MASTER'S THESIS

Toward an IoT Analytics capability framework for business value creation

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Toward an IoT Analytics capability framework for business value creation

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Abstract

Data Analytics capabilities and value creation have been an increasingly researched topic in the past years. Capabilities and value creation in specific domains such as IoT. However, have not been explored yet. Additionally, existing research explicitly calls for more empirical research on IoT and Analytics business value, including such IoT Analytics (IoTA) capabilities. With the aim of bridging that gap, this study develops a first conceptual framework of IoTA capabilities and business value typologies. First, a conceptual framework was developed through a systematic literature review of general Data Analytics capabilities and business value. Second, a multiple case study with nine case organizations and 16 participants was conducted, involving semi-structured interviews and a subsequent thematic data analysis. The analysis indicates that although DA capabilities are relevant for IoTA, new capabilities are needed to cope with unprecedented situations. When these unprecedented situations are overcome through the right IoTA capabilities at the right time, they may lead to both operational and strategic business value. Adding to existing scientific research, this research makes a first contribution toward a holistic IoTA capability framework for business value creation.

Key terms

Internet of Things, IoT, Analytics, Data Analytics, Capabilities, Business Value, Value Creation

Summary

The concept of Internet of Things has existed for many years now, providing organizations an opportunity to connect the physical world with the digital world. For many, it is the number one means of striving for operational excellence, as it can be embedded in critical business operations. Nevertheless, the value of IoT data and its consequent analytics remains often unclear, perhaps due to the continuously new and evolving IoT technologies.

Understandably, IoT has received much attention in technical papers. Management science perspectives, however, are largely missing. In contrast, Data Analytics in general has been researched frequently as a continuation of the well-researched Information Systems research stream. Based on this stream, Data Analytics (DA) research has focused their attention on capabilities and business value creation. Capabilities are the orchestration of resources by an organization to create abilities toward a specific goal. Consequently, this research stream could provide a strong base to research analytics in the IoT domain, which can be referred to as IoT Analytics (IoTA). To that end, this research aims to fill the IoT research gaps in management science, but also to answer the unclarities surrounding IoTA value creation.

The objective of this research is to explore IoTA capabilities and typologies of business value by building on existing Data Analytics capability and value creation research. A systematic literature review of relevant existing studies was conducted. This resulted in a conceptual framework based on DA capabilities and business value and served as a guide for the primary research.

Because of the exploratory nature of this study, a multiple case study design was chosen for the possibility to dive deeper into each case while aiming to replicate data between cases. The case study design further consisted of semi-structured interviews based on the DA capabilities identified in the conceptual framework. Although the goal was to study five cases with three participants each, this proved to be a challenge. To maintain the possibility for replication, nine case organizations were researched with a total of 16 participants. The collected data was then analyzed through a thematic content analysis involving the analysis of different levels of themes, which were partially based on the DA capabilities in the conceptual framework.

The results of the analysis show that the conceptual framework could be confirmed with several refinements. Namely, the high-level Technology, Organizational and Human capabilities, and the Operational and Strategic business value they create were relevant for IoTA. In the Technology sub-capabilities, a total of 13 capabilities were discovered, ranging from Data and Systems Integration to Data Science and Automation. The seven Organizational sub-capabilities found in the results included high-value capabilities such as Management Support and Vision, but also Change Management and Scalability and Planning. From a Human capabilities' perspective, four sub-capabilities were found, including Interdisciplinary Collaboration as well as Entrepreneurship and Innovation.

This study has contributed to existing research by taking the first step in closing the research gap through working toward an IoT Analytics capability framework for business value creation. Such capabilities could support organizations deal with the novelties and ambiguities often involved in IoTA endeavors. Despite a high degree of replication across cases, the results should be viewed critically. The relatively small number of participants per case do not allow broad generalization. To further confirm and refine the IoTA conceptual framework, additional qualitative and quantitative research is needed.

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1. Introduction

1.1. Background

Technological advancements in the past decade have made data and analytics one of the most promising investments for organizations. And with the coming of Internet of Things (IoT), new data applications have started to form, which require specific capabilities and bring new sources of business value. Despite research on Data Analytics (DA) capabilities, there is a shortage of agreement. Coincidentally, managerial perspectives on DA within the IoT domain are largely missing. This creates an opportunity to explore DA capabilities relevant to IoT and their business contribution.

The vision of IoT is to connect 'things' and processes using networks and services, combined with sensing technologies. Data collected from IoT devices are distinct from other sources of data, as they bring the physical world closer to users and organizations (Lu et al., 2018). Therefore, DA capabilities within the IoT domain should be explored and will be referred to as IoT Analytics, or IoTA in short.

The objective of this research is to discover capabilities specific to IoT Analytics and what types of business value they create. This provides both academics and practitioners with an IoTA value creation framework.

1.2. Exploration of the topic

Information Technology (IT) has become one of the main drivers of change in the 21st century, and data is now seen as a primary source of value. However, the extent of value created depends on the capabilities built with IT and organizational resources (Soto-Acosta & Meroño-Cerdan, 2008). Since the introduction of Decision Support Systems in the 1970s, organizations have tried to capture data to gain valuable insights for better decision-making. Extracting valuable information from data remains one of the top investment priorities, but is also among pressing management issues for Chief Information Officers (Kappelman et al., 2019).

Most DA terminology means different things to different people. This study adopts the understanding of Sharda et al. (2017) that DA is the process of developing insights generated from historical and real-time data through a combination of architectures, databases, tools, applications, and methodologies.

Both practitioners and scholars agree that DA can bring tremendous value. Academics have found that DA alone is unlikely to bring value, as resources have become increasingly commoditized. Business value, and specifically competitive advantage, is created through a unique blend of resources and capabilities (Bharadwaj, 2000; Cosic et al., 2015). Capabilities have become an important academic topic within Information Systems (IS) research, which are mainly based on the resource-based view (Barney, 1991). These two theories have been picked up by many streams of IT research, including DA (Ardito et al., 2019).

Nevertheless, Mikalef et al. (2018) recognize that research on Big Data Analytics (BDA) capabilities is scarce and differs in opinions. Although definitions for DA capabilities vary, many articles follow the premise that capabilities are an organization's competence or ability to orchestrate those resources for a specific purpose (Gupta & George, 2016; Wamba et al., 2017a). Consequently, the question ‘what capabilities do organizations need to succeed in data efforts?’ is among the most asked. Examples of capabilities include data integration, management or security (Cosic et al., 2015; Ramakrishnan et al., 2020).

DA is an important part of a paradigm shift, also known as the ‘next Industrial Revolution’. This shift is seen as the next revolution since the invention of computing, driven by various technological advancements. The Internet of Things (IoT) plays a significant role in driving this revolution, and can be described as a relationship between ‘things’, such as products or services, and people (Schwab, 2017). IoT devices with embedded sensors generate data previously not accessible and transmit it through networks to a central platform. Data is then used to discover and resolve business issues and opportunities, such as operational efficiencies and value-added services to customers (Lee & Lee, 2015).

Within the DA capabilities literature, IoT is considered a major source of data (Jha et al., 2020; Mikalef et al., 2018; Siow et al., 2018). What differentiates IoT from other sources, like enterprise systems or social media, is the interconnectedness of machines and the physical world. As a result, it is deeply engrained in critical and high-value processes.

The human, organizational, and technological needs of IoT and analytics are considerably more far-reaching than other DA applications. Siow et al. (2018) explain this in their research by identifying IoT as enabling cross-domain applications, including smart cities and smart transportation. Consequently, this research posits that IoTA capabilities are different and unique compared to general DA capabilities.

1.3. Problem statement

DA seems invaluable for many organizations, yet calls for more empirical research on the benefits of DA have only partially been fulfilled (Gupta & George, 2016; Mikalef et al., 2018; Van De Wetering et al., 2019). There is still a theoretical divide, and most studies only provide general perspectives of DA capabilities. This might not be indicative of specific DA applications, such as IoT. Moreover, much IoT research is technical, demanding a management focused study (Mittal et al., 2019; Piccarozzi et al., 2018).

Despite many studies on DA capabilities and IoT, the convergence of these two areas is still rare from a management perspective. Bordeleau et al. (2018) in particular emphasize the need for a business value framework for DA adapted to IoT applications. In addition, Lu et al. (2018) suggest that future IoT studies could examine essential capabilities. To date, no IoT Analytics capabilities have been identified, highlighting a gap to conceptualize a comprehensive overview of IoTA capabilities and business outcomes. Identifying these capabilities will create opportunities for flourishing IoT Analytics.

1.4. Research objective and questions

This work takes note of the research gap to systematically identify and categorize capabilities and value creation for IoTA. The objective is to introduce a theoretically grounded framework of IoTA capabilities and business value based on DA capability research, and empirically strengthen the framework through interviews.

The main research question (MRQ) serves as the guideline for the framework creation:

> ***MRQ: What IoT Analytics capabilities lead to the creation of what business value?***

To aid in the development of this study, the following sub-research questions (SRQs) are posed:

> *SRQ1: What DA capabilities can be found in the literature?*

> *SRQ2: What types of business value do DA capabilities create?*

> *SRQ3: How can DA capabilities and business value be integrated in a conceptual framework for IoTA?*

These questions are answered through a systematic literature review to build a conceptual framework from existing knowledge on DA capabilities. In the next phase, the conceptual framework is validated through the following two questions.

> *SRQ4: What capabilities are needed for IoT Analytics and how are they different from DA capabilities?*

The above question is answered through empirical research. Utilizing the DA conceptual framework, field research provides a deeper understanding of the DA capabilities relevant for IoTA, but also potentially new and specific capabilities to IoTA.

> *SRQ5: What are the most important IoT Analytics capabilities and what types of business value do they lead to?*

As IoTA is a young research theme, empirical research will provide the foremost source of information in understanding IoTA capabilities and business value typologies.

By answering the above questions, a framework is created of IoTA capabilities, considering their business value, which is rooted in literature and validated empirically.

1.5. Motivation and relevance

The research outcome should contribute to the understanding of capabilities in DA initiatives concerning IoT environments, helping both practitioners and researchers plan for their undertakings.

Executives must decide for strategic IT initiatives, which increasingly include IoTA. By clarifying how a combination of IoTA capabilities allows them to reach their goals and create business value, organizations can better understand where to invest efforts and resources, both on a strategic and operational level.

Scholars can take note of this IoTA framework, validate the framework by building hypotheses with further research. This work should inspire researchers to explore other DA domains to compare the different capabilities. IoT research can also use the framework for further exploration of IoT characteristics.

1.6. Main lines of approach

To build an initial set of capabilities and business outcomes, a literature review was carried out in which the most apparent DA capabilities were discovered. A theoretical framework was proposed from literature, which served as the building block for the empirical part of the study. Chapter three explains the methodological choices of the empirical study. Chapter four summarizes the main findings of the case studies, after which chapter five discusses the gathered information. This study ends with a conclusion and recommendations for both researchers and practitioners.

2. Theoretical framework

This chapter provides a theoretical background with an understanding of the theoretical foundations relevant to this study.

2.1. Research approach

The systematic review (SR) is taken as a research approach, providing a way to summarize relevant and available evidence in a structured and predefined method. Systematically reviewing literature is more reliable, as it allows other researchers to replicate the steps taken. Integrative SR's focus on generalization and quantitative research, while interpretive reviews focus primarily on qualitative research and developing theoretical structure (Dybå et al., 2007; Kitchenham & Charters, 2007). This SR adopts an interpretive approach, with the aim to conceptualize an IoTA framework from existing concepts.

As research on IoT in management science is sparse, and both IoT and IoTA capabilities have not been researched yet, the initial framework is based on DA capabilities. The goal of this literature review is to better understand the DA capabilities literature and answer the first three sub-research questions.

> *SRQ1: What DA capabilities can be found in the literature?*

> *SRQ2: What types of business value do DA capabilities create?*

> *SRQ3: How can DA capabilities and business value be integrated in a conceptual framework for IoTA?*

The review seeks to synthesize existing DA capabilities and what business value they achieve. This should render a first evidence-based taxonomy of IoTA capabilities, containing definitions and consequent business value.

First and foremost, this study adopts a protocol-driven search method. By utilizing a protocol, a higher degree of replicability and consistency can be provided (Lefebvre et al., 2013). As an extension, relevant papers are also found through following references citing a relevant article, also known as the snowball-method.

The key terms are derived from the research questions, namely Data Analytics and Capabilities. A preliminary search revealed that the most common terms in this field of study and practice are Business Intelligence, Business Analytics, Data Analytics, and Big Data (Ardito et al., 2019; Chen et al., 2012; Grover et al., 2018; Sharda et al., 2017). These are used to create a search string, which can be found in Appendix A. While developing the search protocol, inclusion and exclusion criteria were created and applied as filters (Appendix A).

The results were skimmed on title level for relevance, including the abstract if the relevance was unclear. Articles passing through this first stage were referenced in a citation manager and listed in a data extraction table. In the second stage, the introduction, conclusion, and where needed, the findings were read to screen against the inclusion and exclusion criteria, including quality criteria (Appendix B).

Besides the query results, relevant articles were identified in the preliminary reading. Additionally, using the snowball method, referred studies were also considered. Several articles meeting the criteria were included in the final selection.

The selected articles were again collected in multiple data extraction forms to extract relevant information. A content analysis aims to classify words and sentences within the relevant literature into smaller categories. Six phases of thematic analysis (Nowell et al. 2017) served as the main approach (Appendix A). Before starting, the introductions and conclusions were read again to become well acquainted with the collected data.

The full content of the selected journals was analyzed by open coding in the Atlas.ti application. The concept of a DA capability, its different construct orders, and business value formed the unit of analysis for coding. A coding manual can help justify codes and create clear evidence (Nowell et al., 2017). Subsequently, the code groups *Capabilities*, *Definitions,* and *Business Value* supported the initial coding process. Through this process, a first set of codes and groups were created with different hierarchies.

Themes can arise both deductively from the models, and inductively from raw text (Nowell et al., 2017). While creating the initial codes, they were compared and continuously adjusted to a higher abstraction level into themes and subthemes within the code groups. For this study, an inductive approach was used because the identified literature and their constructs were sufficiently clear. For example, from the preliminary research, it was expected that within the code group *Capabilities*, three themes could emerge: *Technology*, *Human*, and *Organizational*.

In phase four, the themes were further refined and checked for coherent patterns. Extracting codes and data into a form ensures the information is systematically collected, analyzed, and synthesized (Nowell et al., 2017). A final data extraction form was created from the codes, including important data points, such as themes, related constructs, definitions, and main findings per article.

At the synthesis stage, the identified themes were defined, their relationships discovered, and the data was further analyzed for developing a description of each theme. These descriptions formed the results of the literature review. Once the codes and themes had been scrutinized twice, the results and conclusions were reported (Appendix C).

2.2. Literature search results

The search query returned 786 results, of which the first 360 were screened on title and abstract. After the first 360 results, the articles became irrelevant, so the screening was stopped. The screening resulted in a list of 29 articles which were fully read for final eligibility. Eight articles were found irrelevant based on the inclusion, exclusion, and quality criteria (Appendix A).

Next to the 21 articles that remained, five articles from the preliminary phase were included through the snowball method. The final number of studies included in the literature review amounted to 26. Appendix A provides an overview of the search flow in each stage.

2.3. Literature review

This section synthesizes the literature through reviewing the 26 articles. The main goal is to understand what DA capability and business value constructs can be identified. It also searched for information about IoT to explore contextual relationships with DA.

2.3.1. DA capability constructs

The literature theorizes DA capabilities either as a one-dimensional construct or multiple capability dimensions with sub-capabilities (Appendix E). Exemplary to these differences are the views of Wang et al. (2019) and Fink et al. (2017). The former refers to five specific core capability constructs, for example a data interpretation capability, while the latter only identifies two core capabilities, operational and strategic.

The studies that show similarity conceptualize capabilities under three core constructs (Akter et al., 2016; Bordeleau et al., 2018; Wamba et al., 2017a). These include DA Technology Capabilities, DA Organizational Capabilities, and DA Human Capabilities, and contain sub-capabilities within them. These understandings are mainly based on the seminal works of Davenport et al. (2012) and others (Akter et al., 2016, p. 117). Since most literature uses these three capability classifications, they are adopted for this study, including a synthesis of their most frequently identified sub-capabilities.

Within the first of the core constructs, DA Technology Capabilities, four specific sub-capabilities are frequently mentioned, either explicitly or implicitly. These include Data Generation (Arunachalam et al., 2018; Grover et al., 2018), Data Management and Security (Akter et al., 2016; Arunachalam et al., 2018), Analytics (Jha et al., 2020; Popovič et al., 2018), and Data and Systems Integration (Arunachalam et al., 2018; Ramakrishnan et al., 2020).

DA Organizational Capabilities refer to the organizational and managerial setup and processes that enable all components to drive DA initiatives. Most studies argue these include all organizational capabilities, although some view them only in the context of technology. For this study, a holistic viewpoint is taken, and therefore the organizational view is adopted. This study embraces four sub-capabilities, including Planning and Investment of DA resources and capabilities, Process and Coordination of routinized activities, and Control to ensure commitment and utilization of resources (Akter et al., 2016; Mikalef et al., 2018). Many studies also refer to the importance of a Data-driven Culture capability, embracing evidence-based decision-making (Cosic et al., 2015).

Finally, DA Human Capabilities encapsulate all human skills and expertise concerning DA. This includes the sub-capability Technical Knowledge to set up and maintain DA infrastructure (Akter et al., 2016; Cosic et al., 2015). Business Knowledge is also important in understanding business problems and opportunities (Akter et al., 2016; Cosic et al., 2015). Relational Knowledge is essential in for example cross-functional collaboration (Akter et al., 2016; Cosic et al., 2015). Entrepreneurship and Innovation is seen as the ability to foster technological and business innovation in the organization (Cosic et al., 2015; Ramakrishnan et al., 2020).

2.3.2. DA capabilities and business value

The DA capabilities research focuses mostly on how DA capabilities lead to business value. From an exploratory perspective, it is more important to discover typologies of IoTA business value. There are few studies which include such business value typologies in their DA capability studies. Most literature follows Fink et al., (2017) and conceptualizes business value as operational and strategic. Operational business value includes benefits such as administrative decision-making and business process optimization, including cost-reduction and productivity enhancements. Business value from a strategic standpoint includes benefits such as meeting organizational objectives, competitive performance, and new business opportunities (Grover et al., 2018).

2.3.3. DA capabilities and IoT characteristics

Based on the results of the literature review, it seems there are no specific DA capabilities for IoT. Nevertheless, the IoT domain is regularly mentioned in literature as one of the technologies of Big Data which collects information from sensors and actuators (Ardito et al., 2019; Jha et al., 2020). Rialti et al. (2019) note that IoT can be one of the components of a BDA Infrastructure. Categorically, IoT is an enabler of data that can be used for many purposes, such as monitoring situations to preempt future problems (Grover et al., 2018), driving sustainable service performance (AlNuaimi et al., 2021), or more generally, convert the physical world into a virtual environment (Arunachalam et al., 2018) which can be analyzed.

2.3.4. Conclusion & framework

The literature does not reveal a single conclusive answer to the research questions. Different ideas have been explored and validated in the extant works of DA researchers. A few themes stand out, which support framing the theoretical framework for this study.

Perspectives differ on capabilities and their paths to business value. Overall, there is some agreement to the tridimensionality of capabilities, namely Technology, Human, and Management.

Based on the literature review, this study proposes a first set of general Data Analytics Capabilities with definitions, which can be found in Table 1.

