89	89	89	89

*** Correlation is significant at the 0.01 level (2-tailed), * correlation is significant at the 0.05 level (2-tailed), standard error between brackets*

Model 3 checks whether the relationship between BA and sensing ability is affected by DDE. Adding DDE to the model leads to a significant change in variance explained ($\Delta F = 9.405$, $p < .01$). DDE has a direct significant effect on sensing ability (B = .819 $p < .01$). The findings in model 2 do not support H2 as in model 3 the addition of the variable DDE renders the coefficient of BA2 insignificant ($p = .074$). A possible scenario that explains this occurrence is that a data-driven environment mediates the effect of BA2 on sensing ability. This scenario is also suggested by Cao (2015). This first scenario is based on the ideas of Baron and Kenny (1986), who have argued that a variable M mediates a relationship between X and Y when the relationship between X and Y is reduced when M is added in the regression equation

Models 4 and 5 check for the possible interaction effect between DDE and BA. Neither of the interaction terms BA1xDDE nor BA2xDDE lead to a significant change in variance explained in the dependent variable, therefore H3 is not supported.

The largest significant model (model 3) explains 34.6% of the variance in sensing ability. This model therefore explains an additional 22.4% of variance in the dependent variable as opposed to the model including only the control variables.

4.6.2.2 Multiple regression results on responding ability

Table 9 shows the outcomes of the hierarchical regression analysis with responding ability as the dependent variable. Model 1 includes the control variables environmental dynamism and organizational age. The control model explains 22.8% of the variation in the dependent variable with an adjusted R^2 of .228 (R^2 =.248, F = 12.374, $p < .01$). Environmental dynamism has a significant positive effect on the dependent variable (B=.914 $p < .01$).

In Model 2 the variables for BA are added to the regression. BA1 has no significant predicting ability over the dependent variable. BA2 is found to have a positive significant effect on responding ability (B = .669 $p < .01$).

The variable for data-driven decision-making is added in model 3, this leads to an increase of variance explained of 8.6% over model 2, and 17.7% over the control model. Hypothesis 4 will be tested in model 3 as this is the largest significant model (ΔF = 11.620 $p < .01$). Even though it is reduced by the addition of DDM to the model, the positive direct effect of BA2 on responding ability remains significant (B = .544 $p <.05$). No effect of BA1 on responding ability is found and therefore H4 will be partially supported. That is, H4 is supported for those types of BA that are included in the construct BA2. H4 is not supported for those types of BA that are included in construct BA1.

Based on the regression coefficients, the same argument for mediation could be made for the variables BA2, DDM, and Responding. I.e. the relationship between BA2 and responding is reduced when DDM is added to the regression equation. Even though there is currently no theoretical foundation for this, the possibility will be explored in an additional analysis.

The models 4 and 5, which include the interaction terms of data-driven decision-making are not found to have a significant additional variance explained on the dependent variable, therefore H5 is not supported. The data from model 3 suggests however, that Data-driven decision-making has a direct effect on responding ability (B = .788 $p < .01$).

Table 9 Hierarchical regression analysis predicting scores of Responding ability

Variable	*Model 1* *B*	*Model 2* *B*	*Model 3* *B*	*Model 4* *B*	*Model 5* *B*
Dynamism	.914** (.188)	.695** (.189)	.561** (.181)	.564** (.182)	.559** (.183)
Age	-.080 (.470)	-.522 (.463)	-.427 (.433)	-.419 (.437)	-.559 (.183)
BA1		.316 (.311)	.026 (.303)	-.135 (.672)	.032 (.309)
BA2		.669** (.291)	.544* (.275)	.554* (.279)	.459 (.722)
DDM			.788** (.231)	.600 (.738)	.719 (.586)
BA1xDDM				.056 (.209)	
BA2xDDM					.029 (.223)
R^2	.248	.354	.444	.444	.444
Adjusted R^2	.228	.319	.405	.397	.397
F	12.374**	10.002**	11.489**	9.463**	9.447**
ΔF	12.374**	5.984**	11.620**	0.072	0.017
ΔR^2	.248	.106	.090	.001	.000
N	83	83	83	83	83

*** Correlation is significant at the 0.01 level (2-tailed), * correlation is significant at the 0.05 level (2-tailed), standard error between brackets*

4.7 Additional analyses

Quantitative research can be used to test hypotheses based on theoretical research. However, it can also be used in a more explorative way to reveal relationships, interpretations, or characteristics (Swanson & Holton, 2005). The explorative nature of quantitative research will be the basis of this paragraph.