Table 1: Conceptual Framework and Definitions - General Data Analytics Capabilities and Business Value

Category	Core Capability	General DA Sub-capability	Definition and understanding	References
General Data Analytics Capabilities	-	-	An organization's overall ability to assemble, integrate, and deploy its Data Analytics resources through a unique combination of Management, Technology, and Human Capabilities.	(Akter et al., 2016; Bordeleau et al., 2018; Gupta & George, 2016; Wamba et al., 2017a)
	Technology	-	The ability of the Data Analytics technology (e.g., applications, infrastructure, data, and networks) to enable staff to quickly develop, deploy, and support necessary system components.	(Akter et al., 2016; AlNuaimi et al., 2021; Bordeleau et al., 2018; Cosic et al., 2015; Grover et al., 2018; Işık et al., 2013b; Mikalef et al., 2018; Ramakrishnan et al., 2020; Rialti et al., 2019; Sun & Liu, 2020; Wamba et al., 2017a; Yasmin et al., 2020)
	Technology	Data Generation	The ability of organizations to seek, identify, create, and access data from heterogeneous data sources across organizational boundaries. This capability facilitates the availability data to an organization's disposal by establishing data sources, procedures, and policies to generate required data for decision-making.	(Arunachalam et al., 2018; Işık et al., 2013b; Vidgen et al., 2017)

	Technology	Data and Systems Integration	The ability to transform diverse types of data into a data format that can be read and analyzed by analytics platforms, so that data is consistent, visible, accessible and interoperable for analysis.	(Arunachalam et al., 2018; Cosic et al., 2015; Işık et al., 2013b; Jha et al., 2020; Ramakrishnan et al., 2020; Vidgen et al., 2017; Wang et al., 2019)
	Technology	Data Management and Security	The ability to manage data from different perspectives, such as data quality, flexibility, availability, and integrity, including the ability to ensure the data, networks, and systems are secure.	(Akter et al., 2016; Cosic et al., 2015; Ramakrishnan et al., 2020)
	Technology	Analytics	The ability to drive decisions and actions through the extensive use of data and different analytical techniques, based on the specific mechanisms used for analytics, thus addressing the various needs of users and other stakeholders.	(Arunachalam et al., 2018; Cosic et al., 2015; Grover et al., 2018; Jha et al., 2020; Popovič et al., 2018; Wang et al., 2018, 2019)
	Organizational	-	The ability to plan, invest, organize, and control all resources and capabilities in accordance with business needs and priorities through a thriving data-driven culture.	(Akter et al., 2016; AlNuaimi et al., 2021; Bordeleau et al., 2018; Cosic et al., 2015; Işık et al., 2013b; Jha et al., 2020; Mikalef et al., 2020; Popovič et al., 2018; Ramakrishnan et al., 2020; Rialti et al., 2019; Sun & Liu, 2020; Torres et al., 2018; Wamba et al., 2017a; Yasmin et al., 2020)
	Organizational	Planning and Investment	The ability to identify business opportunities, do cost-benefit analyses of Data Analytics initiatives, make investments, and determine how they can create business value.	(Akter et al., 2016; Cosic et al., 2015; Mikalef et al., 2018; Sun & Liu, 2020; Wamba et al., 2017a)
	Organizational	Process and Coordination	Represents a form of routine capability that structures the cross-functional synchronization of analytics activities across an organization and ensures processes are in place for each step in the project.	(Akter et al., 2016; Cosic et al., 2015; Ramakrishnan et al., 2020; Sun & Liu, 2020; Vidgen et al., 2017; Wamba et al., 2017a)
	Organizational	Control	The ability of controlling functions, which are performed by ensuring proper commitment and utilization of resources, either implicit or explicit through documentation, including budgets and human resources.	(Akter et al., 2016; Cosic et al., 2015; Rialti et al., 2019; Sun & Liu, 2020; Wamba et al., 2017a)
	Organizational	Data-driven Culture	The set of collective values, beliefs, norms and principles that embrace and guide an evidence-based and data-driven culture.	(Arunachalam et al., 2018; Cosic et al., 2015, 2015; Gupta & George, 2016; Mikalef et al., 2020; Ramakrishnan et al., 2020; Vidgen et al., 2017; Wang et al., 2019)
	Human	-	The relevant professional ability of all employees involved in Data Analytics (e.g., skills or knowledge) to undertake assigned tasks or generate new ideas.	(Akter et al., 2016; AlNuaimi et al., 2021; Bordeleau et al., 2018; Cosic et al., 2015; Grover et al., 2018; Jha et al., 2020; Mikalef et al., 2019a;

				Popovič et al., 2018; Rialti et al., 2019; Torres et al., 2018; Vidgen et al., 2017; Wamba et al., 2017a; Wang et al., 2018, 2019; Yasmin et al., 2020)
	Human	Technical Knowledge	The ability of technical knowledge elements, including operational systems, networks, statistics, programming languages, and database management systems.	(Akter et al., 2016; AlNuaimi et al., 2021; Cosic et al., 2015; Jha et al., 2020; Mikalef et al., 2020; Wamba et al., 2017a)
	Human	Business Knowledge	The ability to understand other business functions and the overall business environment. For example, analytics professionals can be nurtured to develop their feel for business issues and empathy for customers.	(Akter et al., 2016; Cosic et al., 2015; Rialti et al., 2019; Torres et al., 2018; Wamba et al., 2017a)
	Human	Relational Knowledge	The ability of analytics professionals to communicate and work with people from other business functions.	(Akter et al., 2016; Rialti et al., 2019; Wamba et al., 2017a)
	Human	Entrepreneurship and Innovation	The ability to mobilize and deploy Data Analytics functionalities to support innovation in the organization through infrastructure, culture and technological improvements.	(Cosic et al., 2015; Ramakrishnan et al., 2020)
Category	**Business Value Type**		**Definition/understanding**	**References**
General Data Analytics Business Value	Operational Business Value		Operational value represents improvements in for example the efficiency of business processes, including cost reduction and productivity enhancement.	(Bordeleau et al., 2018; Fink et al., 2017; Grover et al., 2018; Gupta & George, 2016; Mikalef et al., 2018; Popovič et al., 2018; Wang et al., 2018; Wang & Hajli, 2017; Yasmin et al., 2020)
	Strategic Business Value		Strategic value represents improvements in for example business transformation, corporate performance management, customer relations optimization, business activity monitoring. High-level outcomes also include positive financial or market performance.	(Bordeleau et al., 2018; Fink et al., 2017; Grover et al., 2018; Gupta & George, 2016; Mikalef et al., 2018; Wang et al., 2018; Wang & Hajli, 2017)

A conceptual framework (Figure 1) for general DA capabilities is proposed with core and sub-capabilities. When capabilities are operationalized, business value starts to form with a distinction between Operational and Strategic value.

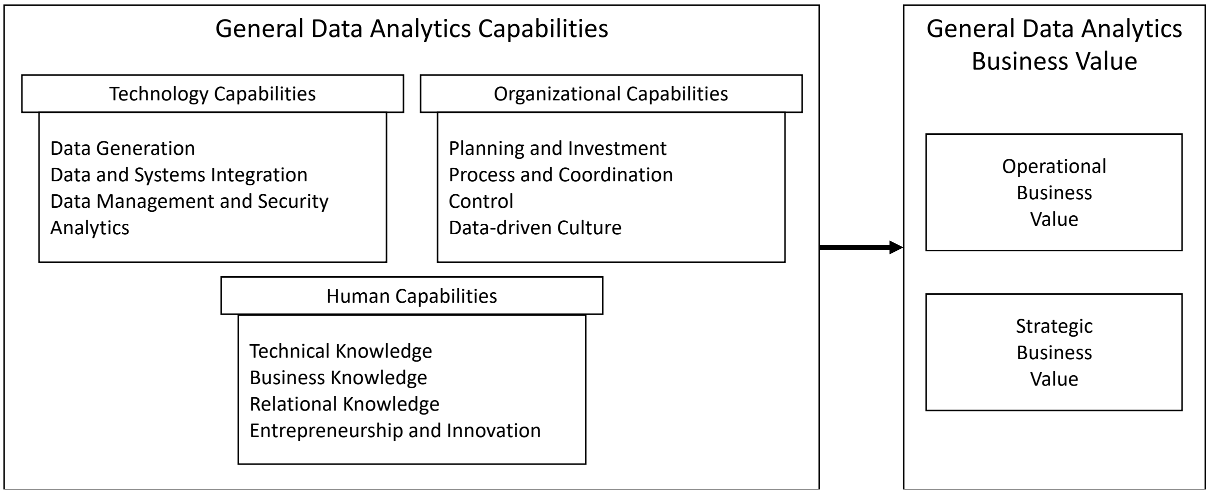

Figure 1: Conceptual Framework - General Data Analytics Capabilities and Business Value

2.4. Objective of the follow-up research

This study asserts that for DA concerning the IoT domain, specific capabilities are needed. From reviewing literature on DA capabilities, a set of synthesized capabilities were identified and classified (Table 1). As most included studies have a different focus and context, their relevance for the context of IoT should be evaluated in practice. In the follow-up research, an empirical study was conducted to evaluate their relevance for IoTA and dive deeper into specific IoTA capabilities. Subsequently, the types of business value could present itself differently, which was researched in more detail. The objective of the follow-up research was to explore this position and answer the last two research questions:

> *SRQ4: What capabilities are needed for IoT Analytics and how are they different from DA capabilities?*

> *SRQ5: What are the most important IoT Analytics capabilities and what types of business value do they lead to?*

The conceptual framework in Figure 1, including the definitions in Table 1, formed the basis for the design of the follow-up research. Through empirical research, the constructs were tested for validation and refinement. The aim was to arrive at specific typologies for IoT Analytics Capabilities and consequent business value.

3. Methodology

This chapter outlines how the empirical research is operationalized through presenting the methodological design.

3.1. Conceptual design

The research onion by Saunders et al. (2019) informs the high-level strategy of the empirical study phase. In the literature review, it became apparent that the frameworks built for capabilities are created from interpretive explanations of the way organizations extract value from DA. Therefore, the interpretive paradigm guided this research, in which organizations are seen as combinations of human meanings (Burrell & Morgan, 2017).

The design of the research should be guided by the nature of the research questions. Through asking what and how questions, this study attempts to learn more about the phenomenon of IoTA. These questions fit within an exploratory research purpose, which commonly adopts qualitative research design and has the objective to derive meaning from non-numeric data (Saunders et al., 2019).

An abductive approach is applied through proposing a framework based on extant literature, which is reiterated in subsequent stages. The iterative process of the Design Science Research Method (DSRM) approach (Hevner et al., 2004; Peffers et al., 2007) fits well into the iterative design of this study. The DSRM approach is relevant, as it has become rooted in the IS research stream, and because it is based on both behavioral theories and the technical design view of IT.

Peffers et al. (2007) detail the elements and steps of a DSRM, which are implemented for this study (Figure 2). The purpose of design science in IS research is "to create and evaluate IT artifacts intended to solve identified organizational problems" (Hevner et al., 2004). This aligns with the researcher's pragmatist view, in which the conceptual framework should address the problem of a lack of insights in IoT Analytics and its value.

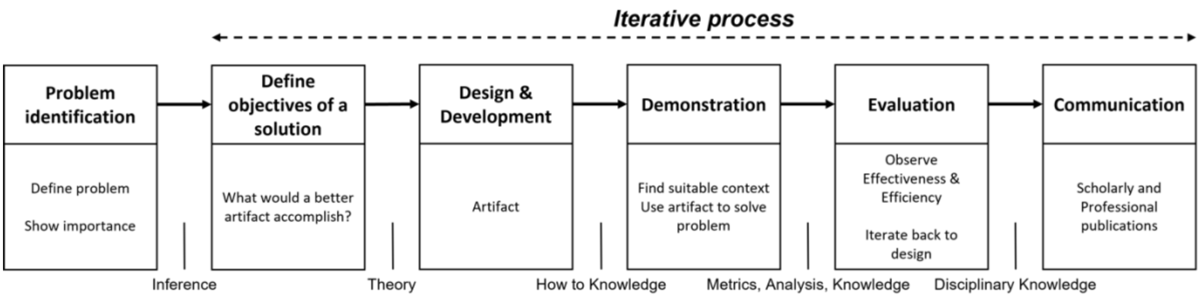

Figure 2: Design Science Research Method process (Peffers et al., 2007)

The first three activities are explained already, with an identified research problem of importance, research objectives, and an initial framework design. Artifacts refer to constructs, models, methods or instantiations (Hevner et al., 2004). Constructs are most suitable, as they are a means through which problems and solutions are defined (Hevner et al., 2004). As such, the proposed framework in the previous section includes artifacts in the form of capability and business value constructs.

The next step demonstrates the use of the artifacts. The strategies Action Research, Case Studies, and Grounded Theory have been evaluated. At first glance, Action Research seemed like a sensible choice due to its pragmatic nature. However, it would require significant resource investment and hinder data saturation from different organizations. The same applies to Grounded Theory, and it would inhibit drawing knowledge from existing research (Saunders et al., 2019). The most suitable strategy to gain in-depth insights into the unexplored phenomenon is therefore a case study, as it allows deep analyses of specific organizational level constructs (Yin, 2017).

3.2. Technical design

In this section, the technical design for the empirical phase is described. Figure 3 shows an overview of the design mapped on the DSRM process.

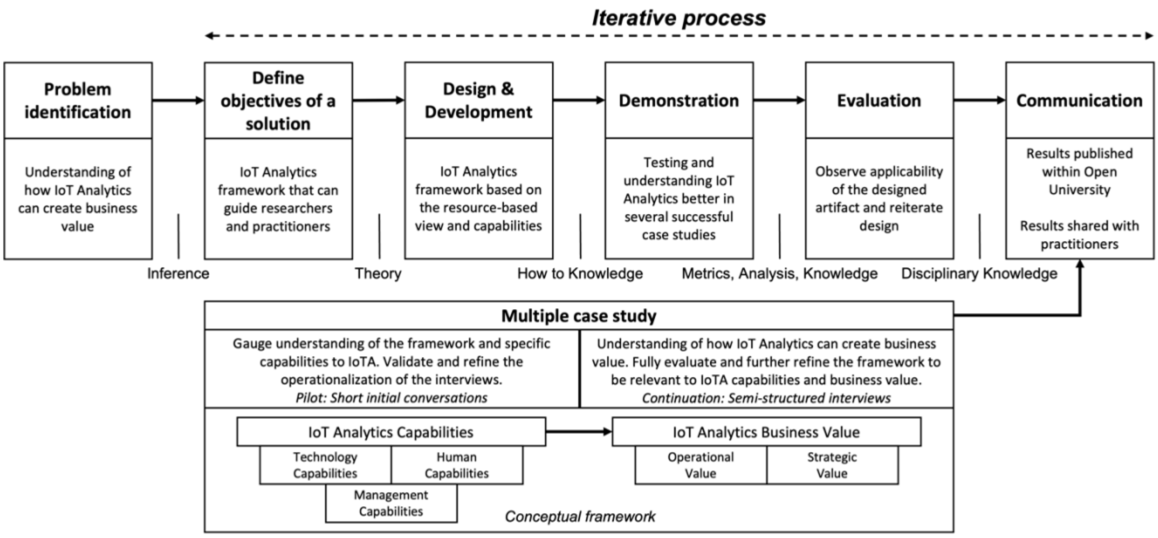

Figure 3: Specified DSRM process for this study

Qualitative studies typically adopt data collection techniques such as interviews or Delphi studies. Although a Delphi study and focus group interview have been considered, they would require significant time investment, which would inhibit the case study. Interviews are therefore considered the most appropriate data collection technique. Also because of their semi-structured nature guided by the conceptual framework, and the opportunity to dive deeper into specific constructs and typologies per participant and case. Instead of a pilot focus group, which would require significant time and resources, initial conversations are used as a pilot to improve the design of the in-depth inquiry within each case study.

3.2.1. Multiple case study

Further decisions needed to be made on the approach, the number of cases, unit of analysis, and replication technique (Saunders et al., 2019; Yin, 2017).

Structuring the case study and proceeding linearly is important to stay true to the objectives. As this study is clear in its objectives, an orthodox approach is taken in favor of an emergent case study approach that evolves during the research.

Contextual factors are the most important in case studies (Yin, 2017) and because these start to vary mainly from organization to organization, a single organization was seen as a case. The aim is to study multiple cases simultaneously to reach data saturation and replicate capabilities and business value across cases, concluding the final framework. The design choices are summarized below.

Table 2: Case study design choices (Yin, 2017)

Case study design options	Chosen design	Explanation
Case study approach	Orthodox case study	Focus and objectives are sufficiently clear. Structured approach ensures rigor.
Single/multiple case study	Multiple case study	Possibility for replication, stronger validation of findings and consequent framework
Unit of analysis	Holistic cases on organizational level	Fits best with the research questions and contextual variability that is largest at organizational level, for example industry and implicit ways of working.
Replication technique	Literal replication	Cases are purposefully chosen where similar results are predicted. I.e., cases with successful IoTA initiatives

3.2.2. Case selection and data collection

Before conducting interviews, the population needs to be defined. For this study, the population was defined as all organizations engaging in IoT Analytics initiatives. Only a sample was feasible to study, so a manageable size of 5 cases was aimed to be studied. To represent the population best, one case per domain was intended to be sampled.

The cases were selected through non-probability sampling according to an in-depth focus, which made the homogeneous purposive sampling technique most appropriate (Saunders et al., 2019, p. 316). An explanation and justification of the selection criteria is given below.

Table 3: Case and participant selection criteria

Subject	Topic	Criteria	Explanation and justification
Case organization	Domains	One case per domain (5)	Five domains have been identified by Siow et al. (2018) in their IoT Analytics survey (Appendix H). As IoTA is studied holistically, replication across domain cases allows for overall generalization of the results.
	Organization size	Large organizations >4000 employees	IoT Analytics is a relatively new topic, leading to the assumption that mainly large organizations have been able to successfully work on IoT Analytics. This also ensures enough relevant participants are available to interview.
	IoT Analytics success	At least one successful project	Each organization needs to have worked on at one successful project as part of the case. When multiple projects have been undertaken, they are seen as a holistic initiative.
Participants	Number of participants per case	Three participants per case	Three participants are likely to ensure triangulation and enough data saturation to occur. Depending on the saturation level and feasibility, this number can change.
	Expertise	High degree of expertise and experience with IoTA initiatives	A high level of understanding of IoTA is important in extracting all relevant information. Ideally, the three participants should have worked on the same IoTA initiatives, which helps reach data saturation, as the subject matter is the same.
	Job level	Highest level of responsibility within IoTA initiatives	Due to the limited number of participants and the holistic framework that includes full organizational capabilities, it is expected that the higher the job position, the more relevant information can be gathered from the participants. An example of job titles and responsibility can look like this: - Lead data engineer / scientist - IT manager - Enterprise Architect

As structured interviews would not allow further clarifications or exploration into certain topics it was not seen as appropriate. Using unstructured interviews, the conceptual framework could not have been validated. Semi-structured interviews fit this research best, as the structured part could be based on the identified capabilities and definitions.

An overview of the interview process can be found below, and a detailed overview of the interview protocol in Appendix L.

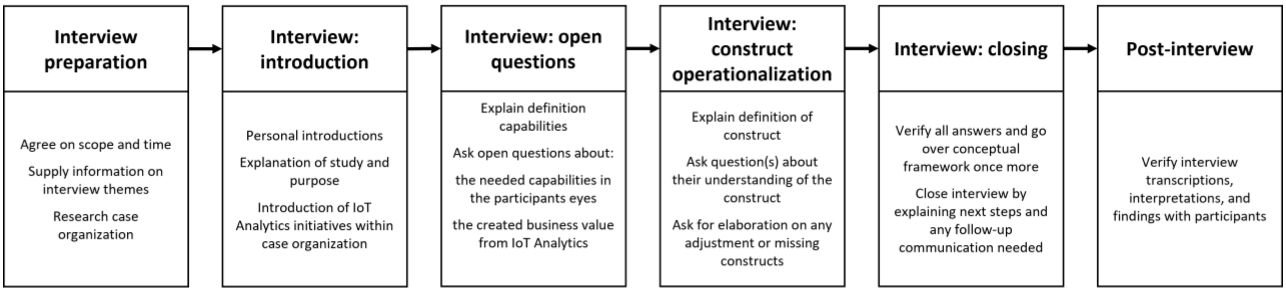

Figure 4: Interview process

3.3. Data analysis and evaluation

After the interviews were taken, they needed to be transcribed into text, analyzed, structured, and compared. Operationalizing the data analysis follows the same methodology as in the literature review, adapting the six phases of thematic analysis by Nowell et al. (2017). Pre-existing themes and codes from the conceptual framework served as initial themes. This, including themes and codes produced from skimming the transcripts, facilitated a coding framework (Appendix N). A coding framework helps identify interesting excerpts, cross-analysis of pre-existing themes, and fosters credibility and replicability (Nowell et al., 2017). Figure 5 below outlines the phases and steps taken.

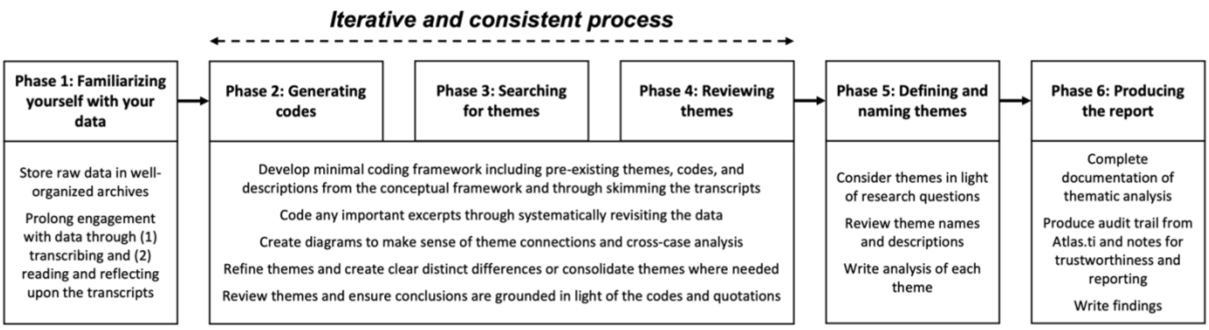

Figure 5: Thematic Analysis phases adopted from Nowell et al. (2017)

These phases are not sequential, but rather iterative yet consistent, along the principles of the DSR Method. Peffers et al. (2007) note that the DSR Method evaluation includes observing and measuring to what extent the artifact, in this research capabilities, provides a solution to the identified problem.