During the testing of Hypotheses 2, 3, 4, and 5 an interesting finding was done: the effect of the variable BA2 on the dependent variable is reduced when the organizational variable (DDM or DDE) is added to the regression equation. This statistical occurrence is similar to what happens when testing a mediation model with the Baron and Kenny method (Baron & Kenny, 1986). The following two analyses will use the process macro for SPSS as designed by Hayes (2013) which allows testing for direct and indirect mediation effects using a bootstrapping technique.

The first additional analysis will test whether DDE mediates the relationship between BA2 and sensing ability. As control variables BA1, environmental dynamism, and organizational age are added to the model. Table 10 shows the effect of BA2 on DDE (a) is significant (B = .471, $p < .001$), and the effect of DDE on Sensing is also significant (B = .889, $p < .001$). The indirect effect of BA2 on Sensing ability through DDE is .4192 and found to be significant at a 95% confidence interval (CI) (.108, .8575). No significant direct effect of BA2 on Sensing is found. The outcomes of this mediation analysis are shown in figure 3.

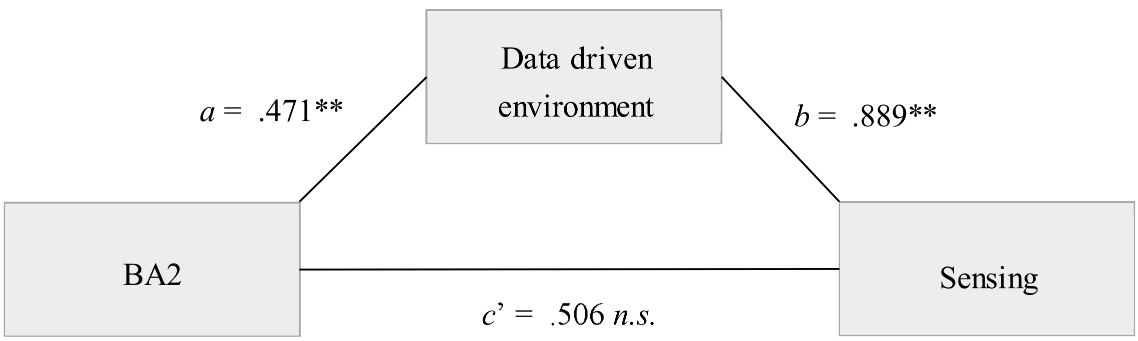
Table 10 Model coefficients for the mediation effect of DDE

		Consequent		
		M (DDE)		Y (Sen)
Antecedent		B		B
X (BA2)	*a*	.471** (.144)	c’	.506 (.349)
M (DDE)		-	b	.889** (.264)
BA1		.313 (.155)		.099 (.360)
DYN		.069 (.0912)		.5414* (.206)
Age		.083 (.216)		-.417 (.487)
		R^2= .3737		R^2= .4148
		F = 10.889, $p < .001$		F = 10.209, $p < .001$

*** Correlation is significant at the 0.01 level (2-tailed), * correlation is significant at the 0.05 level (2-tailed), standard error between brackets*

Testing whether DDM mediates the relationship between BA2 and responding ability, while controlling for the effects of BA1, environmental dynamism, and organizational age shows no significant indirect effects 95% CI (-.189, .396).

Figure 3 Statistical diagram of the mediating effect of DDE on BA2 and Sensing



5 DISCUSSION

This research aims to statistically analyse the possible relationship of the frequency of use of BA in day-to-day business process activities on BPA. Additionally, this research takes into account two organizational factors: the presence of a data-driven environment, and the extent of data-driven decision-making.
The constructs are measured at a departmental level. A MANOVA analysis showed that no significant statistical differences exist between department types with regard to their scores on the measured constructs. Theory has suggested that possible relationships with BPA should be examined by addressing both sensing and responding ability rather than assessing BPA as one construct. The results will therefore be discussed in separate sections: categorization of BA tools, sensing ability, and responding ability. Furthermore, a section will be devoted to discussing the creation of a single measurement for BPA.

5.1 Categorization of business analytics tools

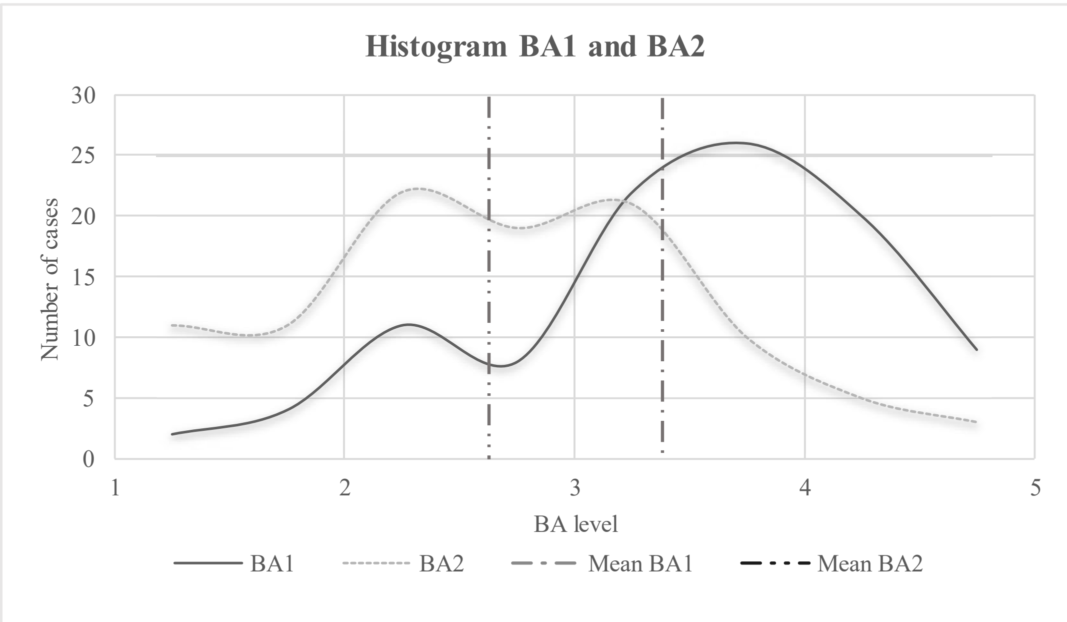
First, based on a factor analysis, the types of BA tools were divided into categories. These categories would indicate which tools are likely to be observed together as being frequently used within departments. This resulted in two categories, BA1 and BA2. The division of the BA tools is shown in table 11. The interpretation of the descriptive statistics of BA1 and BA2 shows that, on average, the tools in BA1 are used more frequently as opposed to those in BA2. Furthermore, the skewnesses of the scores indicate that BA1 is skewed to the right of its mean, and BA2 to the left of its mean. This skewness can be the result of a few extreme scores on one side of the mean. This suggests that the scores of BA1 and BA2 for the majority of the cases are further apart than the means would suggest. The histograms of BA1 and BA2 can be observed in figure 4.