The evaluation phase in this study involved synthesizing the empirical evidence from each case independently and with each other. To maintain consistency and validity, the inclusion rule was that new capabilities could only be considered when they were present across more than half of the cases.

3.4. Research design reflection

Throughout all the design choices, it is important to account for the quality of this study. This section reports the quality implications according to three items (Saunders et al., 2019; Yin, 2017).

3.4.1. Reliability

The reliability of a research study is the extent to which the research results are consistent and give the same results under the same research procedure (Saunders et al., 2019). To minimize errors and biases in this study, the choices, procedures, and references were documented as far as possible. Despite this measure, there are limitations in the amount of detail that can be accounted for due to time constraints, and the interpretive nature of this study.

3.4.2. Validity

Construct validity refers to the correctness of operational measures. As this study's constructs are based on a literature review of DA capabilities, their validity is proven. It could however be that the constructs were not fully valid due to varying interpretations. To limit the subjectiveness, constructs were validated in the interviews and the transcripts were validated afterwards (Yin, 2017).

External validity refers to the generalizability of the study results and is one of the main obstacles of case studies (Yin, 2017). To limit the effect of this obstacle, cases have been purposively sampled to represent the population and the unit of analysis was specified as much as possible.

3.4.3. Ethical aspects

This study implemented a few measures to account for potential ethical issues. First, all participants were notified of this study's purpose and design. Second, all participants were asked for consent to record, transcribe, and analyze the interview's data. Participants could always withdraw from the research. Finally, all collected data has been anonymized to an agreed level and handled with confidentiality.

4. Results

This chapter presents the implementation of the empirical research, as well the results of the thematic data analysis.

4.1. Research implementation

4.1.1. Case and participant selection

During the case and participant selection, it became clear that achieving three participants per case would be a challenge due to the new and specific nature of IoTA. To maintain replicability, nine case organizations were included (Appendix M) with two participants per case, for except two cases which included one participant. Several cases below the assumed 4,000 employee-size matching the criteria were included. The included participants are at the forefront of IoT Analytics initiatives, with responsibilities for the IoTA platform, architecture, or analytics (Appendix M).

4.1.2. Interviews

The interview plan and protocol were successfully followed, with one deviation. To validate and iterate the protocol, pre-interview conversations with six organizations were held, followed by a pilot interview. To inform the participants before the interview, more information was provided through this site: https://sites.google.com/view/iot-analytics-research/.

4.1.3. Data analysis

The thematic analysis phases (Figure 5) were effectively followed to keep structure in the analysis. A coding framework (Appendix N) included a preliminary codebook with codes based on the conceptual framework and a reflection of the data analysis process. The inclusion rule designated in the methodology proved to be an effective measure to analyze the codes until a majority support was reached. All capabilities presented below were validated across more than half the cases, more specifically five out of nine cases.

4.2. Research findings

This section with research findings is structured following the research questions and includes results about the differences between general DA and IoTA, IoTA Capabilities, and Business Value. The participant answers per interview section are presented in a data extraction form in Appendix P.

Adjunct to the findings, a quantitative cross-case analysis with tables for the above-mentioned sections can be found in Appendix O, which includes the number of quotations per case and the groundedness per construct.

4.2.1. Differences between IoT Analytics and general Data Analytics

In this subsection, the major differences between general Data Analytics and IoT Analytics are laid out. It touches upon the initial position of this research that IoT Analytics require specific capabilities, and introduces an answer to the latter part of sub-research question four:

> *SRQ4: What capabilities are needed for IoT Analytics and how are they different from DA capabilities?*

The participants' answers were synthesized into several themes, as seen in Figure 6. The leading difference of IoTA compared to general DA, is the breadth of both technological and organizational requirements. IoTA development often requires unique resources, such as hardware devices, sensors, and gateways at a physical location, which usually touches upon critical business processes. This can create a distinct complexity challenge in IoTA initiatives, as ParAA noted.

Participants further referred to differences in the data with more of a real-time and timeliness element, alongside the enormous volume and diversity of data. This results in unprecedented challenges in scalability, data management and quality, analytics, and cost management. Besides challenges, IoTA offers many opportunities for organizations that have not been explored before, which adds to the innovative nature of IoTA. ParDA and others however note that IoTA does not necessarily bring more value than other DA applications.

Interviewees explained that not only from a technological perspective, IoTA has specific differences from general DA, but also organizationally. For example, the specific technologies and novelties that IoTA introduces require specific knowledge and multidisciplinary collaboration to interpret and work with IoT data. Many case organizations realized they had to shift their business units to be more integrated. And while IoTA requires an 'out-of-the-box' mindset, it involves many moving components, requiring organizations to think ahead about their envisioned business value outcomes.

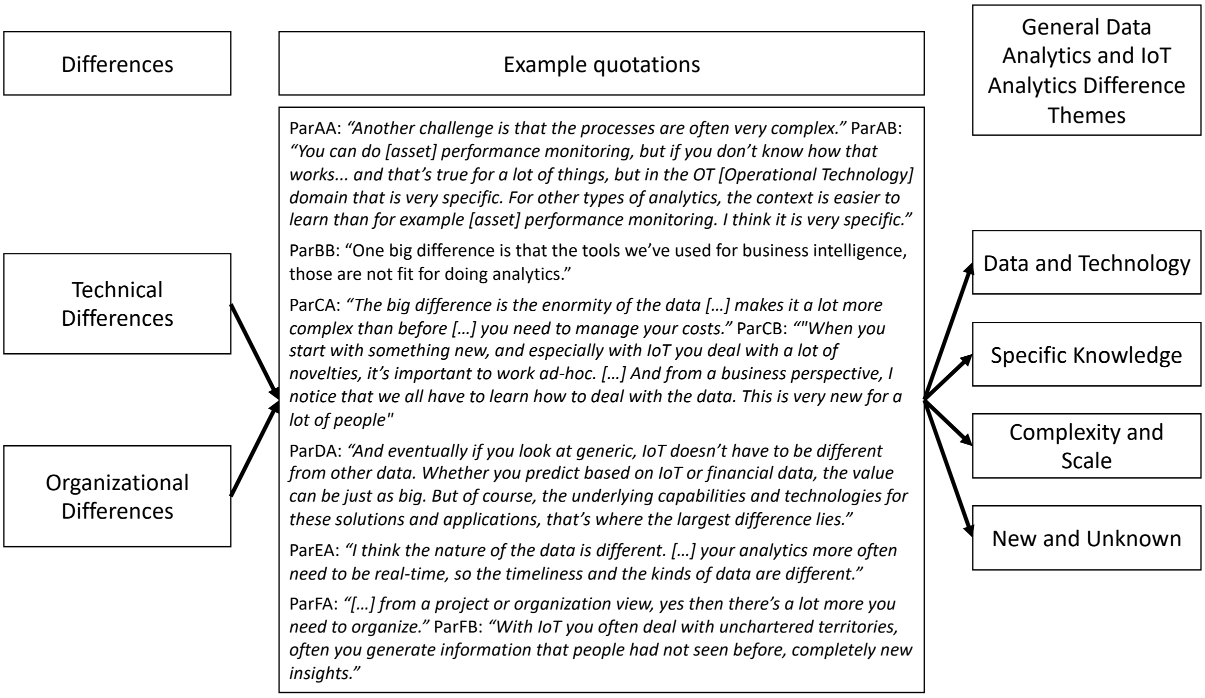

Figure 6: Findings – Differences between IoT Analytics and general Data Analytics

4.2.2. Capabilities

This subsection proceeds with the previous introductions to the findings and presents the analyzed capabilities, covering the first part of sub-research question four:

> *SRQ4: What capabilities are needed for IoT Analytics and how are they different from DA capabilities?*

The data analysis has demonstrated that all capability constructs meet the inclusion criteria and are sufficiently present in most cases. The results of the analyzed capabilities are presented one by one, according to the structure of the conceptual framework. Figures above the capability explanations guide the presentation of results. These show how the data analysis results compare to the general Data Analytics Capabilities in the conceptual framework. Example quotations represent a summary of the logic for the resultant IoT Analytics Capabilities.

Technology Capabilities

Technical challenges were most apparent, as presented in the previous subsection. This also holds true for the Technology Capabilities, with 13 different capabilities identified from the analysis. Two capabilities were directly valid, and two capabilities required more detailed capabilities. Additionally, six new capabilities are presented as per the data analysis and participant feedback.

Data Generation

Having a Data Generation capability was seen as important, because for many organizations, data had to be actively generated. This goes both for the IoT data itself, which needs to be generated in the physical world, but also labeled data that needs to be created by employees for data science. Furthermore, organizations had to deliberately decide what data needs to be generated for their IoTA, as the startup time is usually longer.

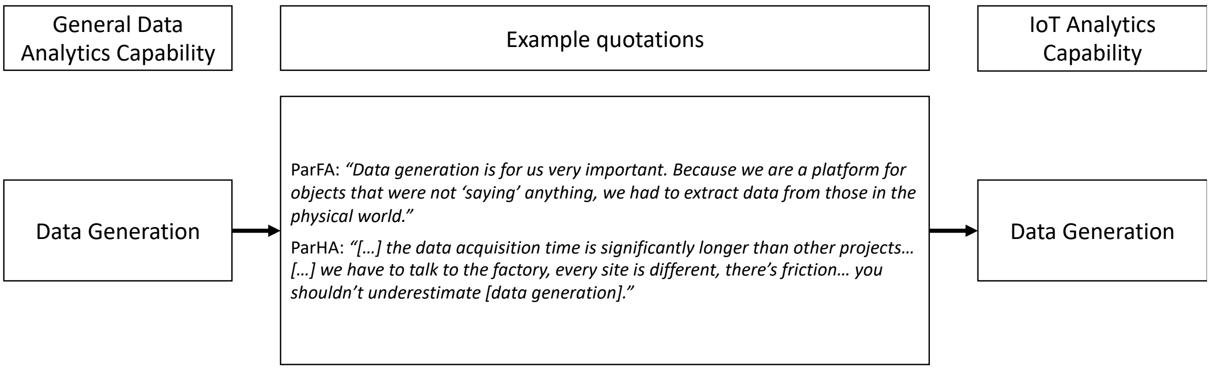

Figure 7: Findings - Data Generation

Data and Systems Integration

While IoT data alone can be useful and valuable, oftentimes it is necessary or useful to combine and integrate that data with other data and with different systems. In all cases, it was important to integrate context from other systems. It is hard, if not impossible, to interpret the data without this capability. Besides that, integrating with legacy Operational Technology was also part of this capability for OrgA, B, E, H and I.

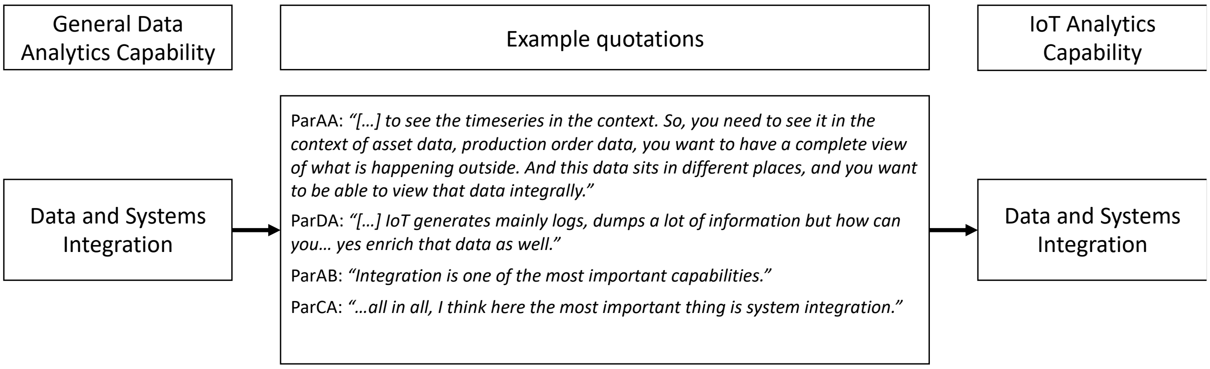

Figure 8: Findings Data and Systems Integration

Data Storage, Management and Governance

The interviewees mentioned that once data starts flowing from the edge into a central location, data needs to be stored, managed, and governed, potentially in different places and forms. Many participants particularly said this is where IoT differentiates itself with other data. Because there are enormous amounts of data that can be generated from many different systems and business processes, especially if one does that at full scale.

Not only does data need to be stored and managed for its purpose, but seeing IoT generates enormous amounts of data, one needs to pay close attention to the needed data structures. Data needs a governance structure to account for data quality, integrity, ownership, and sources.

Security and Compliance

Besides a dedicated security team, IoTA teams also need to think about and implement security. And while security is often seen as non-functional, the value of security shouldn't be underestimated either. At OrgE, their Security Capability even gained a competitive advantage, which was echoed by OrgB, C, F, and G. On the other hand, for OrgA, H, and I it was not seen as an IoTA capability.

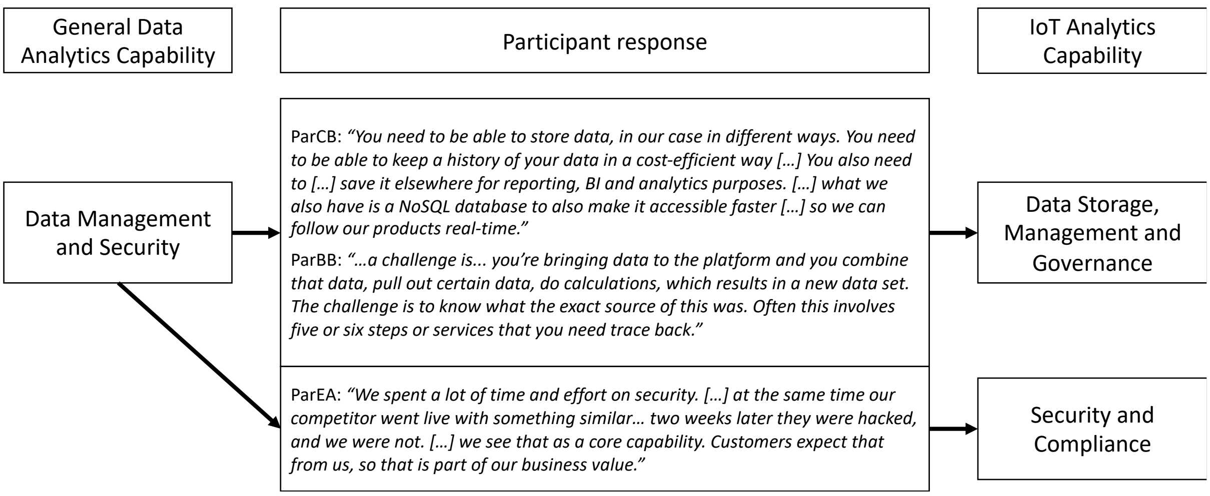

Figure 9: Findings – Data Storage, Management and Governance & Security and Compliance

Data Science and Automation

This capability was most often mentioned, as many organizations have a dedicated Data Science team to enable more advanced analytics, such as predictive and prescriptive analytics. Participants also made a distinction between Business Intelligence and Data Science capabilities, as they require different resources, skills and knowledge and generate different kinds of business value. At OrgE, this was also explained as real-time analytics, which requires machine learning models to make short-term predictions. Next to that, process automation was also mentioned in OrgA, B, C, D, I, and G. Multiple participants also commented that this capability does not necessarily drive the most business value.

<u>Business Intelligence</u>

Participants ParAA, ParBA, ParCB, ParEA, and ParFA clarified Business Intelligence, which includes more descriptive analytics, is the other half of the broader analytics capability. As part of this capability, dashboards and visualizations are an enabler to make data actionable, so that people can make decisions based on the data. Additionally, data visualization is used across all end-users, including data scientists, to better understand the data, before doing more advanced analytics.

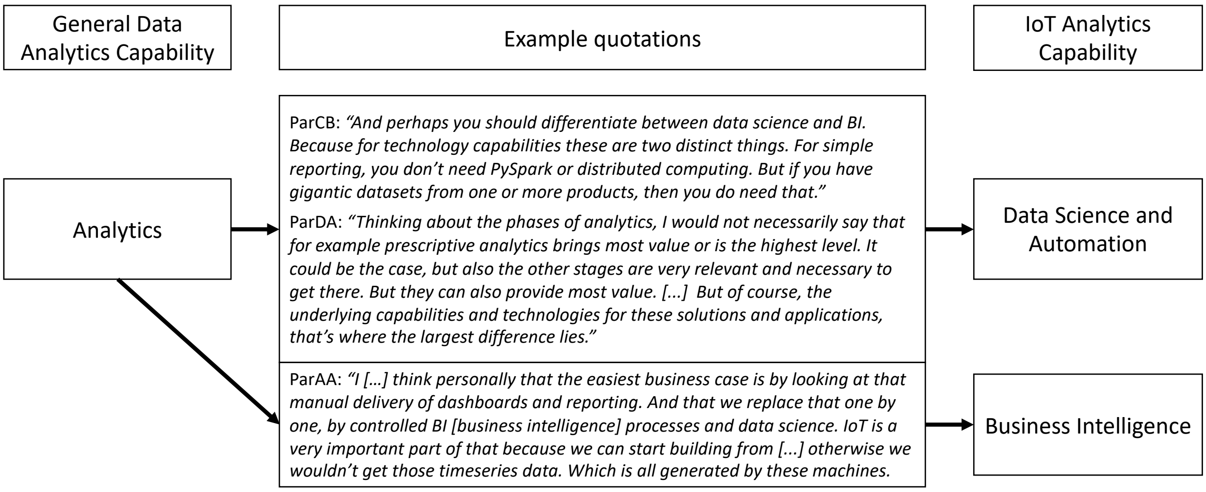

Figure 10: Findings - Data Science and Automation & Business Intelligence

<u>Platform Architecture and Design</u>

Most case organizations IoT Analytics built on a deliberately architected IoTA platform, mostly on cloud technologies, which has capabilities built in and makes it easier to get started. Being able to design and architect such a platform has been important for most case organizations to ensure that the solutions and use cases are robust and scalable. The value of a platform capability results in an abstract layer on which one can build different use cases, instead of a single purpose application that one builds or buys.

General Data Analytics Capability	Example quotations	IoT Analytics Capability
	ParEA: *"[…] you need to be able to strategize the roll out of IoT […] I think that's a very important element as well, that you do not build a single-purpose IoT solution. You build a capability or IoT chain, not for one solution or application."* ParCB: *"The largest initiative is undertaking all of this by yourself."* ParCA: *"I think here you need to make a really good system architecture to know what data you need and what do I need to send. So that's system architecture. Especially if you want to be able to communicate bidirectionally and you want to give commands."* ParFA: *"[…] thinking about [capabilities] that I miss here. You also need a capability to determine per use case which technological solution the correct one is. […] So you need a capability to determine what will be your solution design."*	→ Platform Architecture and Design

Figure 11: Findings - Platform Architecture and Design

Edge and Hardware Development

Many organizations have investigated a hardware development capability to enable an IoT environment. The decision must be made whether to buy or build this capability, which is more cost-efficient than off-the-shelf hardware, as ParAB explained. Whichever decision organizations make, all organizations must deal with the placement and management of hardware at the edge. This means organizations will need to have access to operational technology (OT), whether assets or products, to embed the IoT hardware into. They also need access to the physical locations of those technologies.

General Data Analytics Capability	Example quotations	IoT Analytics Capability
	ParFA: *"[…] we continue to develop robots, also new ones, new devices, new sensors, so that's ongoing work to generate and process that new or changing data. [...] we have […] a split between embedded engineering and data engineering."* ParAB: *"[…] we said, can we do that differently, and we approached a smaller party asking if they could develop a status notifier […] and are a tenth of the price [of off the shelf hardware] or something."* ParGB: *"Few IT people understand the hardware and the software that relates to that hardware, so you need that capability. So it's about going from bare metal to data."*	→ Edge and Hardware Development

Figure 12: Findings - Edge and Hardware Development

Connectivity

Besides developing hardware, Connectivity was mentioned many times as a unique capability to IoT Analytics. In other data analytics applications, this is not as important, already taken care of, or not a prerequisite at all. Participants say about the importance of connectivity that it is the basis of IoTA. Without it, the data can only stay on-premises. Developing network connectivity involves many considerations, including a buy or build decision again. For OrgD and potentially others, this includes machine to machine connectivity too, requiring multiple layers of connectivity.