When assessing the division of BA tools as provided by the factor analysis one might look at how the tools in BA1 differ from those in BA2. Even though the factor analysis was not conclusive on whether this is the only way in which the categorization of tools should be made, a speculative meaning could be given to both categories. For providing such meaning, one might look at the underlying techniques of the BA tools. With the exception of Web analytics, all tools in BA2 to some extent rely on machine-learning technology (Özköse, Arı, & Gencer, 2015). Machine-learning technology has been growing in use in the last decade (Laursen & Thorlund, 2016; Özköse et al., 2015), not in the least because of the increased accessibility and decreased cost of computing. On the contrary, the tools shown in BA1 have been around since the 1980's and 1990's (Applegate, Konsynski, & Nunamaker, 1986; Banker & Kauffman, 1991). Following this distinction, it is not surprising to see that the tools in BA2 have not (yet) been included in day-to-day activities as much as the tools in BA1. This distinction also has an implication for the scope of the tools. That is, machine learning tools allow organizations to not only analyse structured data from within the organization, but also larger datasets with unstructured data from outside the organization (Mortenson et al., 2015). This outward focus also explains why the non-machine-learning tool Web analytics is included in this category. Web analytics have a strong customer focus (Waisberg & Kaushik, 2009), and therefore might factor with the tools in BA2.

Table 11 Division of BA tools in BA1 and BA2

BA1	BA2
Statistical analysis	Predictive modelling
Forecasting	Simulation
Query and analysis	Data and text mining
Business reporting/KPI's	Web analytics
Model management	Social media analytics
Optimization	Text-audio-video analytics

Figure 4 Histogram of BA1 and BA2



5.2 Sensing ability

The first part of BPA that is discussed is a department's sensing ability. The results from the regression analysis on sensing ability suggest that, contrary to what was hypothesized, only a data-driven environment has a direct positive impact on sensing ability. The regression model does not find evidence for hypotheses 1 and 2. No evidence is found that either of the BA categories has a positive direct impact on sensing ability (H1). Furthermore, no evidence is found that a data-driven environment acts as a moderator on the relationship between BA and sensing ability (H2). In contrast, the regression results alongside a theory by Cao (2015) suggest the probability that a data-driven environment is acting as a mediator between BA and sensing ability. Further statistical analysis shows that the effect of BA2 on sensing ability is fully mediated by a data-driven environment. These statistical results however do not necessarily imply a time-ordered relationship (Tate, 2015). That is, mediation analysis cannot distinguish between simple correlates of the predictor variable, spurious mediators, and actual mediators (Tate, 2015). Research by Cao (2015) theorizes that the Data-driven environment is an actual mediator. This means, that the mechanism through which sensing ability is achieved is as follows: a more frequent use of BA2 predicts a more data-driven environment which in turn predicts a higher sensing ability.

A possible interpretation of this statistical mediation might come from the distinction made between the focus of BA1 and BA2. It is evident that the potential data to be captured outside of the organization is larger as opposed to inside the organization. Such data outside of the organization is likely to be less structured as opposed to data captured within the organization. Therefore, BA tools that are not limited to analysing structured data (BA2) can deliver a greater amount of data. Such volume of data might drive an organization to create a data-driven environment in order to cope with, and regulate, this potential of data collection. This data-driven environment in turn allows a department to more easily and quickly sense opportunities and threats in its environment.

Perceiving this reasoning in line with the information systems triangle (Pearlson & Saunders, 2010) as shown in chapter 2, one can identify the complexity of data created by using BA2 as an unintentional consequence of IT. An organizational strategy measure is created to cope with this unintentional consequence and comes in the form of a data-driven environment, which in turn influences business strategy, i.e. BPA.

From a more practical perspective, if an organization wishes to improve its sensing ability, it could do this by creating a more data-driven environment. This means that by having in place explicit strategy, policies, rules, and structure for BA activities together with a performance-based investment for BA tools an organization will be enabled to more easily and quickly sense opportunities and threats in the environment. An environment which might be enabled by the frequent use of BA2.

5.3 Responding ability

The second part of the regression analysis addresses the second part of BPA: responding ability. Following previous literature on BPA and BA, two hypotheses were constructed: more frequent use of BA has a positive effect on responding ability (H3), and this positive effect is moderated by the level of data-driven decision-making in the department (H4). In this analysis the use of BA was also subdivided into BA1 and BA2.