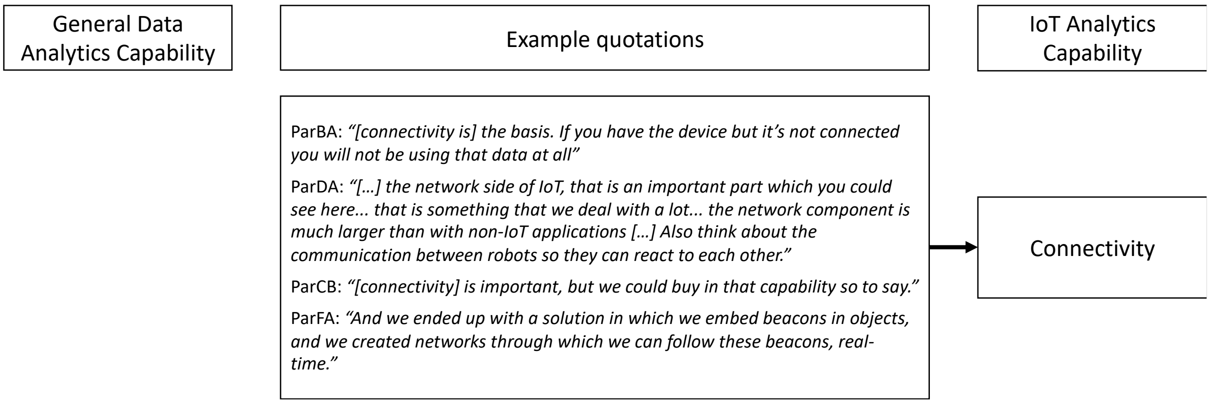

Figure 13: Findings - Connectivity

Software Development

Being capable of developing software was in many cases critical in IoTA. Several organizations, such as OrgF, built their IoTA platform from scratch, to ensure full control over the IoT platform. Participants broadly defined Software Development, as it can potentially include many targets, such as firmware on the hardware, API development, and application development.

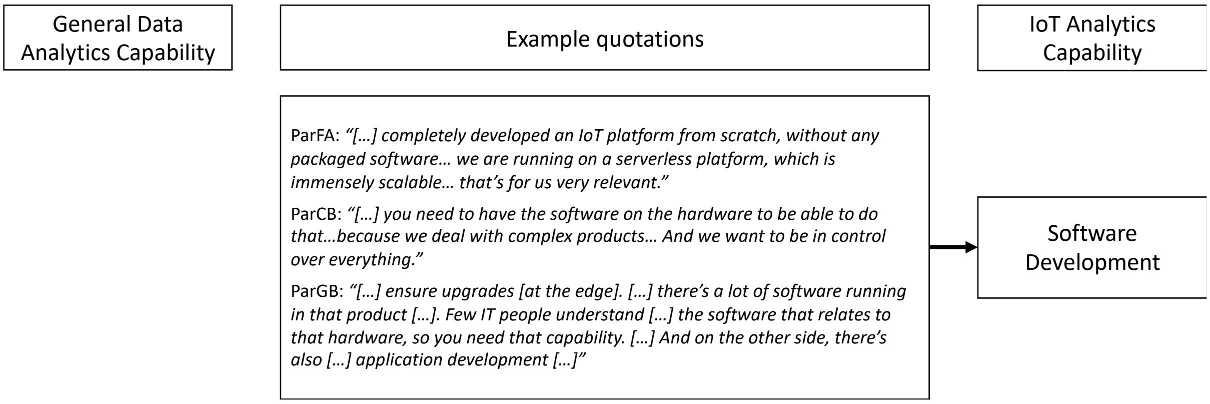

Figure 14: Findings - Software Development

Data Processing and Standardization

Respondents explained that IoT data comes with many features and formats, and that it’s crucial to process and standardize that data. Otherwise, one is not able to build comprehensive dashboards and correlate and analyze data across the IoT landscape. They also mentioned that this capability is more emphasized in IoTA due to the complexity of processes that IoT often touches upon.

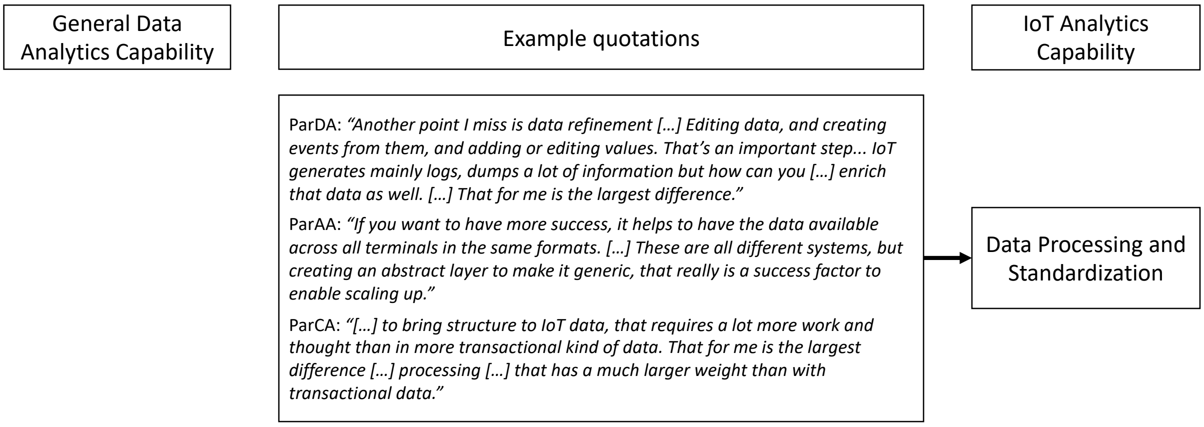

Figure 15: Findings - Data Processing and Standardization

Operational Maintenance and Monitoring

Most participants found that an Operational Maintenance and Monitoring is a necessary capability for IoTA. This is especially emphasized by ParDB and ParEA, who said the IoT platform and chain needs to be monitored, from hardware to connectivity to the data itself and delivery of data. ParFA added that monitoring the quality of service of IoT is also a major difference due to the physical environment that needs to be checked to ensure data validity and reliability.

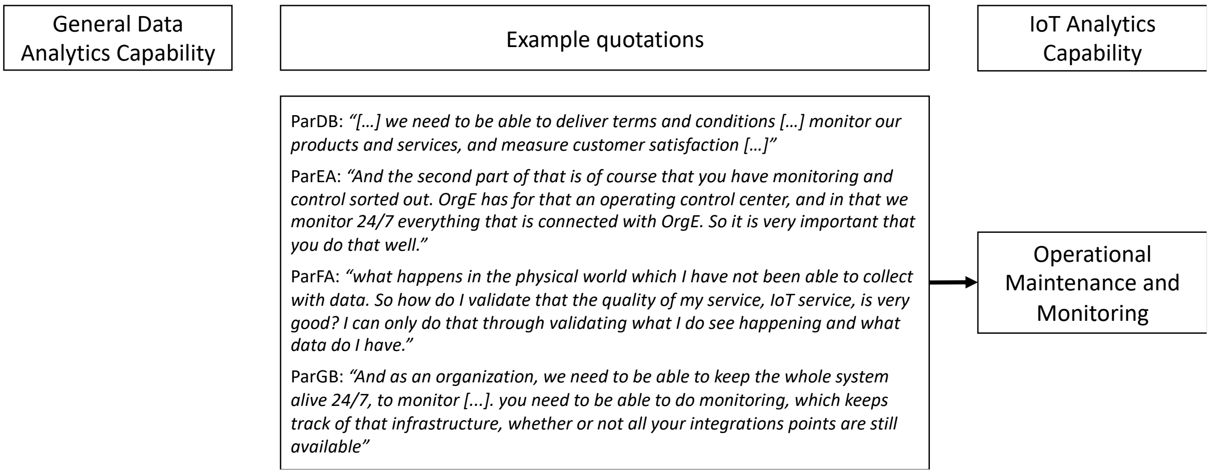

Figure 16: Findings - Operational Maintenance and Monitoring

Data Accessibility

As part of delivering value with IoT data, it needs to be accessible in the organization to the end-users and applications. Participants named various ways to Data Accessibility, such as API’s. What is most important is that it is easily accessible in the format and presentation that users expect.

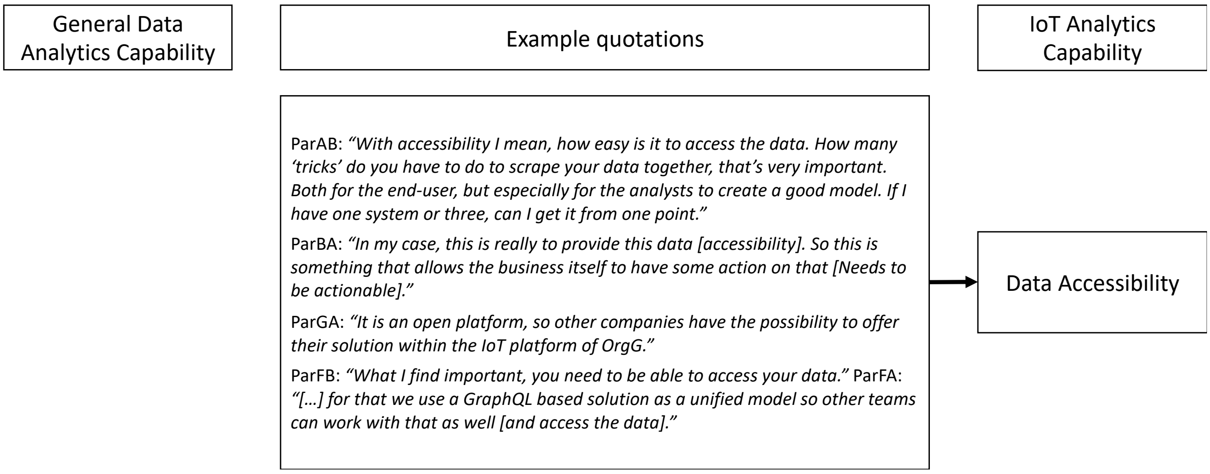

Figure 17: Findings - Data Accessibility

Organizational Capabilities

The results for Organizational Capabilities show that the conceptual framework DA capabilities are also applicable for IoTA. And in line with the IoTA themes communicated in section 4.2.1. Organizational Capabilities include several new capabilities. In total, seven Organizational Capabilities arising from the data analysis are presented below. There is one capability which needed a stronger distinction compared to the conceptual framework, creating two separate capabilities. One capability was merged, one capability renamed, and three new capabilities were found during the data analysis.

<u>Scalability and Planning</u>
While being agile, innovative, and entrepreneurial is critical for IoT Analytics, having a Scalability and Planning capability becomes especially important when scaling use cases across multiple processes, sites, or products. ParDB and others noted that abundance of opportunities is one of the challenges of IoT Analytics, necessitating a capability to plan, create a roadmap, and scale proven concepts. Participants’ answers are characterized by the fact that without planning there is no scaling, and without scaling there is less planning needed.

<u>Management Support and Vision</u>
In many cases, management support for IoTA was seen as a critical driving factor for success. Not only support was seen as important, but also a high-level vision from management. Such vision guides the technical with high-level goals to innovate against. Gaining investments directly correlates with the ability to develop successful concepts based on the trust and vision of top management.

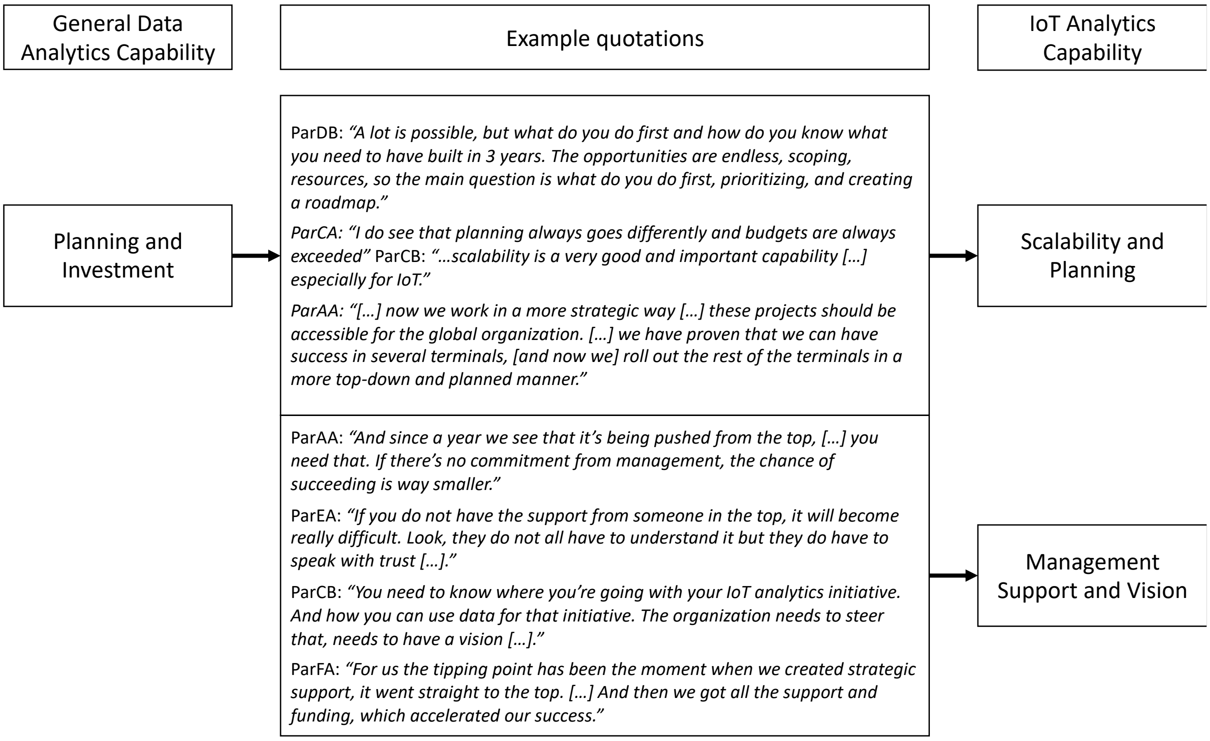

Figure 18: Findings - Scalability and Planning & Management Support and Vision

Process and Coordination

Because IoT Analytics is for many organizations a new initiative, there are many unknown paths organizations must venture into, as ParCB indicated. Therefore, working according to set processes is not desirable. Nevertheless, many organizations have found that an agile workflow works best, which includes a certain process while remaining flexible. ParAA introduced the idea that Process and Coordination and Control are one and the same capability, which was validated in the data analysis.

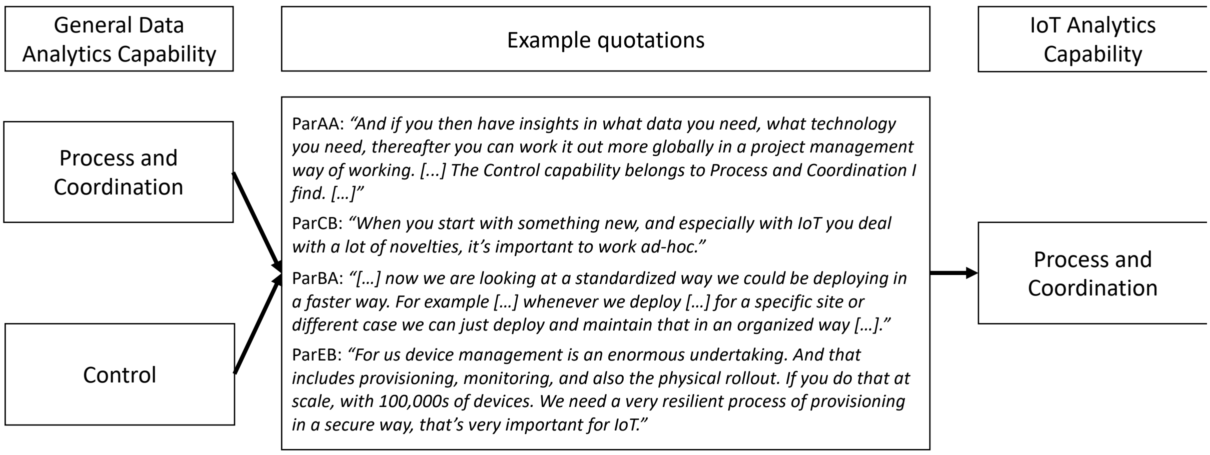

Figure 19: Findings - Process and Coordination

Change Management

One repeatedly mentioned challenge and capability is that IoTA needs to bring along the journey many people who might not be ready to innovate. To cope with these challenges, a Change Management capability is needed, which speeds up the path to value. While this capability was initially named data-driven culture, Change Management better reflects what organizations need to be capable of in this regard.

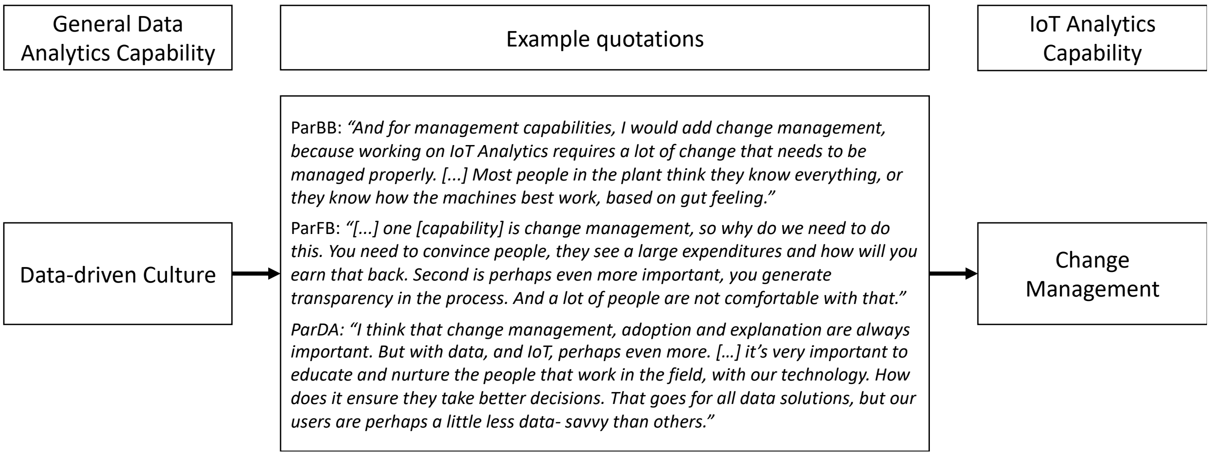

Figure 20: Findings - Change Management

Knowledge Management and Training

The interviews revealed that one of the most important capabilities for IoT Analytics is knowledge management. The possibilities and technologies of IoT Analytics have been growing significantly, making it a knowledge intensive venture that is very specific and new to many organizations. Attaining knowledge at the intersection of both Information Technology (IT) and Operational Technology (OT) is a challenge, several participants, such as ParBB, noticed.

And once that knowledge is attained, it is important to record, maintain, and share that within the organization. As a result, OrgE have already gained enormous value from recording and accumulating such organizational knowledge.

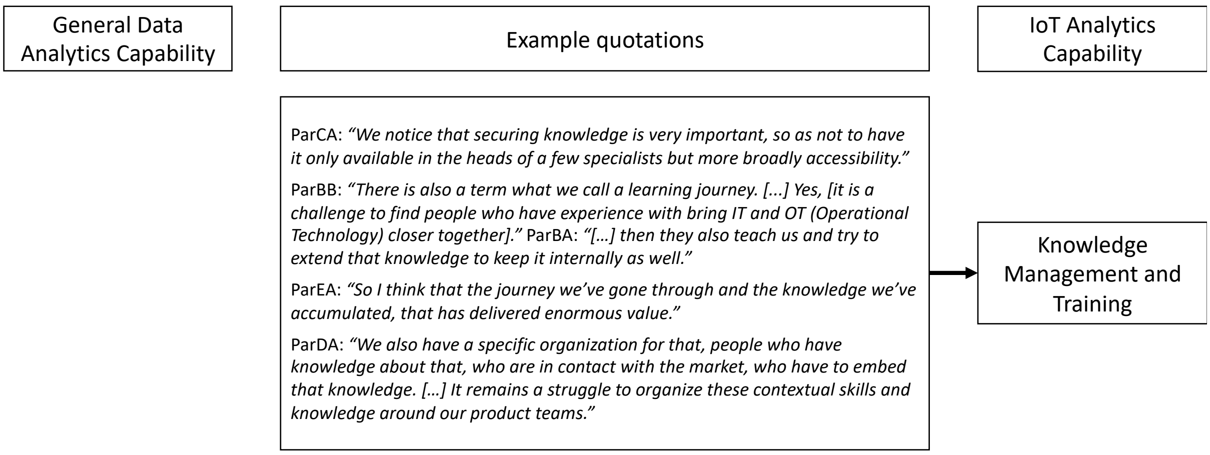

Figure 21: Findings - Knowledge Management and Training

Business and Ecosystem Synergy

One of the major challenges of IoT Analytics mentioned in the interviews is that it touches upon many business units. Organizations who want to undertake such projects realize they need to bring silos together, both internally and externally. And they might not be able to do everything themselves, demanding external synergy decisions. Both OrgE and OrgF explicitly expressed the importance of having a data science practice fully embedded into the business and processes. Other participants agreed with this and added that because IoT Analytics can become a critical part of businesses, they might want to decide to integrate these capabilities. For example, OrgA decided to directly invest in the synergy with their technology partner.