Consistent with what was hypothesized, a positive direct effect of the frequency of use of BA2 in day-to-day business processes on a department's responding ability is found. No evidence is found however for such an effect regarding the tools described in BA1. Following these findings, hypothesis 3 can be only partly supported. That is, hypothesis 3 is supported for those tools that are divided into BA2, and it is rejected for those tools that are divided into BA1. Additionally, no moderating effect of data-driven decision-making on either of the BA constructs is found in the data. In contrast, data-driven decision-making is found to have a direct positive effect on a department's responding ability. This shows that the tools in BA2 provide benefits to responding ability independent of the level of data-driven decision-making in the organization.

The results from the regression analysis show similarities with a model of mediation, therefore a possible mediating role of data-driven decision-making on the relationship between BA2 and responding ability was tested. The analysis provided no evidence that this was the case.

Following the speculative meaning given to the distinction of BA1 and BA2, a possible explanation can be given for their different effects on responding ability. The speculative meaning here is that tools in BA2 have the ability to analyse unstructured data, which is mostly obtained from outside of the organization (Mortenson et al., 2015). Being able to analyse such data will provide information on factors in the environment, e.g. customers or competitors. Such information might be used in order to respond more quickly and easily. As the tools in BA1 are less capable of analysing unstructured data from outside the organization, these tools will not have an impact on responding ability.

These results can also be discussed from the perspective of the information systems triangle (Pearlson & Saunders, 2010). In this case the business strategy would be to achieve BPA, or more specifically responding ability at the business process level. This research shows that two factors influence this ability: the frequency of use of BA2 and the extent of data-driven decision-making, the former of which refers to an IT factor, the latter of which refers to an organizational factor. This research hypothesized an interaction between the IT factor and the organizational factor which was not supported, however it is clear that a culture of data-driven decision-making is interconnected with the abundance of data that is enabled by analytics (Davenport, Harris, De Long, & Jacobson, 2001; Sharma et al., 2014).

Practically, these results suggest that if a department wishes to improve its responding ability it can gear its efforts towards the more frequent use of tools as shown in BA2, as well as towards enabling more data-driven decision-making.

5.4 Creation of business process agility construct

An important feature of this research was to reassess the way in which BPA is measured. The commonly used conceptualization of BPA by Tallon (2008) only focuses on responding ability rather than both on responding and sensing ability. This conceptualization therefore is considered an incomplete one. In order to provide a more complete analysis in this research, the antecedents of BPA are measured by their independent effects on sensing and responding. Additional to measuring antecedents of BPA, a sidestep was made by addressing the way in which BPA should be measured in order to use it as a single construct. Such a single construct for BPA is useful when one wants to analyse BPA as an independent variable. Additional to sensing and responding ability, a complete measurement of BPA should include the alignment between sensing and responding ability (Sambamurthy et al. 2006). This research aimed to develop a construct for BPA that has all these features based on research by Sambamurthy et al. (2006). Therefore, a construct for agility alignment was created and a way of calculating BPA was explained. A factor analysis however, shows that the developed indicators for agility alignment do not discriminate well from the other constructs. Therefore, the goal to create a single complete construct for BPA is not considered satisfied. However, a start is made in the direction of the creation of such a construct as the constructs for sensing and responding ability were found to be reliable and valid.

6 CONCLUSION

This research quantitively addressed the research question: "To what extent does the frequency of use of BA in day-to-day activities influence BPA and to what extent is this relationship moderated by a data-driven environment and data-driven decision-making?". This research question was analysed at a departmental level. A synthesis of the research questions, hypotheses, and results can be found in table 12.

Based on a factor analysis, BA tools were divided into categories (BA1 and BA2), which can be seen in table 11. These categories were subsequently used to assess the hypotheses. The data suggests that the tools in BA1 are more frequently used in day-to-day activities as opposed to the tools in BA2. A speculative meaning is discussed for the two categories. Apart from one (Web analytics), all of the tools in BA2 are based on machine-learning technology, such tools are able to deal with unstructured data from outside the organization. This is in contrast with the tools described in BA1 which are characterized by a more inward focus.