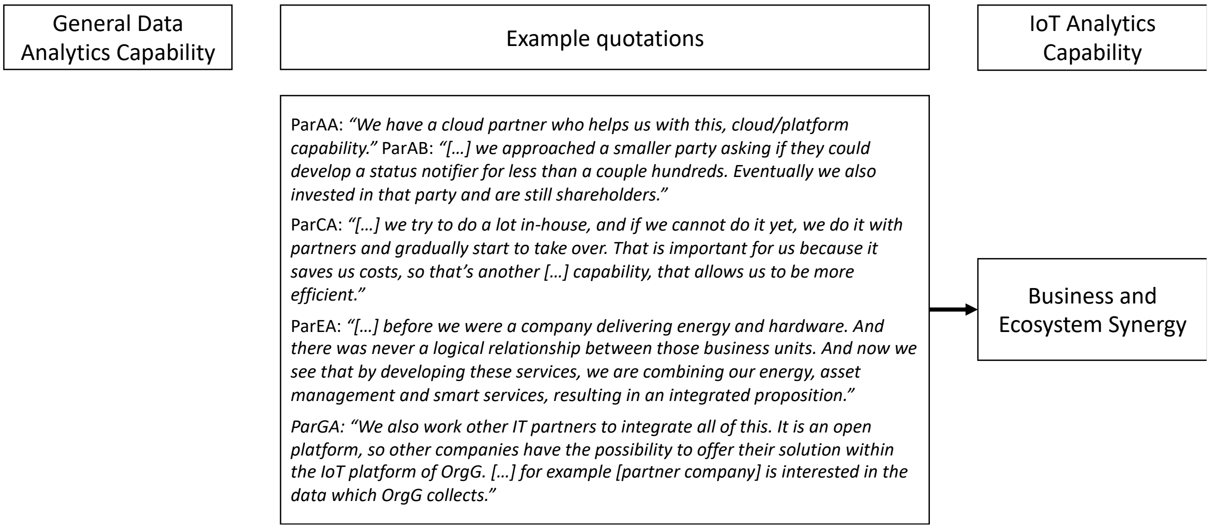

Figure 22: Findings - Business and Ecosystem Synergy

<u>Product and Service Development</u>

One of the main goals for IoTA is to productize the data and insights that are generated, resulting in a new business model and added revenue. For many organizations developing products and services centered around IoTA will be an important capability. However, such a capability is often new, as many case organizations have never been involved in productizing software or data. ParEA even went as far as saying it was the first capability they needed to build. ParDB further stated that the difference between IoT and other product development lies in its approach, which is another difference with the common ways of working.

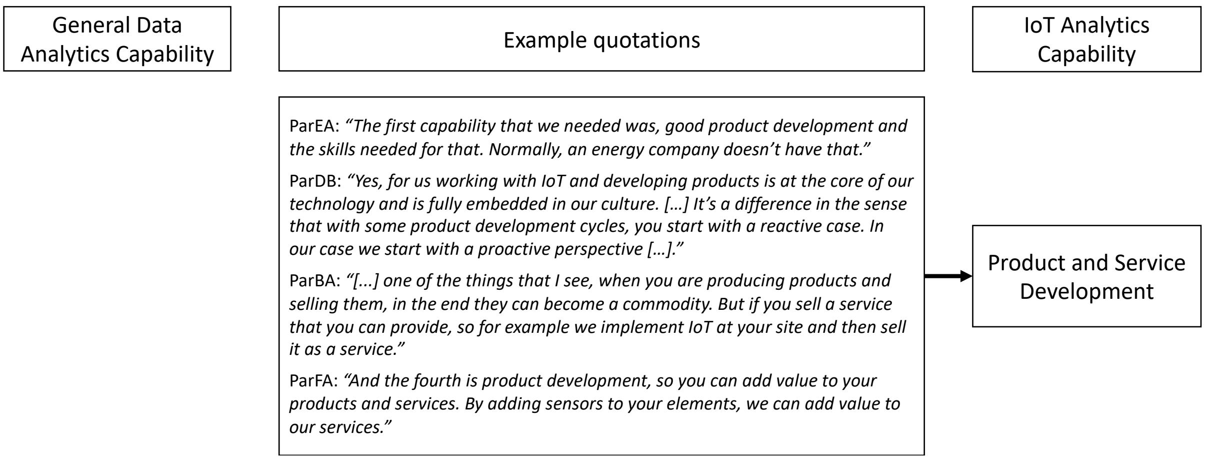

Figure 23: Findings - Product and Service Development

Human Capabilities

Knowledge was one of the themes that stood out in the results of section 4.2.1. and the importance should not be understated. The analysis has revealed that all four Human Capabilities in the conceptual framework apply to IoTA. Furthermore, two capability names were slightly altered, and one capability was fully renamed.

Technical Skills and Knowledge

IoTA projects to be highly technological by nature, and many participants found that this directly translates into a need for specialized technical knowledge. Findings show Strong Technical Skills and Knowledge also directly impact success. A distinction can be made between knowledge over Information Technology, such as cloud computing and specific data technologies, and knowledge of Operational Technology, such as industrial machines, equipment, and sensors. As ParGA put it, knowledge is required to go from "bare metal to data" and insights.

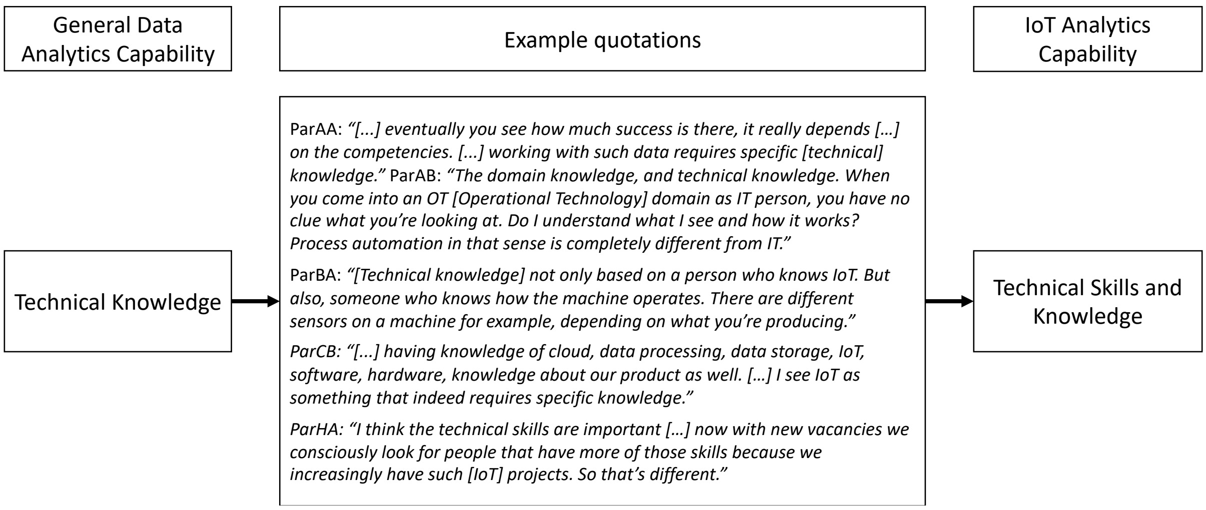

Figure 24: Findings - Technical Skills and Knowledge

Business Skills and Knowledge

This capability includes many soft skills and knowledge, as participants pointed out. To illustrate this, respondents mentioned skills like strong communication, presentation, and management of IoTA programs to align processes and people. What is more, technical people with Business Skills and Knowledge were seen as a must, as they must be able to translate business needs into technological solutions.

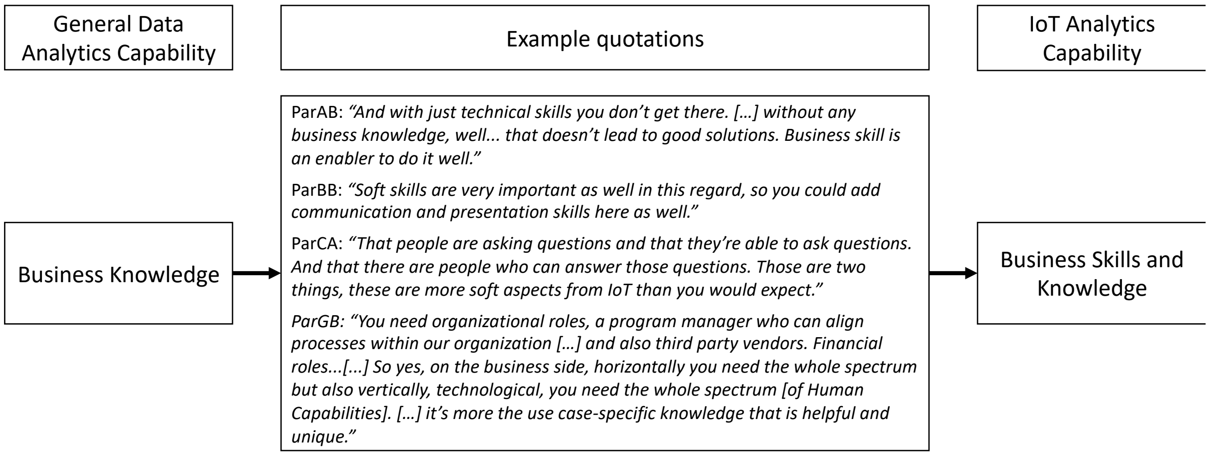

Figure 25: Findings - Business Skills and Knowledge

<u>Interdisciplinary Collaboration</u>

One of the most critical capabilities to cope with this reality is the collaboration between IT and other disciplines, participants echoed. While IT and data teams always need to collaborate with different domains, the collaboration with subject matter experts in IoTA is different. Often IoTA is engrained in critical business processes, such as industrial production, supply chain, or logistics. The variety of people working on such processes and information involved is often greater than general DA projects. This challenge requires a strong Interdisciplinary Collaboration capability and was often seen as part of the Relational Knowledge. The collaboration part was missing, which is a precursor to Relational Knowledge.

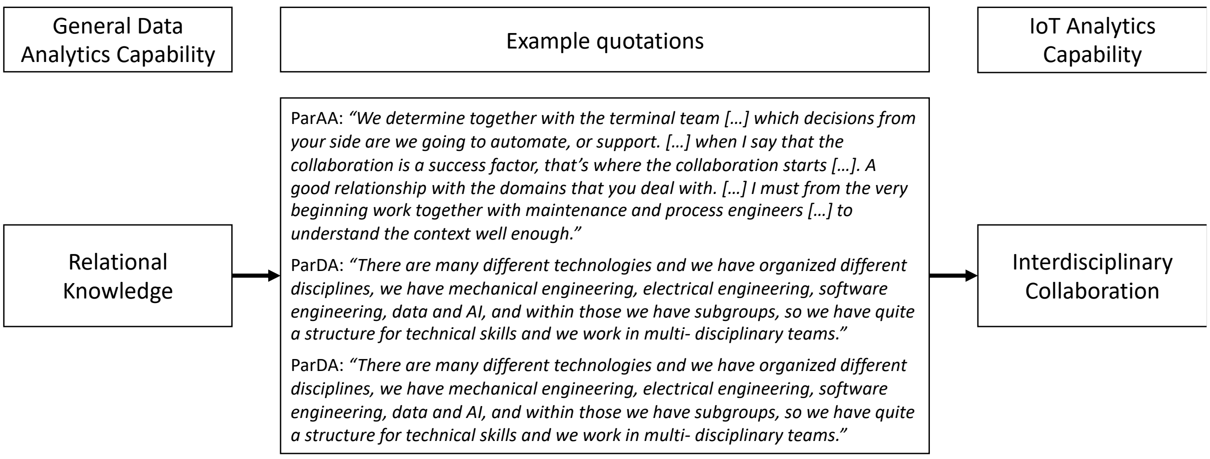

Figure 26: Findings - Interdisciplinary Collaboration

<u>Entrepreneurship and Innovation</u>

Section 4.2.1. already presented that IoTA brings with it many novelties, raising the need for an Entrepreneurship and Innovation capability. This was often confirmed by the participants, saying they had to actively think like entrepreneurs and 'sell' their solutions and services internally. Closely aligning with this notion, thinking 'out of the box' and having strong innovation skills were also seen as especially important to IoTA compared to general DA.

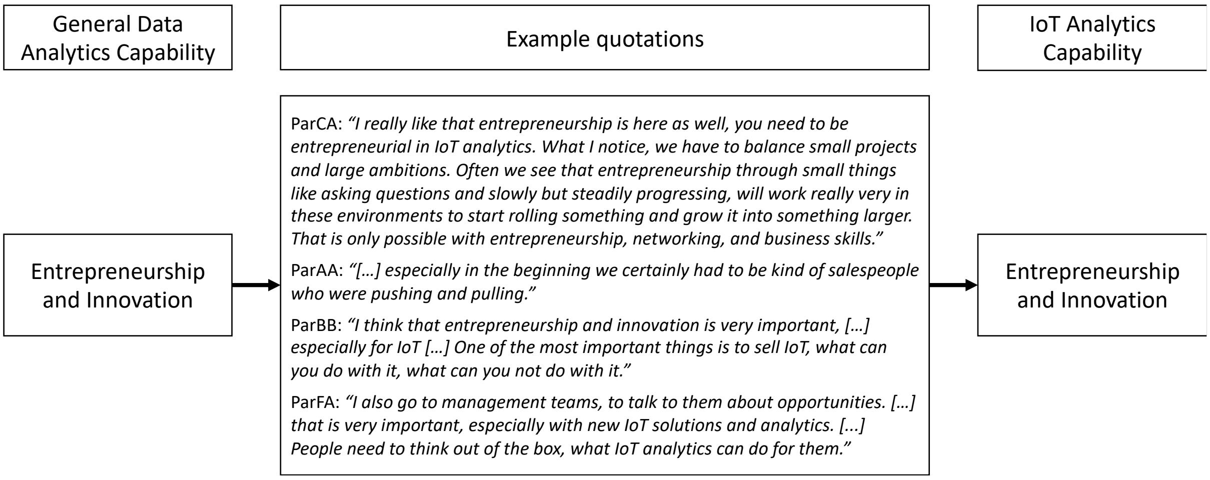

Figure 27: Findings - Entrepreneurship and Innovation

4.2.3. Business Value

In this subsection, findings are presented relating to the latter part of sub-research question five:

> *SRQ5: What are the most important IoT Analytics capabilities and what types of business value do they lead to?*

Both Operational and Strategic Business Value in the context of IoTA are defined in Table 4.

Operational Business Value

Because IoTA is embedded in critical business processes, the first mentioned business value was often of operational nature. Most case organizations were initially motivated to invest in IoT Analytics for real-time insights through visualizations and dashboards, and eventually operational excellence through more advanced use of IoT data and automation. The typologies of Operational Business Value extracted from the data analysis can be seen in Figure 28 below.

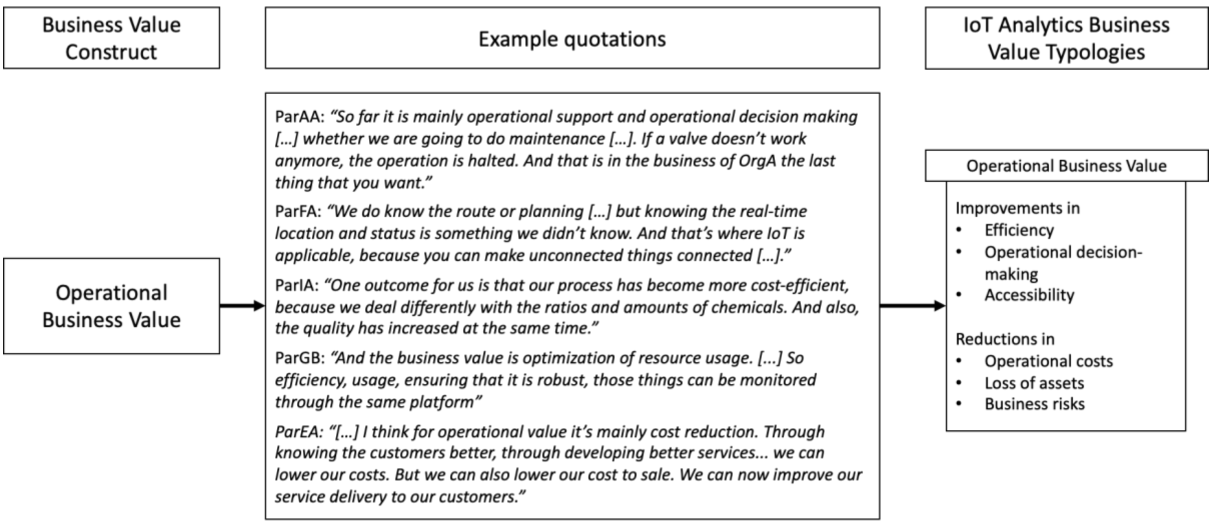

Figure 28: Findings - Operational Business Value

Strategic Business Value

There were several cases where IoTA provided significant strategic value. Creating new business models and revenue drivers were seen as a strategic goal, resulting in more revenue. In many cases, such as at OrgC, D, E, and G, IoTA also resulted in better customer interaction and satisfaction, as they had more insights into the products they are selling. Furthermore, IoTA provides insights to improve process design and product development on the long-term. For the more industrial IoT cases, such as OrgB, D, and H, sustainability was also seen as a strategic goal and value, which will only become increasingly important in the coming years.

Indirectly, IoTA also provides strategic value by improving quality, robustness, recognition by the public and customers, and time to market. One last outcome that stood out was that many organizations, and OrgE in particular, created a stronger business synergy between business units over the years. In Figure 29 the typologies of Strategic Business Value can be found.

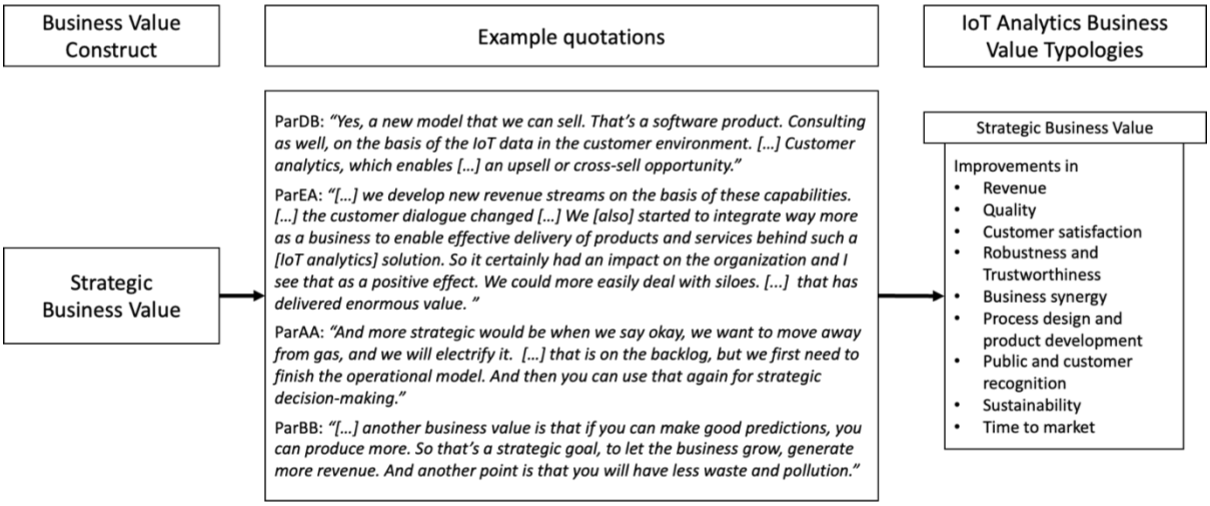

Figure 29: Findings - Strategic Business Value

4.2.4. Summary of findings

Evolving from the literature review and the primary data analysis, the findings are summarized in Table 4 which includes the names of all IoT Analytics sub-capabilities and business value constructs, including their definitions and understandings. Further below, the conceptual framework for IoT Analytics Capabilities and Business value is presented in Figure 30.

Table 4: Conceptual Framework and Definitions - IoT Analytics Capabilities and Business Value

Category	Core Capability	IoTA Sub-capability	Definition and understanding based on findings
IoT Analytics Capabilities	-	-	The ability to design, plan, coordinate and scale an IoT Analytics platform inspired by an innovative management vision, involving technology development, integration and analytics, knowledge management, as well as organizational change to create strong business synergies.
	Technology	-	The ability of the IoT Analytics technology (e.g., applications, infrastructure, data, and networks) to enable staff to quickly develop, deploy, and support necessary system components.
	Technology	Data Generation	The ability to plan for and generate the needed data based on measurements from the hardware and sensors at the edge.
	Technology	Data and Systems Integration	The ability to integrate hardware at the edge, software at the edge, software applications for the end-users, but especially data between different systems.
	Technology	Data Storage, Management and Governance	The ability to store, manage, and govern data in a scalable, effective, and efficient way, potentially across different architectures, storage layers, and structures for different applications. Includes ensuring data quality, data integrity, data ownership, and data source.
	Technology	Security and Compliance	The ability to secure the IoT Analytics platform and comply with all required regulations, especially regarding data compliance and privacy.
	Technology	Data Science and Automation	The ability to develop advanced analytics through algorithms and machine learning models that make predictions of a process, product, asset, or otherwise. This varies from predicting maintenance to predicting how to tweak parameters, enabling improved process or product design. It is also important to consider the factor of time, where predictions can be done near real-time, per hour, per day, or on a longer term. Taking it one step further, this capability also enables giving recommendations or automating processes based on predictions and smart business logic.
	Technology	Business Intelligence	The ability to build descriptive intelligence from IoT data, which enables reporting, continuous monitoring, and new insights of the IoT environment, whether that be products or assets.
	Technology	Platform Architecture and Design	The ability to design and architect an IoT platform for multiple applications with dedicated resources, which encompasses the combination of technological services, infrastructure, and applications, most commonly in cloud computing. An IoT platform enables the Edge and Hardware, Connectivity, Data and Systems Integration, Data Accessibility, Data Management, Security, Operational Maintenance and Monitoring capabilities. It also fosters the Scalability capability and further improves collaboration, because IoT is approached with a centralized platform mindset.
	Technology	Edge and Hardware Development	The ability to plan, develop, maintain, and organize the hardware and software placed in the physical world, also known as the edge.

	Technology	Connectivity	The ability to build connectivity on the edge, between 'things' such as machines, devices, and sensors, and the cloud or platform infrastructure where the data needs to be sent to.
	Technology	Software Development	The ability to develop and maintain software code for the edge, the integration layer, the application layer, and for data science. The higher the desired level of control, automation, and need to service IoT data in an application to end-users, the higher the degree to which this capability is important.
	Technology	Data Processing and Standardization	The ability to process, standardize, and label IoT data across all sources, from the edge to the cloud, enabling comprehensive and correlated analysis as well as predictive analytics.
	Technology	Operational Maintenance and Monitoring	The ability to operationally maintain and monitor the IoT infrastructure, from the IoT devices and connectivity at the edge, to the data flowing through the IoT platform, to the services and applications in the cloud.
	Technology	Data Accessibility	The ability to make data easily accessible, especially for the end-users and data scientists.
	Organizational	-	The ability to plan, invest, organize, and control all resources and capabilities with flexible processes in accordance with a high-level management vision for IoT Analytics.
	Organizational	Scalability and Planning	The ability to operationalize top management vision for IoT Analytics, make decisions on the planning and scalability of the IoT Analytics platform.
	Organizational	Management Support and Vision	The ability to gain management support and trust to research and develop IoT Analytics, while the management has a clear vision of the role of IoT within the organization, providing a starting point. Thereafter, it is important to secure investment for further development.
	Organizational	Process and Coordination	The ability to work according to agile processes and coordination to allow flexibility in the research and development of IoT Analytics at the edge and in the infrastructure. This is important both in the initial phase and in the operational phase, where controlling the initiative will become more important.
	Organizational	Change Management	The ability to drive change in the organization internally but also potentially in the rest of the ecosystem of customers and partners through close collaboration, clear communication, and simply investing time and resources.
	Organizational	Knowledge Management and Training	The ability to attain, record, maintain, and share knowledge concerning IoT Analytics and train and enable all stakeholders involved in the IoT analytics initiative, both internally and externally.
	Organizational	Business and Ecosystem Synergy	The ability to synergize business units and teams in the IoT Analytics initiative, as well as the wider IoT ecosystem including customers and partners, to strengthen the required IoT Analytics capabilities or close any capability gaps.
	Organizational	Product and Service Development	The ability to develop products and services with a fully integrated Internet of Things, generating data which is transformed into insights or actions for internal and external users.
	Human	-	The relevant professional ability of all employees involved in IoT Analytics (e.g., skills or knowledge) to undertake assigned tasks or generate new ideas.
	Human	Technical Skills and Knowledge	The ability to develop the IoT Analytics technology capabilities with technical skills and knowledge, ranging from hardware knowledge to specific knowledge about hardware and operational technology, networking, data

			processing tools, databases, data structures, cloud computing, mathematics and machine learning, and software development.
	Human	Business Skills and Knowledge	The ability to drive IoT Analytics outcomes through business skills and knowledge including effective communication, presentation, use case and business value selling, decision-making, and embedding IoT Analytics in the organizations' business processes and go to market.
	Human	Interdisciplinary collaboration	The ability to collaborate across disciplines and domains with subject matter experts and understand each other's goals and challenges. This is instrumental in building the right business cases and align the technological implementation with those business cases.
	Human	Entrepreneurship and Innovation	The ability to lead IoT Analytics initiatives with entrepreneurial and innovative skills to develop creative solutions based on strong business cases.
Category	**Business Value Type**		**Definition and understanding based on findings**
IoT Analytics Business Value	Operational Business Value		The business value and outcomes which improve the daily operations of an organization, typically on the short-term. Such high-level business value outcomes include reductions in cost, risks, loss of resources, or improvements in short-term decision-making such as business planning, security and safety, ease of use, and data quality.
	Strategic Business Value		The business value and outcomes which improve the strategic direction of an organization, typically on the long-term. Such high-level business value outcomes include improvements in business design, business synergies, quality of results, robustness and trustworthiness, time to market, sustainability, and company image. Most strategically, IoT Analytics can drive revenue through creating new business models, consultancy, and up and cross-sell opportunities.

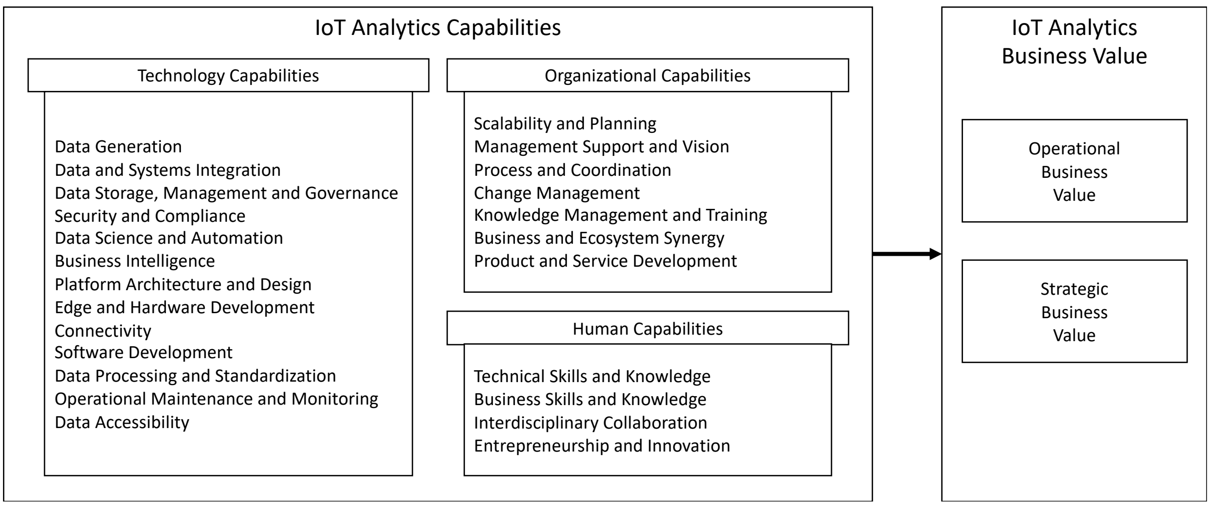

Figure 30: Conceptual Framework – IoT Data Analytics Capabilities and Business Value

5. Discussion

In this last chapter, the main findings are discussed against the backdrop of the conceptual framework, including a reflection of the methodological rigor and recommendations for practitioners and academia.

5.1. Reflection of findings

This study reasoned that IoT Analytics has distinctions from general Data Analytics and requires specific capabilities, leading to various types of business value. To answer the research questions in this study, these capabilities and business value types are discussed below.

Technology Capabilities

With 13 capabilities in total (Table 4), the Technology sub-capabilities can be seen as most significant, while in the literature review four Technology sub-capabilities were extracted (Figure 1).

More specifically, the IoTA capabilities Data Generation and Data and Systems Integration are both comparable to the theory. Interestingly, Data Management and Security were seen as two critical discrete capabilities (ParAA; ParBA; ParEA). The findings are in line with the increasing security and compliance challenges mentioned in literature (Arunachalam et al., 2018; Ramakrishnan et al., 2020; Vidgen et al., 2017). Data Management was renamed to Data Storage, Management and Governance, as managing IoT data involves a multitude of new ways to store, manage, and govern the enormous amounts of data (ParAA; ParBA; ParCB). No emphasis on storage or governance was found in the most cited literature (Akter et al., 2016; Wamba et al., 2017a). Among others, ParBB suggested that the Analytics capability should be seen as two separate capabilities, Business Intelligence and Data Science and Automation. This is a new perspective, as literature sees it as a singular Analytical capability (Wang et al., 2019) or Analytics Portfolio (Grover et al., 2018).

Several new IoTA sub-capabilities originating in the analysis were not found in the literature. Most case organizations approached IoTA with a platform mindset driven by platform owners or architects (ParAA; ParBA; ParCA; ParDB; ParEB; ParFA; ParGA) and designed it accordingly. Such a Platform Architecture and Design capability was not present in the literature, which could be because IoTA is seen as a more all-encompassing and strategic initiative (ParAA; ParEA; ParFA). Another difference with literature is the development of software and hardware, which were seen as two proper sub-capabilities (ParAB; ParBA; ParCB; ParEA; ParFA). Developing hardware and maintaining a physical environment is not present in the literature. One might wonder why software development was not included in the DA capabilities, but that could be because many organizations want full control over their IoTA platform. Connectivity is arguably the most unique to IoTA, to guarantee connectivity between the edge and among devices. This concept is only mentioned as 'networks' in the Technology core capability definitions (Akter et al., 2016; Wamba et al., 2017b). Data Processing and Standardization was seen as an important capability by ParAA and others to ensure that data is correctly processed and standardized before being stored. This concept was not noted as a capability, only as part of Technology capability definitions (Fink et al., 2017; Işık et al., 2013b). The Operational Maintenance and Monitoring capability also seems like a completely new capability, as no literature found this to be an important part of DA initiatives. Data Accessibility was not seen as important in the literature review. While it is present in the findings, the code analysis in this study showed it was minimally mentioned (Appendix O), which indicates it could potentially be part of another capability.

Organizational Capabilities

Seven unique Organizational sub-capabilities were found, compared to four in the conceptual framework (Table 1).

The findings show that Planning and Investment split into two. The first, Scalability and Planning, was seen as one dedicated sub-capability by ParAA and ParEB, among others. This is in alignment with Akter et al. (2016) and Wamba et al. (2017), although they conceptualize Planning and Investment as two separate constructs, but did not include Scalability. However, all participants noted that scaling is key to driving IoTA business value. Moreover, a management vision, together with trust, and investments were critical to not only get started but also to gain strategic value. This conception was different from the investment capabilities in the conceptual framework (Akter et al., 2016; Sun & Liu, 2020; Wamba et al., 2017a). The broad understanding of Process and Coordination (ParAA; ParDB; ParEB) appears to align with the literature (Akter et al., 2016; Fink et al., 2017; Işık et al., 2013b; Wamba et al., 2017a). One noteworthy difference is that all participants saw agile processes as imperative to the success of IoTA, due to the novelties and ambiguities of IoTA.

Three new Organizational sub-capabilities were extracted from the interview analysis, the first being Knowledge Management and Training. Although specific knowledge is also included in the Human Capabilities, Knowledge Management relates to the organizational capability of attaining and maintaining IoTA knowledge in the organization (ParBB, ParCA, ParEA). A good example is OrgA establishing a data academy to train the organization in matters relating to IoTA. No resemblance to such capabilities is present in the literature, resulting in new findings. Another aspect found in the findings that needs to be managed is change (ParBB, ParCB, ParEB). Change Management was only established as a capability in the literature by Cosic et al. (2015) and as part of the challenges noted by Vidgen et al. (2017). Finally, Product and Service Development was seen by ParEA, and almost all case organizations, as a capability that had to be actively developed anew, since they were not used to develop such products and services based on data. Remarkably, no literature mentioned this, either implicitly or explicitly.

Human Capabilities

The findings are all in line with the four Human sub-capabilities in the literature (Akter et al., 2016; Rialti et al., 2019; Wamba et al., 2017a).

Relational Knowledge was noted as important by all participants, although with the understanding that is more about different disciplines coming together at the intersection between Information Technology (IT) and Operational Technology (OT) who need to collaborate and create new knowledge. This capability was therefore renamed to Interdisciplinary Collaboration and is particularly in line with the responses of ParAA and ParBB. Although Technical Skills and Knowledge were confirmed in the findings, it became apparent that for IoTA, this knowledge is specific and does not always apply to DA (ParAB; ParCB; ParDA; ParGB). Finally, Entrepreneurship and Innovation was seen as a critical capability throughout the maturity of IoTA (ParBB), but especially at the start (ParAA).

Business Value Typologies

The other research question was regarding capabilities and the typologies of business value they lead to, which have been validated against the literature (Fink et al., 2017; Grover et al., 2018). Operational Business Value was the most frequently mentioned outcome, with results ranging from reduced costs (ParAB; ParBA; ParCB) to improved planning and efficiency (ParGA; ParFA). To achieve this, an important capability to realize is Business Intelligence, which is more descriptive. Ensuring data is available in real-time and developing data visualizations of flowing IoT data could be seen as a high-value and low effort capability. Participants further mentioned that developing advanced models with a Data Science capability does not necessarily lead to higher or Strategic Business Value.

Although IoTA primarily aims for operational excellence, Strategic Business Value is certainly within reach. This was confirmed by many participants who shared such outcomes, including new business models or revenue drivers (ParCB; ParDB; ParEA; ParGB) and improved quality (ParFA; ParIA), time to market (ParGA), customer satisfaction (ParFA; ParGA), and long-term decision-making (ParEB). Despite Fink et al. (2017) validating the distinction between operational and strategic value, the findings demonstrate there is a gray line between Operational and Strategic Business Value. For example, ParGA noted that competitive advantage is all about improving efficiency at OrgG, suggesting that operational value can gradually lead to strategic outcomes.

Cross-case Analysis

This multiple case study facilitates a cross-case analysis. According to Yin's (2017) suggestions, this analysis is presented according to various case categories. Table 5 discusses the synthesis in detail, with the support of Appendix O.

Replication was expected and aimed for in this study. Observing the cross-case analyses in Appendix O, it seems that overall, there is strong replication across all domains, company sizes, and maturity ranges. The most notable observation is that in the maturity ranges, most variations start to occur. Participants also mentioned in the interviews that the importance of capabilities depends on the IoTA maturity stages. This should be investigated further in future research.

Table 5: Cross-case synthesis

Case characteristic	Characteristic	Total	Cases	Cross-case synthesis
Domains as per Siow et al. (2018) (Table O6)	Transport	4	A, C, F, G	Between domains it seems there are no clear differences as all constructs are equally present. There are however some observations to be made. For example, Product and Service Development and Software Development seem to be less mentioned in the Environment domain than others. This could be because the Environment domain usually is not used to developing products and services, as ParEA noted. Secondly, Technical Skills and Knowledge were more present in the Transport domain. Perhaps this is because in Transport, more knowledge is required to develop and integrate specific the hardware and connectivity.
	Industry	3	B, D, H	
	Environment	2	E, I	
Company size in number of employees (Table O7)	500 – 1,000	1	I	Most constructs are equally present in all company size ranges, with some variations. It appears that larger companies might need more Technical Skills and Knowledge due to the added complexity in their business processes. On the other hand, Data Storage, Management and Governance as well as Management Support and Vision stand out as being mentioned most by smaller companies. Potential
	1,000 – 5,000	2	D, E	
	5,000 – 10,000	2	A, G	
	10,000 – 20,000	1	C	
	20,000+	3	B, F, H	

				explanations for these differences should be further investigated in future studies.
Maturity in years (Table O8)	0 – 3	2	B, I	Maturity is a concept that was mentioned several times by participants, who indicated that the most important capabilities depend on the maturity of the IoTA initiative. Overall, there do not seem great differences among the maturity stages. One interesting observation is that Management Support and Vision was mentioned most in the 0-3 years maturity. A plausible clarification for this would be that at the start of IoTA projects, it is important to have management support and execute according to such a vision. For organizations with longer maturity this might be a given already. Relating capabilities to that notion are Business and Ecosystem Synergy and Scalability and Planning, which are also increasingly present in organizations with more maturity. Reason for this could be that the longer organizations work on IoTA, the more they scale, the more they need to plan and synergize business units. Analyzing business value, it seems it is mentioned more in the higher maturity cases. For example, Strategic Business Value is mentioned more than double in the 5 – 10+ maturity than in the 0 – 5 maturity range.
	3 – 5	3	D, F, H	
	5 – 10	3	A, C, G	
	10+	1	E	

5.2. Reflection of methodology

This research study was based on a confirmation of the problem statement in the literature and has attempted to follow a rigorous methodology design. The methodology included a literature review protocol, a case study design, participant selection criteria, an interview protocol, and thematic analyses phases, which have all been documented as far as possible. Additionally, a coding framework was developed with a preliminary codebook. It also includes a coding journal to retrace the researcher's choices and potential biases in this study, which are inevitable in every qualitative exploratory study. These measures should contribute to the reliability of the study.

The case and selection criteria as designed could not be fully met. To strengthen the validity of the research, four more cases have been included in the study. On the other hand, two participants per case were interviewed, except for OrgH and I, which included one participant. This could jeopardize the validity, as it did not allow further verification of the themes within each case. From a holistic perspective, however, the capabilities were verified through inclusion rules. The participants were also well distributed over three participant responsibilities (Appendix M). This could be seen as a strong methodological outcome, adding to the research validity.

Validated constructs from the literature and conceptual framework were used in the interviews. Although this strengthened the internal validity of the research initially, it became clear that certain constructs might not have been fully covered in the interviews due to time pressure and ambiguities.

5.3. Conclusion

The motivation for this study was twofold. The Internet of Things has received much attention in the past years as a promising technology driving specific data applications. From an academic perspective, there is an inconclusive view of Data Analytics capabilities. Nor have capabilities and business value been researched for specific domains, such as IoT. This study therefore aimed to explore IoT Analytics capabilities and the business value they generate.

By investigating the differences between DA and IoTA capabilities, this study shows that DA capabilities can largely be applied to IoTA. One major observation, however, is that IoTA is different because of its novel and often complex character. IoTA also requires specific technologies and knowledge to manage enormous volumes of data touching upon critical business processes. These differences translated into 10 newly discovered IoTA capabilities which add to the existing body of knowledge.

Technology Capabilities were seen as most apparent, with 13 capabilities, while Organizational Capabilities included seven and Human Capabilities four. Developing these capabilities can lead to many types of business value. Most organizations look primarily for Operational Business Value through improvements in efficiency and short-term decision-making. Such Operational Business Value can gradually lead to Strategic Business Value such as long-term decision-making and improvements in effectiveness and quality. As an ultimate outcome, IoTA can generate revenue through new or added products and services.

5.4. Recommendations for the practice

IoTA can provide insights into critical business processes and serve value to organizations in many ways. The study results can be enlightening to practitioners in two ways. First, the differences observed between DA and IoTA show that practitioners need to cope with unprecedented complexity and scale, new and specific knowledge, and potentially unique technologies. Second, the capabilities found in this study can be of help in planning for IoTA endeavors and the right business goals.

Organizations should realize that there are both technical and organizational differences between IoTA and DA initiatives. IoTA keeps evolving rapidly, requiring flexibility, entrepreneurship, and an innovative mindset. Technologically, IoTA differs with DA too, involving specific hardware and software technologies that need to be developed against. The skills and knowledge needed to bring such IoTA technology to fruition should not be underestimated. But perhaps most important, managers should realize that IoTA requires a long-term and realistic IoTA vision, which helps shifting the organization toward a new, more integrated, future.