The answer to the research question can be described as follows: No effects are discovered for BA1 on either sensing or responding ability. Therefore, no evidence is found that the frequency of use of BA1 in day-to-day activities influences BPA. The tools described in BA2, however, are found to have a direct positive impact on responding ability. Furthermore, BA2 impacts sensing through the mediation of a data-driven environment. Therefore, the frequency of use of BA2 in day-to-day activities positively influences BPA in two ways. First, BA2 directly influences responding. Second, BA2 positively influences a data driven environment, which in turn positively influences sensing ability. No moderation effect is found for either of the organizational constructs: data-driven environment or data-driven decision-making. However, a direct positive effect of data-driven decision-making on responding ability is suggested by the data.

This research contributes to theory in multiple ways. It starts to fill the scientific gap that exists with regard to the existence of empirical work on the combination of BA and BPA. Furthermore, it argues that the commonly used measurement for BPA is incomplete and it suggests a more complete measurement construct, this is done by measuring sensing and responding ability separately. Third, a suggestion is made for categorizing BA tools.

This work also provides managerial implications for departments that are aiming to become more agile in their business processes. The data suggests that the BA tools that are currently being used most frequently, are not the ones that contribute to BPA. Looking at the contribution to BPA, considerable untapped potential resides within the use of BA tools that are categorized in BA2. Furthermore, in their pursuit of BPA, departments should not solely focus on using BA technology, they should also devote their attention to the organizational aspects of BA. That is, they should focus both on creating a culture in which day-to-day decisions are driven by data. And, they should focus on enabling and facilitating BA activities from a top down perspective with a data-driven environment.

Agility has received considerable attention from both business practitioners as well as researchers. However, one has to reflect on the advantages of agility realistically. Whereas traditionally, organizations used to focus on long term goals, agility focuses on the sensing of, and the responding to, short term opportunities and threats. There, however, is a balance to be struck: whereas only focusing on a long-term strategy might lead an organization to become obsolete in turbulent environments, a focus solely on agility might lead an organization into losing track of its core business. A balance between long-term stability and short-term agility might therefore be worthwhile pursuing. A balance that might be achieved by having in place the proper BA tools as well as the proper management practices surrounding them.

Table 12 Overview of research questions, hypotheses, and results

Research questions	*Hypothesis*	*Result*
To what extent does the frequency of use of BA influence BPA?	**H1**: Greater use of BA at the business process level has a positive influence on sensing ability.	*Not Supported*
	H3: Greater use of BA at the business process level has a positive influence on responding ability.	*Partially Supported*
To what extent does a data-driven environment moderate the relationship between the frequency of use of BA, and BPA?	**H2**: The effect of BA on sensing is positively moderated by a data-driven environment.	*Not Supported*
To what extent does data-driven decision-making moderate the relationship between the frequency of use of BA, and BPA?	**H4**: The positive effect of BA on responding ability is positively moderated by the extent to which decision-making is data-driven.	*Not Supported*

6.1 Limitations

In order to put the findings of this research into perspective, this section will provide a set of limitations of this research.

First, after analysing the results of the questionnaire, some limitations and improvements of the instrument arose. Even though there were sufficient respondents active in other departments to do a MANOVA test, a large number of respondents are active in an IT department. This is mainly due to the nature of the population, which consisted of the client base of Quint. A dataset with respondents more equally distributed across department types will have positive effects on the external validity.

Second, as this research is of cross-sectional nature, it is not possible to generate cause-effect conclusions from the data. The causal relationships therefore are derived from literature. In order to create a stronger causal argument for this research, a longitudinal research should be conducted.

The third limitation builds on the second limitation. In an additional analysis, this research finds that Data-driven environment is a mediation variable. However, as this study is of cross sectional nature, this mediation finding does not give certainty on whether this variable is a spurious mediator, or an actual mediator. This research uses the research by Cao (2015) to suggest data-driven environment as an actual mediator. Cao's research however, is also of cross sectional nature, and therefore, this suggestion should be treated with caution.