5.5. Recommendations for further research

This study has explored IoTA capabilities and value creation and contributes a set of new IoTA capabilities to the literature. However, the results cannot be generalized and should be viewed with caution, due to researcher and participant bias. In addition, many new capabilities with ambiguous relationships were found that could not be validated against literature. A limitation is therefore that the results are inconclusive. Further research on the population is required to refine and confirm the relevance and categorization of the capabilities.

Academics are recommended to validate the 24 IoTA capabilities, their interrelationships, and connection with value creation through both qualitative and quantitative research. Additionally, the cross-case analysis indicated that the importance of capabilities depends on the maturity of IoTA endeavors. Accordingly, researching capability maturity and relevance to value creation could be another research topic. Finally, another research venue is to test the relevance of the identified capabilities for broader DA research.

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Appendix A: Literature Review Protocol

1 Search string in the Open University Online Library

((TitleCombined:("data analytics")) OR (Abstract:(data analytics)) OR (TitleCombined:("business analytics")) OR (Abstract:(business analytics)) OR (TitleCombined:("big data analytics")) OR (Abstract:(big data analytics)) OR (TitleCombined:("analytics")) OR (Abstract:(analytics)) OR (TitleCombined:("business intelligence")) OR (Abstract:(business intelligence)) OR (TitleCombined:("business intelligence and analytics")) OR (Abstract:(business intelligence and analytics)) OR (TitleCombined:("BI&A")) OR (Abstract:(BI&A))) AND ((TitleCombined:("capabilities")) OR (Abstract:(capabilities)) OR (TitleCombined:("capability")) OR (Abstract:(capability)))

2 Filters as part of the query in the Open University Online Library – first screening phase

- *Publication date: from 01-01-2012.* Results from before 2012 are filtered out, because DA is a theme that is constantly evolving. Therefore, only results of the past 9 years are included.
- *Content type: Journal Article, Conference Proceedings.*
- *Discipline: Business.* A large part of studies done on the topic is of technical nature, which is irrelevant for this study. Therefore, articles should not be of technical nature, and only management and business science studies are included in the selection. In the OU Library, the discipline 'business' is selected as a filter.
- *Language: English.*
- *Limit to: Peer-reviewed.* Through including only peer-reviewed material, a high level of quality is maintained.

3 Inclusion and exclusion criteria – second screening phase

- The focus lies on identifying DA capabilities and underlying resources in this search. Consequently, any papers will be included that reference a list of DA capabilities or resources. Note that some articles refer to capability dimensions or factors, these will also be considered if deemed relevant. Conversely, studies that mention DA capability as a general concept and do not reference or propose DA capabilities or dimensions are excluded.
- Studies that adopt existing DA capabilities will be included at first but excluded later if the study does not add any new insights to the capabilities in the empirical research part. This way, only grounded knowledge on DA capabilities is included.
- Both primary and secondary studies are included in the search.
- When studies reference or adopt DA capabilities, the snowball method is used to trace back the referenced articles that might have been missed in the database search. These articles are included in the selection.
- Articles that focus on dynamic capabilities in DA initiatives are generally excluded. Nevertheless, if there are specific DA capabilities mentioned the capabilities are included.
- After the above criteria have been met, the article will be assessed on several quality criteria which are adopted from Dybå et al. (2007). The following criteria should all be met to be included in the final selection:

    - Is the paper is based on research, not on a 'lessons learned' report?
    - Is there a clear statement of the aims of the research?
    - Is there an adequate description of the research context and design that is appropriate to the aim of the study?
    - Is the data collection and analysis sufficiently described?

4 Literature search flow and results

Table A1

Identification	Records identified through database query	786
Screening	Records screened	360
	Records excluded	-331
Eligibility	Full-text articles assessed for eligibility	29
	Full-text articles excluded, with reasons	-8
	Full-text articles added through preliminary research and snowball method	+5
Included	Studies included in qualitative analysis	**26**

5 Six phases in thematic analyses (Nowell et al., 2017)

- Phase 1: Familiarizing yourself with your data
- Phase 2: Generating initial codes
- Phase 3: Searching for themes
- Phase 4: Reviewing themes
- Phase 5: Defining and naming themes
- Phase 6: Producing the results and conclusion

Appendix B: Data Extraction Form – Eligibility Assessment

Table B1

Reference	Meets inclusion/exclusion criteria	Meets quality assessment	Full-text analysis (yes/no)
Chen et al.	No	-	No. No specific DA capabilities are mentioned.
Wang et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
Akter et al.	Yes	Yes	Yes. Resources as well as capabilities in three levels identified.
Wang et al.	No	-	No. No specific DA capabilities are mentioned.
Wamba et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
Wang et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
Bordeleau et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
Gupta et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
Mikalef et al.	No	-	No. No specific DA capabilities are mentioned.
Popovič et al.	No	-	No. No specific DA capabilities are mentioned.
Mikalef et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
Janssen et al.	No	-	No. No clear division between capabilities are mentioned nor empirically researched.
Mikalef et al.	Yes	Yes	Yes. Resources as well as capabilities identified.
van Rijmenam et al.	No	-	No. No specific DA capabilities are mentioned.
Ferraris et al.	No	-	No. No clear division between capabilities are mentioned nor empirically researched.
Rialti et al.	Yes	Yes	Yes. Adds more depth to the dimensions proposed by Wamba
Jha et al.	Yes	Yes	Yes. Do not clearly adopt any specific capabilities or dimensions but rather empirically induce dimensions from their primary research that make up BDA capability as a general concept.
Torres et al.	Yes	Yes	Yes. Adopt BI&A capabilities from multiple sources and add depth through an empirical study.
Mikalef et al.	Yes	Yes	Yes. Very valuable literature review study of BDA capabilities and resources.
Ardito et al.	Yes	Yes	Yes. Very helpful in setting the tone in the introduction of the literature review. Four themes identified, BDA resources and capabilities being one of them.
Yasmin et al.	Yes	Yes	Yes. Helpful literature review with table of capabilities of different papers. Useful for snowball method. They furthermore distinguish 15 second-order capabilities.
Sun et al.	Yes	Yes	Yes. Sees capabilities as dual higher-order construct, brings new perspective. Focus on new business model designs (strategic value).
Wang et al.	Yes	Yes	Yes. IT business value framework and capabilities are adopted, also tested empirically for more depth and focus on challenges/most important factors.
Vidgen et al.	Yes	Yes	No. No clear division between capabilities are mentioned nor empirically researched.
Grover et al.	Yes	Yes	Yes. Good insights on business value creation and set of underlying constructs that create capabilities.
Bag et al.	No	-	No. No specific DA capabilities are mentioned.

Pappas et al.	No	-	No. Capabilities based on existing literature and no further empirical research.
Akter et al.	No	-	No. Main focus on dynamic capabilities and applied to service system analytics which is not relevant to IoT.
AlNuaimi et al.	Yes	Yes	Yes. Create higher- and lower order structure of capabilities that are empirically researched with some notes on business outcomes.

Appendix C: Data Extraction Form – DA Capability Definitions

Table C1

ID	Reference	DA Capability construct	Definition/understanding
1	(Wang & Hajli, 2017)	Big Data Analytics Capability	The ability to acquire, store, process and analyze large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion.
2	(Akter et al., 2016)	Big data analytics capability (BDAC)	The competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force (Kiron et al., 2014).
3	(Wamba et al., 2017a)	Big data analytics capability (BDAC)	The competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force.
4	(Wang et al., 2018)	Big data analytics capability	The ability to manage a huge volume of disparate data to allow users to implement data analysis and reaction (Hurwitz et al., 2013).
5	(Bordeleau et al., 2018)	Capabilities	The ability to exploit resources (Bharadwaj 2000; Elbashir, Collier, and Davern 2008; Melville, Kraemer, and Gurbaxani 2004).
6	(Gupta & George, 2016)	Big Data Analytics Capability	A firm's ability to assemble, integrate, and deploy its big data-specific resources.
7	(Mikalef et al., 2019b)	Big data analytics capability (BDAC)	The ability of a firm to capture and analyze data towards the generation of insights by effectively orchestrating and deploying its data, technology, and talent (Mikalef et al., 2018).
8	(Popovič et al., 2018)	Draw from IT capabilities definition	The firm's ability to mobilize, deploy and use IT-based resources to improve the firm's business processes (Santhanam and Hartono 2003).
9	(Mikalef et al., 2020)	Big Data Analytics Capability	The ability of a firm to effectively deploy technology and talent to capture, store, and analyze data, toward the generation of insight (Gupta et al., 2016)
10	(Mikalef et al., 2019a)	Big Data Analytics Capability	The ability of the firm to capture and analyse data towards the generation of insights by effectively deploying its data, technology and talent through firm-wide processes, roles, and structures.
11	(Rialti et al., 2019)	Organizational BDA capabilities	Ensemble of capabilities related to the "ability to mobilize and deploy BDA-based resources in combination with other resources and capabilities" (p. 357, Wamba et al. 2017)
12	(Jha et al., 2020)	Big data analytics capability (BDAC)	No clear definition.
13	(Torres et al., 2018)	Business Intelligence & Analytics capabilities	An organization's ability to deploy BI&A technology and personnel resources to produce valuable information outputs.
14	(Mikalef et al., 2018)	Big data analytics capability (BDAC)	The distinctive capability of firms in setting the optimal price, detecting quality problems, deciding the lowest possible level of inventory, or identifying loyal and profitable customers in big data environments (Davenport and Harris, 2007)

15	(Ardito et al., 2019)	BDA capabilities and resources research	The research that has first attempted to provide empirical insights regarding the implications of the adoption of Big Data analytics for managerial purposes.
16	(Yasmin et al., 2020)	Big data analytics capabilities	No clear definition.
17	(Sun & Liu, 2020)	Big data analytics capability (BDAC)	BDA capabilities refer to a firm's competency to provide business insights using technology, management, etc. to transform big data into a competitive force (Kiron et al., 2014; Akter et al., 2016).
18	(Wang et al., 2019)	Big data analytics capabilities	The ability to acquire, store, process and analyse large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion (Wang and Hajli, 2017)
19	(Vidgen et al., 2017)	Business analytic capability	A mediator between the data the organization generates and accesses (internal and external) and the value the organization can leverage from that data through actions based on better decisions.
20	(Grover et al., 2018)	Capability building process	Converting IT investment in BDA to valuable capabilities is a dynamic process that involves identification of where, how, and what value will be created. Capabilities include the ability to both manage and analyze data to create new insights.
21	(AlNuaimi et al., 2021)	Big Data Analytics Capabilities	No clear definition.
22	(Fink et al., 2017)	Capabilities	Capabilities are repeatable patterns of actions in the use of assets (Sanchez et al., 1996)
23	(Cosic et al., 2015)	Overall BA capability	The ability to utilise resources to perform a BA task, based on the interaction between IT assets and other firm resources.
24	(Ramakrishnan et al., 2020)	Business Intelligence Analytics Capability	All the elements to create and manage BI&A activities (Popovič, Hackney, Coelho, & Jaklič, 2012; Seddon, Constantinidis, Tamm, & Dod, 2017)
25	(Işık et al., 2013b)	BI Capabilities	No clear definition.
26	(Arunachalam et al., 2018)	BDA Capabilities	No clear definition.

Appendix D: Data Extraction Form – DA Capabilities Core Constructs

Table D1

ID	Reference	DA capability core constructs	Definition/understanding	Adapted from, if applicable
1	(Wang & Hajli, 2017)	Traceability	Integrate and track the patient data from all of the IT components throughout the various healthcare service units	-
		Analytical capability	The ability to process clinical data with an immense volume (from terabytes to exabytes), variety (from text to graph) and velocity (from batch to streaming) by using descriptive analytics techniques	-
		Speed to decisions	The ability to effectively generate outputs regarding patients, care process and service to guide diagnostic and treatment decisions	-
		Predictive Analytics	The ability to explore data and identify useful correlations, patterns and trends and extrapolate them to forecast what is likely to occur in the future	-
		Interoperability	The ability to integrate data and process to support collaboration and other healthcare activities.	-
2	(Akter et al., 2016)	BDA Management Capability	An important aspect of BDAC ensuring that solid business decisions are made applying proper management framework. Four core themes were found to constitute perceptions of BDAMAC; these were termed as BDA planning, investment, coordination, and control.	Multiple authors, no specific reference
		BDA Technology Capability	The flexibility of the BDA platform (e.g., connectivity of cross-functional data, compatibility of multiple platforms, modularity in model building, etc.) in relation to enabling data scientists to quickly develop, deploy, and support a firm's resources. Three core themes underpin perceptions of BDATEC: connectivity, compatibility and modularity.	Multiple authors, no specific reference
		BDA Talent Capability	The ability of an analytics professional (e.g., someone with analytics skills or knowledge) to perform assigned tasks in the big data environment. Skill sets: skill sets: technical knowledge (e.g., database management); technology management knowledge (e.g., visualization tools, and techniques management and deployment); business knowledge (e.g., understanding of short-term and long-term goals); and relational knowledge (e.g., cross-functional collaboration using information).	Multiple authors, no specific reference
3	(Wamba et al., 2017a)	BDA Management Capabilities	The BDA unit's ability to handle routines in a structured (rather than ad hoc) manner to manage IT resources in accordance with business needs and priorities.	Kim et al. (2012, p. 336)
		BDA Infrastructure Capability/Flexibility	The ability of the BDA infrastructure (e.g., applications, hardware, data, and networks) to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm.	Kim et al. (2012, p. 335)
		BDA Personnel Expertise Capability	The BDA staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks.	Kim et al. (2012, p. 336)
4	(Wang et al., 2018)	Analytical capability	Analytical techniques to process data with immense volume, variety, and velocity via unique data storage, management, analysis, and visualization.	Chen et al. (2012)
		Unstructured data analytical capability	The main difference in analytical capability between big data analytics systems and traditional data	-

			management systems is that the former has a unique ability to analyze semi-structured or unstructured data. Unstructured and semi-structured data in healthcare refer to information that can neither be stored in a traditional relational database nor fit into predefined data models.	
		Decision support capability	Decision support capability emphasizes the ability to produce reports about daily healthcare services to aid managers' decisions and actions.	-
		Predictive capability	Predictive capability is the ability to build and assess a model aimed at generating accurate predictions of new observations, where new can be interpreted temporally and or cross-sectionally	Shmueli and Koppius, 2011
		Traceability	Traceability is the ability to track output data from all the system's IT components throughout the organization's service units.	-
5	(Bordeleau et al., 2018)	Operational BI capabilities	Exploitation of resources in process activities	Fink et al. (2017)
		Strategic BI capabilities	Exploitation of resources at the strategic management level.	Fink et al. (2017)
6	(Gupta & George, 2016)	No specific capabilities, focused on resources	-	
7	(Mikalef et al., 2019b)	No specific capabilities, focused on resources	-	
8	(Popovič et al., 2018)	Data provisioning	Data sourcing, access, integration, and delivery	-
		Analytical capabilities	-	-
		People's expertise	-	-
9	(Mikalef et al., 2020)	No specific capabilities, focused on resources	-	Grant
10	(Mikalef et al., 2019a)	No specific capabilities, focused on resources	-	Bharadwaj
11	(Rialti et al., 2019)	BDA Infrastructure Flexibility	BDA infrastructures, which are the ensemble of information systems capable of collecting, storing, processing and analyzing big data, should be able to adapt themselves to different types of data. This capability is fundamental to ensuring that technologies will be able to process different data flows and formats in any situation (Rialti et al., 2018).	Rialti et al 2018
		BDA Management Capabilities	BDA managerial capabilities are critical with regard to selecting and implementing the right BDA infrastructure and identifying the right information to extract from the datasets (Ferraris et al., 2018).	Ferraris et al. 2018
		BDA Personnel Expertise Capability	The presence of personnel who are skilled in BDA. Improves functioning of BDA infrastructure.	Wamba et al. 2017
12	(Jha et al., 2020)	Data management and use of advanced software packages	Data management includes the ability to manage data quality, integration, storage, and software packages	
		Skilled human resources and training for analytics	Presence of skilled resources that can deal with evolving technologies.	
		Intra-organizational power dynamics	Support from top management and representation of BDA roles in top decision-making body of an organization.	
		Global connectedness	The need to efficiently connect and disperse information to internal or external stakeholders drive organizations to build advanced technological capabilities.	

		External landscape and analytics capabilities	External landscape, for example competitive pressure, drives companies to adopt and build analytics capabilities.	
13	(Torres et al., 2018)	BI&A Management Capability	The ability of management processes and support within BI&A. This is critical to the attraction, selection, development, and retention of necessary expertise among producers and consumers of BI&A output	Multiple
		BI&A Technical Infrastructure Quality	The ability to gather and analyze data implied by the BI&A sensing capability requires specialized IT infrastructure, often consisting of data storage, management and analysis tools	
		BI&A Personnel Expertise	The level of professional skills and knowledge possessed by BI&A staff. The skill of technical employees is a significant practical concern, and human competency is a critical element of the successful delivery of BI&A services	
14	(Mikalef et al., 2018)	Planning	-	Not explained
		Sourcing	-	Not explained
		Deployment	-	Not explained
		Management	-	Not explained
15	(Ardito et al., 2019)	No specific capabilities	-	
		3 levels of capabilities mentioned however; aspirational, experienced, and transformed	-	LaValle et al. (2011)
16	(Yasmin et al., 2020)	Infrastructure Capabilities	-	Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien, 2005
		Human Resource Management Capabilities	-	Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien, 2005
		Management Capabilities	-	Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien, 2005
17	(Sun & Liu, 2020)	BDA Technology Capability	The flexibility of a firm's BDA platform in relation to enabling data analysts to quickly develop, deploy, and support a firm's resources	Akter et al., 2016
		BDA Management Capability	The organizational competence that supports BDA planning, investment, coordination, and control.	Akter et al., 2016
18	(Wang et al., 2019)	Data integration capability	The ability to transform diverse types of data into a data format that can be read and analysed by the data analysis platform	Wang and Bird (2017)
		Analytical capability	The ability to drive decisions and actions through the extensive use of data and different analytical techniques based on the specific mechanisms used for analytics, thus addressing the various needs of users and other stakeholders	Ghosh and Scott (2011)
		Predictive analytics	The ability to apply diverse statistical analysis methods, modelling, machine learning and data mining to both structured and unstructured data to determine future outcomes	Wessler (2013, p. 21)

		Data interpretation capability	the ability to produce a healthcare matrix and reports that evaluate patient care and service and identify areas for improvement	Ghosh and Scott (2011)
		Analytical personnel's technical skills	The members of an organization who have an analytical mindset and help derive value from BDA. Analytical staff fulfill a hybrid role that requires a broad combination of technical and soft skills and multidisciplinary knowledge domains. Technical skills include technical, analytical, and data skills.	Davenport, Harris and Morison (2010)
		Analytical personnel's business skills	The members of an organization who have an analytical mindset and help derive value from BDA. Analytical staff fulfill a hybrid role that requires a broad combination of technical and soft skills and multidisciplinary knowledge domains. Business skills include decision-making, governance, and identifying business opportunities.	Davenport, Harris and Morison (2010)
19	(Vidgen et al., 2017)	Data	-	-
		Organization and management	-	Nerur et al., 2005
		People	-	Nerur et al., 2005
		Process	-	Nerur et al., 2005
		Technology	-	Nerur et al., 2005
20	(Grover et al., 2018)	BDA Infrastructure	A big data infrastructure includes data sources (e.g., transactional, clickstream, social media, user-generated, external databases) and a platform needed for collecting, integrating, sharing, processing, storing, and managing big data.	Kumar (2004)
		BDA Capabilities	The ability to both manages and analyze data to create new insights. Firms need to develop a BDA strategy and be clear about how tangible (e.g., increased revenue or decreased cost) and/or intangible (e.g., increased customer satisfaction) value can be created from BDA	Kohli and Grover (2008)
21	(AlNuaimi et al., 2021)	Technological capabilities	Bundles of technological infrastructure (cloud, big data systems, NoSQL, deep learning, etc.), data connectivity/integration, and basic resources (such as investment).	Mikalef et al. (2019), Wang and Shi (2018)
		Human capabilities	Bundles of BDA managerial and technical skills as well as human learning.	Mikalef et al. (2019), Wamba et al. (2017)
22	(Fink et al., 2017)	BI Infrastructure	The BI infrastructure represents the physical aspect of BI assets. Davenport argues that deploying BI systems, that is, BI hardware and software, is necessary for becoming an organization that uses analytics as a main element of its strategy. A typical BI infrastructure consists of data storage, processing, and delivery.	Davenport, 2006. Wixom and Watson, 2001.
		BI Team	The BI team represents the human aspect of BI assets. The literature suggests that there are various approaches to the formation of a BI team, ranging from decentralized groups of super users who assist other users in interacting with BI systems to centralized, cross-functional competency centers with permanent, formal organizational structures.	Davis et al., 2006. Foster et al., 2015.
		Strategic BI capabilities	Repeatable actions of using BI assets to support strategic organizational activities, such as measuring organizational performance; identifying trends, opportunities, and threats in the business environment; and formulating new corporate strategies.	-