Fourth, this research aims to predict BPA by assessing possible antecedents of BPA within departments. It is not clear however, whether BPA predictors solely exist *within* a department. That is, in the case of a business process that goes across several departments, the BPA of a department might be dependent on the BPA of another department. An example of such interdependencies exists at the organizational level. Sambamurthy (2003) introduces such interorganizational agility as partnering agility. The data that was collected for this research however is limited in that it can only be used to measure characteristics that exist within a certain department.

Fifth, even though the MANOVA showed that no statistical differences exist across different department types, this result has to be interpreted correctly. The data for this research was collected from different organizations, and it is not possible to determine whether multiple departments might come from a single organization (e.g. the sales department as well as the IT department of organization X responded to the research), or whether each responding department is part of a unique organization. Therefore, the MANOVA is limited to showing that department types as groups do not differ from each other. The MANOVA in this research cannot provide insight into the differences of departments within organizations.

Sixth, this research uses two multiple regression analyses to measure sensing and responding as dependent variables. This leads to easily interpretable results, however it does not allow the measurement of possible relation between sensing and responding ability.

6.2 Recommendations for future research

Rather than focusing at the influence of separate BA tools or techniques on BPA, this research categorized these tools into two categories. The reason for this is that no empirical evidence existed for the link between the use of BA and BPA. Before delving into the separate effects of individual tools, it is important to identify whether BA, as a group of tools, affect BPA. Now that a beginning has been made for empirical evidence that different types of BA have different effects on BPA, more specific research can be conducted to delve into these different effects.

Furthermore, it would be useful to further investigate the categorization of BA tools, stronger evidence for the categorization is needed and a more theoretically founded meaning must be given to these categories.

Building on the previous idea, a stronger construct of BA should be created. The frequency of use of BA was measured using one question for every BA technique. A possible way to validate this measurement might be by including a question measuring which tools are used, i.e. by asking for specific brands or tool names. In this way the researcher can validate whether these techniques are provided by the tools. This could be beneficial for the reliability of the construct as it would be measured in more than one way. In addition, this could allow the researcher to better assess the division of BA.

Furthermore, this research focused on a data-driven environment and data-driven decision-making. These organizational factors are measured on a high level. An interesting avenue for research would be to assess them into more detail. Research could assess how these organizational factors are put into practice as well as whether different types of these organizational practices yield different impacts on agility.

Another research possibility would be to investigate the topic of this research in a longitudinal design. This would shed light upon possible causal relationships between the concepts. Up to now, this causality can only be inferred from theory. Such longitudinal research would be particularly interesting to assess the mediation mechanism of the frequency of use of BA2, the presence of a data-driven environment, and sensing ability.

To conclude, an interesting avenue for future research would be to investigate the topics of this research at an organizational level rather than at the departmental level.

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8 APPENDIX

8.1 Constructs

Table 13 Constructs and indicators used in questionnaire

Constructs	*Indicators*	*References*
Business analytics	How often does your department apply these business analytics techniques in its day-to-day business processes? (SA1) Statistical analysis (FA1) Forecasting (QA1) Query and analysis (PM1) Predictive modelling (KPI1) Business reporting / KPIs/Dashboards (OPT1) Optimization (MM1) Model management (SIM1) Simulation and scenario development (DTM1) Data and text mining (WA1) Web analytics (SM1) Social media analytics (TAV1) Text, audio, video analytics	(Cao et al., 2015)
Data-driven environment	To what extent do you agree or disagree with the following statements? (DDE1) My department has an explicit strategy that guides business analytics activities (DDE2) My department has explicit policies and rules that guide business analytics activities (DDE3) My department has a well-defined structure that enables business analytics activities (DDE4) My department prioritises major business analytics investments by the expected impact on business performance	(Cao et al., 2015)
Data-driven decision-making	To what extent do you agree or disagree with the following statements?	(Cao et al., 2015)

	(DDM1) My department uses data-based insight for the creation of new services/products (DDM2) My department is open to new ideas that challenge current practice based on data-driven insight (DDM3) My department's workforce has the data to make decisions (DDM4) My department's workforce relies on data instead of on intuition for making decisions	
Sensing	To what extent do you agree that your department can easily perform the following actions at the business process level? (SEN1): My department can easily capture data/information on opportunities and threats (SEN2): My department can easily integrate data/information on opportunities and threats (SEN 3): My department can easily analyse data/information on opportunities and threats (SEN 4): My department can easily use insights gained from data/information on opportunities and threats	(Cao et al., 2015)
Responding	To what extent do you agree or disagree with the following statements? (RES1): My department can easily and quickly respond to changes in aggregate consumer demand (RES2): My department can easily and quickly customize a product or service to suit an individual customer (RES3): My department can easily and quickly respond to new product or service launches by competitors (RES4): My department can easily and quickly introduce new pricing schedules in response to changes in competitors' prices (RES5): My department can easily and quickly expand into new regional or international markets	(Tallon, 2008)

	(RES6): My department can easily and quickly change the variety of products/services available for sale (RES7): My department can easily and quickly adopt new technologies to produce better, faster and, cheaper products and services (RES8): My department can easily and quickly switch suppliers to avail of lower costs, better quality, or improved delivery times.	
Agility alignment	To what extent do you agree with the following statements? (ALI1) My department senses opportunities and threats in areas in which it can not respond (ALI2) My department senses types of opportunities and threats to which it can not respond	*Based on* (Overby et al., 2006)
Environmental dynamism	To what extent do you agree or disagree with the following statements? (DYN1) In my industry, there is considerable diversity in consumer buying habits (DYN2) In my industry, there is considerable diversity in the nature of competition (DYN3) In my industry, there is considerable diversity in product lines	(Y. Chen et al., 2014)
Controls	Control variables (EMP1) How many employees are currently employed at your organization? (nEMPdep) How many employees are currently employed in your department? (BUS1) Which option best represents the core-business of your organization? (DEP1) Which option best represents your department? (AGE1) How many years ago was your organization founded?	

8.2 Codebook

Table 14 Codebook

SPSS name	*Variable*	*Coding instructions*
Bus	Core-business	1 = Banking/Finance, 2 = Telecom, 3 = Retail, 4 = Manufacturing, 5 = Trading, 6 = Information Technology, 7 = Services, 8 = Logistics, 9 = Government, 10 = Healthcare, 0 = Other (please specify)
nemp	Number of employees in organization	1 = 1-50, 2 = 51-250, 3 = 251-1000, 4 = 1001 – 5000, 5 = Over 5000
Dep	Type of department	1 = Finance, 2 = HR, 3 = IT, 4 = Logistics, 5 = Marketing & Sales, 6 = Operations, 7 = Procurement, 8 = R&D, 0 = Other, please specify
nEMPdep	Number of employees in department	1 = 1-50, 2 = 51 – 250, 3 = 251-1000, 4 = 1001-3000, 5 = Over 3000
Age	Organizational age in years	

SA1 FC1 QA1 KPI1 MM1 OPT1 PM1 SIM1 DTM1 WA1 SM1 TAV1	Use of business analytics	1 = Never, 2 = almost never, 3 = Occasionally, 4 = Frequently, 5 = Continuously
DDE1 – DDE4	Data driven environment	1 = Strongly disagree, 5 = Strongly agree
DDM1 – DDM4	Data driven decision making	1 = Strongly disagree, 5 = Strongly agree
SEN1 – SEN4	Sensing	0 = Strongly disagree, 10 = Strongly agree
RES1 – RES8	Responding	0 = Strongly disagree, 10 = Strongly agree
ALI1 ALI2	Agility alignment	0 = Strongly disagree, 10 = Strongly agree
DYN1 – DYN3	Environmental Dynamism	1 = Strongly disagree, 5 = Strongly agree