		Operational BI capabilities	Repeatable actions of using BI assets to support operational organizational activities, such as integrating certain forms of data analysis within transactional activities; modeling and optimizing production and service processes; and sharing information across business units.	-
23	(Cosic et al., 2015)	Governance Capability Area	A Mechanism for managing the use of BA resources and the assignment of decision rights and accountabilities to align BA initiatives with organisational objectives	Weill and Ross 2004
		Culture Capability Area	Tacit and explicit organisational norms, values and behavioural patterns that form over time and lead to systematic ways of gathering, analysing and disseminating data	Leidner and Kayworth 2006
		People Capability Area	Individuals who use BA as part of their job function	Davenport et al. 2007
		Technology Capability Area	Development and use of hardware, software, and data within BA activities	Negash 2004
24	(Ramakrishnan et al., 2020)	BI&A innovation infrastructure capability	Speaks to BI&A capability's technical aspect. An organization's ability to marshal and use BI&A's functionalities to sustain innovation.	Multiple, inductively created
		BI&A customer process capability	Enables BI&A to improve customer-centric activities such as helping employees solve customer issues, improve customer retention, and also take advantage of the knowledge acquired from customers to compete in the market.	Multiple, inductively created
		BI&A B2B process capability	Speak to BI&A capability's techno-organizational aspect.	Multiple, inductively created
		BI&A integration capability	Speaks to BI&A capability's organizational aspect.	Multiple, inductively created
25	(Işık et al., 2013b)	Technological BI capabilities	Sharable technical platforms and databases that ideally include a well-defined technology architecture and data standards	Ross et al. (1996)
		Organizational BI capabilities	Assets that support the effective application of BI in the organization, such as flexibility and shared risks and responsibilities	Ross et al. (1996)
		Data Generation (DG) capability	The ability of organisations to seek, identify, create, and access data from heterogeneous data sources across organisational boundaries.	Multiple, based on thematic analysis
26	(Arunachalam et al., 2018)	Data Integration and Management (DIM) capability	The ability of organisations to utilise tools and techniques to collect, integrate, transform and store data from heterogeneous data sources. The level of data integration, and ability to integrate different types of data gathered across organisational boundaries in real-time constitutes DIM capabilities.	Multiple, based on thematic analysis
		Advanced analytics capability	The ability of organisations to utilise tools and techniques to analyse supply chain data in batch wise, real-time, near-time, or as it flows and extracts meaningful insights for decision making. Data analytics is the most significant phase in data value chain from raw data to meaningful insights; analytical tools and techniques are leveraged to slice through the data to data-driven insights.	Multiple, based on thematic analysis
		Data visualisation capability	The ability of organisations to utilise tools and techniques to render information visuals and deliver the data-driven insights intuitively in a timely manner to the decision makers. Data visualisation is ''the representation and presentation of data that exploits our visual perception abilities in order to amplify cognition" (Kirk, 2012, p. 17).	Multiple, based on thematic analysis

Appendix E: Data Extraction Form – DA Capabilities Sub-Constructs

Table E1

ID	Reference	Core DA capability constructs	Sub-constructs	Definition/understanding/notes	Adapted from, if applicable
1	(Wang & Hajli, 2017)	Traceability	-	-	-
		Analytical capability	-	-	-
		Speed to decisions	-	-	-
		Predictive Analytics	-	-	-
		Interoperability	-	-	-
2	(Akter et al., 2016)	BDA Management Capability	BDA Planning	Identifies business opportunities and determines how the big data-based models can improve firm performance (FPER). For example, Amazon planned to engage a type of predictive modeling technique called 'collaborative ffltering' using customer data to generate 'you might also want' prompts for each product bought or visited. Amazon revealed at one point that 30% of sales were generated through its recommendation engine (Manyika et al., 2011).	(Barton and Court, 2012)
		BDA Management Capability	BDA Investment	Reflect cost–benefft analyses. For example, Netflix Inc. transformed its BDAC by investing in web data of over one billion movie reviews in categories such as liked, loved, hated, etc. to recommend movies that optimize the ability to meet customer preferences. According to Ramaswamy (2013), "[w]e found that companies with huge investments in Big Data are generating excess returns and gaining competitive advantages, putting companies without signiffcant investments in Big Data at risk".	(Davenport and Harris, 2007)
		BDA Management Capability	BDA Coordination	Represents a form of routine capability that structures the cross-functional synchronization of analytics activities across the firm. For example, analysts of Procter and Gamble work in coordination across operations,	(Kiron et al., 2014).

				the supply chain, sales, consumer research, and marketing to improve total business performance (Davenport, 2006).	
		BDA Management Capability	BDA Control	Controlling functions are performed by ensuring proper commitment and utilization of resources, including budgets and human resources. For example, the controlling functions in Amazon represent an evaluation of BDA proposals with reference to BDA plans, clariffcation of the responsibilities of the BDA unit, development of performance criteria for BDA, and continuous performance monitoring of the BDA unit.	(Schroeck et al., 2012).
		BDA Technology Capability	BDA Connectivity	Connectivity among different business units in sourcing and analyzing a variety of data from different functions (e.g., supply chain management, customer relationship management, etc.). For example, banks in the big data environment often improve customer service operations by combining data from automated teller machine (ATM) transactions, online queries, social media comments, and customer complaints (Barton and Court, 2012).	Multiple authors, no specific reference
		BDA Technology Capability	BDA Compatibility	Enables continuous ffows of information for real-time decisions. It also helps clean-up operations to synchronize and merge overlapping data and to ffx missing information. For example, Amazon embraces compatibility in the BDAC platform by using cloud technologies which help in collaboration, experimentation, and rapid analysis (Davenport and Harris, 2007a).	Multiple authors, no specific reference
		BDA Technology Capability	BDA Modularity	Modularity embodies ffexible platform development which allows the addition, modiffcation or removal of features to, or from, the model as needed. It helps in tapping business opportunities and improving FPER.	Multiple authors, no specific reference

		BDA Talent Capability	BDA Technology Management Knowledge	Refers to knowledge about technical elements, including operational systems, statistics, programming languages, and database management systems. For example, data scientists at Yahoo developed Apache Hadoop and at Facebook created the Hive language for Apache Hadoop projects—the path has been followed by other data-driven companies, such as Google, Amazon, Walmart, eBay, LinkedIn and Twitter, to transform their big data analytics capability (BDAC) (Davenport and Patil, 2012).	Multiple authors, no specific reference
		BDA Talent Capability	BDA Technical Knowledge	Refers to the big data resource management knowledge that is necessary to support business goals. For example, analytics professionals at Netffix use a visualization and demand analytics tool to understand consumer behavior and preferences: this has led them to achieve success in their “House of Cards” program in the United States (USA) (Ramaswamy, 2013).	Multiple authors, no specific reference
		BDA Talent Capability	BDA Business Knowledge	Refers to the understanding of various business functions and the business environment. For example, analytics professionals at Intuit are nurtured to develop their feel for business issues and empathy for customers.	Multiple authors, no specific reference
		BDA Talent Capability	BDA Relational Knowledge	Relational knowledge refers to the ability of analytics professionals to communicate and work with people from other business functions. Data scientists need close relationships with the rest of the business: this has been instrumental in LinkedIn in developing its new feature, ‘people you may know’, and achieving a 30% higher click-through rate. Overall, balanced proffciency needs to be developed through ongoing training and coaching in managing the project, the infrastructure and knowledge (Barton and Court, 2012).	Multiple authors, no specific reference
3	(Wamba et al., 2017a)	BDA Management Capabilities	BDA Planning	-	Kim et al. (2012, p. 336)
		BDA Management Capabilities	BDA Investment	-	Kim et al. (2012, p. 336)

		BDA Management Capabilities	BDA Coordination	-	Kim et al. (2012, p. 336)
		BDA Management Capabilities	BDA Control	-	Kim et al. (2012, p. 336)
		BDA Infrastructure Capability/Flexibilit y	BDA Connectivity	-	Kim et al. (2012, p. 335)
		BDA Infrastructure Capability/Flexibilit y	BDA Compatibility	-	Kim et al. (2012, p. 335)
		BDA Infrastructure Capability/Flexibilit y	BDA Modularity	-	Kim et al. (2012, p. 335)
		BDA Personnel Expertise Capability	BDA Technology Management Capability	-	Kim et al. (2012, p. 336)
		BDA Personnel Expertise Capability	BDA Technical Knowledge	-	Kim et al. (2012, p. 336)
		BDA Personnel Expertise Capability	BDA Business Knowledge	-	Kim et al. (2012, p. 336)
		BDA Personnel Expertise Capability	BDA Relational Knowledge	-	Kim et al. (2012, p. 336)
4	(Wang et al., 2018)	Analytical capability	-	-	Chen et al. (2012)
		Unstructured data analytical capability	-	-	-
		Decision support capability	-	-	-
		Predictive capability	-	-	Shmueli and Koppius, 2011
		Traceability	-	-	-
5	(Bordeleau et al., 2018)	Operational BI capabilities	-	-	Fink et al. (2017)
		Strategic BI capabilities	-	-	Fink et al. (2017)
6	(Gupta & George, 2016)	No specific capabilities, focussed on resources	-	-	-
7	(Mikalef et al., 2019b)	No specific capabilities, focussed on resources	-	-	-
8	(Popovič et al., 2018)	Data provisioning	-	-	-
		Analytical capabilities	-	-	-
		People's expertise	-	-	-

9	(Mikalef et al., 2020)	No specific capabilities, focussed on resources	-	-	Grant
10	(Mikalef et al., 2019a)	No specific capabilities, focussed on resources	-	-	Bharadwaj
11	(Rialti et al., 2019)	BDA Infrastructure Flexibility	-	No specific construct, but operationalize BDA Infrastructure Flexibility on three latent variables: **connectivity, modularity, and compatibility.** See defintion original authors.	Wamba et al. 2017
		BDA Management Capabilities	-	No specific construct, but operationalize BDA Management Capabilities on four latent variables: **planning, decision-making, coordination, and control.** See defintion original authors.	Wamba et al. 2017
		BDA Personnel Expertise Capability	-	No specific construct, but operationalize BDA Personnel Expertise Capability on three latent variables: **technical knowledge, business knowledge, and relational knowledge.** See defintion original authors.	Wamba et al. 2017
12	(Jha et al., 2020)	Data management and use of advanced software packages	-	-	-
		Skilled human resources and training for analytics	-	-	-
		Intra-organizational power dynamics	-	-	-
		Global connectedness	-	-	-
		External landscape and analytics capabilities	-	-	-
13	(Torres et al., 2018)	BI&A Management Capability	-	-	Multiple authors, no specific reference
		BI&A Technical Infrastructure Quality	-	-	Multiple authors, no specific reference
		BI&A Personnel Expertise	-	-	Multiple authors, no specific reference
14	(Mikalef et al., 2018)	Planning	-	-	Not explained

		Sourcing	-	-	Not explained
		Deployment	-	-	Not explained
		Management	-	-	Not explained
15	(Ardito et al., 2019)	No specific capabilities	-	-	-
		3 levels of capabilities mentioned however; aspirational, experienced, and transformed	-	-	LaValle et al. (2011)
16	(Yasmin et al., 2020)	Infrastructure Capabilities	-	-	Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien , 2005
		Human Resource Management Capabilities	-	-	Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien , 2005
		Management Capabilities	-	-	Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien , 2005
17	(Sun & Liu, 2020)	BDA Technology Capability	-	No specific construct, but partially operationalize BDA Technology Capability on different items which include: **connectivity, modularity, and compatibility.** See defintion original authors.	Akter et al., 2016. Ferraris et al., 2019.
		BDA Management Capability	-	No specific construct, but partially operationalize BDA Management Capability on different items which include: **planning, investment decision-making, coordination, and control.** See defintion original authors.	Akter et al., 2016. Ferraris et al., 2019.
18	(Wang et al., 2019)	Data integration capability	-	-	Wang and Bird (2017)
		Analytical capability	-	-	Ghosh and Scott (2011)
		Predictive analytics	-	-	Wessler (2013, p. 21)
		Data interpretation capability	-	-	Ghosh and Scott (2011)

		Analytical personnel's technical skills	-	-	Davenport, Harris and Morison (2010)
		Analytical personnel's business skills	-	-	Davenport, Harris and Morison (2010)
19	(Vidgen et al., 2017)	Data	-	No specific constructs, but 7 data challenge items: 1. Managing data quality 2. Availability of data 3. Getting access to data sources 4. Managing and integrating data structures 5. Managing data security and privacy 6. Data visualization 7. Defining what 'big' data is	-
		Organization and management	-	No specific constructs, but 12 organization and management challenge items: 1. Creating a big data and analytics strategy 2. Building a corporate data culture 3. Making time available for analytics 4. Overcoming resistance to change 5. Agreeing data ownership 6. Managing costs of analytics 7. Defining the scope of analytics projects 8. Securing investment 9. Legislative and regulatory compliance 10. Using the data ethically 11. Safeguarding reputation 12. Working with academia	-
		People	-	No specific constructs, but 3 people challenge items: 1. Building data skills in the organization 2. Analytics skills shortage 3. Technical skills shortage	-
		Process	-	No specific constructs, but 4 process challenge items: 1. Producing credible analytics 2. Managing data processes 3. Manipulating data 4. Performance management	-
		Technology	-	No specific constructs, but 2 technology challenge items: 1.Restrictions of existing IT platforms 2.Managing data volumes	-
20	(Grover et al., 2018)	BDA Infrastructure	Big Data Asset	A big data infrastructure includes data sources (e.g., transactional, clickstream, social media, user-generated, external databases) and a platform needed for collecting,	-

				integrating, sharing, processing, storing, and managing big data. They furthermore identify three challenge items: Data Quality, Data Integration, Data Security.	
		BDA Infrastructure	Analytics Portfolio	Core to developing BDA capabilities to leverage the analytics infrastructure is the portfolio, including text analytics (e.g., information extraction, text mining, sentiment analysis, topic modeling), predictive analysis (e.g., regression, survival analysis, time series analysis), audio analytics (e.g., automatic speech recognition, phonetic-based analysis, Interactive Voice Response), video analytics (e.g., motion and object detection, whole-to-part inductive analysis), social media analytics, geographic (location and spatial) analytics, streaming analytics, and graph analytics (e.g., graph partitioning, network analysis).	-
		BDA Infrastructure	Human Talent	To leverage investments in data and analytics, arguably the most critical element is the human talent infrastructure. Expertise and experience are needed to design and implement BDA strategies. Without the right group of skilled big data experts, it is impossible to develop and carry out a BDA strategy. This is actually one of the biggest challenges for firms. Big data professionals include data scientists, developers, programmers, analysts, and modelers that can serve significant roles in both managing and analyzing data, particularly the plethora of unstructured data in diverse formats. The most intensive use of people occurs during the input (design of BDA strategy) and output (interpretation of results) stages.	-
		BDA Capabilities	-	No specific mentioning of constructs but refer to Big Data Analytics Integration, Management, Sharing, and Analysis.	-
21	(AlNuaimi et al., 2021)	Technological capabilities	Technology infrastructure	Novel technologies that are capable of handling the challenges posed by gigantic, diverse, and fastmoving data such as cloud computing, big data systems, NoSQL database,	(Arifiani et al., 2019), (Gupta and George, 2016), (Wamba et al., 2017), (Jeble

				cognitive systems, deep learning, and other artificial intelligence techniques	et al., 2018) (Akter et al., 2016)
		Technological capabilities	Data	Availability and accessibility of enterprise-specific data, which are created as a result of the firm's internal operations such as inventory updates, accounting transactions, sales, and human resource management	(Gupta and George, 2016), (Wamba et al., 2017), (Jeble et al., 2018), (Akter et al., 2016)
		Human capabilities	Employee skills	The know-how required by employees to use new forms of technology to extract intelligence from big data	(Gupta and George, 2016), (Wamba et al., 2017), (Jeble et al., 2018), (Ferraris et al., 2019)
		Human capabilities	Managerial experience	Firm-specific skills developed by managers over time that allows them to understand the current and predict the future needs of the organizations and to have a sharp understanding of how and where to apply the insights extracted from big data.	(Gupta and George, 2016), (Wamba et al., 2017), (Jeble et al., 2018), (Ferraris et al., 2019)
22	(Fink et al., 2017)	BI Infrastructure	-	The BI infrastructure represents the physical aspect of BI assets. Davenport argues that deploying BI systems, that is, BI hardware and software, is necessary for becoming an organization that uses analytics as a main element of its strategy. A typical BI infrastructure consists of data storage, processing, and delivery.	Davenport, 2006.
		BI Team	-	The BI team represents the human aspect of BI assets. The literature suggests that there are various approaches to the formation of a BI team, ranging from decentralized groups of super users who assist other users in interacting with BI systems to centralized, cross-functional competency centers with permanent, formal organizational structures.	Davis et al., 2006. Foster et al., 2015.
		Strategic BI capabilities	-	-	-
		Operational BI capabilities	-	-	-

23	(Cosic et al., 2015)	Governance Capability Area	Decision Rights and Responsiblities	Assignment of decision rights and responsibilities by determining; (i) those responsible for making certain decisions in relation to the planning, implementation and applications of BA, (ii) where appropriate, those who will provide the input for such decisions, and (iii) those who will be held accountable for the resulting actions and outcomes of these decisions. It is important that a person responsible for making a certain decision is held accountable for the resulting actions and outcomes.	Weill and Ross, 2004.
		Governance Capability Area	Strategic Alignment	Alignment of an organisation's BA initiatives with its business strategy. It is a two-way relationship in the sense that BA initiatives can help measure and enforce a business strategy, whilst business strategy necessarily shapes BA initiatives as they evolve. This requires a clearly defined business strategy that is enunciated to all staff and translated into a set of measurable outcomes. It also requires a genuine commitment to the strategy demonstrated by the decisions and actions of senior people.	Williams and Williams, 2007.
		Governance Capability Area	Dynamic BA Capabilities	Ability to reconfigure and leverage an organisation's BA resources and capabilities in order to respond to changes in the business environment in a timely and efficient manner. Such responsiveness requires the ability to identify potential BA opportunities (Search), prioritise those opportunities based on business need, risk and technology maturity (Select) and then funding and implementing the opportunities (Asset Orchestration) resulting in new and unique resource configurations.	Sharma and Shanks, 2011.
		Governance Capability Area	Impact & Change Management	Ability to manage human, technological and process impacts across the organisation arising from BA initiatives. This involves managing changes to the systems environment and the provision of training and rewards in order to; (i) demonstrate the value and utility of BA, (ii) encourage the	Negash, 2004.

				adoption of new BA technologies and work practices, (iii) mitigate potential resistance, and (iv) manage expectations. Furthermore, it is important that all types of BA users, from managers to operational staff, are involved in the initial planning of a BA initiative.	
		Culture Capability Area	Evidence-based Management	A culture where (i) formal authority, reputation, intuition and ad-hoc decision-making are preceded by decisions based on data, (ii) BA users, including power users, are encouraged to actively participate in the development of a data-driven environment, (iii) there is trust in data and the BA tools used to analyse data, (iv) whenever possible, assertions are substantiated with data, and (v) although the emphasis is on fact-based decision making, there is still some room for intuition and ad-hoc decision-making, particularly when the required data is not available.	Pfeffer and Sutton, 2006.
		Culture Capability Area	Embeddedness	Extent to which BA has permeated the fabric of an organisation e.g. business processes and values (e.g. appreciation for BA analysis tools and data-driven insights). It is reflected in the extent to which people routinely use data and BA tools to solve problems and make decisions. It is facilitated by sharing metadata and the use of a collaboration portal. The portal enables work to be shared and intellectual property to be spread throughout the organisation. Where appropriate, models are used to make decisions on an ongoing and pervasive basis.	Shanks et al., 2012.
		Culture Capability Area	Executive Leadership and Support	Ability of senior managers and executives to advocate the use of BA systems and data-driven decision-making throughout the organisation. This requires (i) a clear vision, (ii) first-hand experience and understanding of the benefits and successes of BA and (iii) the promotion of this vision and understanding throughout the organisation, and (iv) the provision of financial	Laursen and Thorlund, 2010.

				and material support for BA initiatives.	
		Culture Capability Area	Communication	BA personnel across the organisation foster a culture of open communication and trust between themselves and other business users. This involves listening carefully to the needs of business users and translating BA concepts into every-day business language. It is facilitated by close and frequent contact via a variety of different communication channels.	Davenport and Harris, 2007.
		People Capability Area	Technology Skills and Knowledge	Combined skills and knowledge of BA technology specialists across the organisation including; programming, optimisation software, algorithms, database/file management, ETL (Extraction, Transformation and Loading), data warehousing, software development methodologies and high level architectures. Some level of business domain and industry knowledge is necessary to apply these skill sets. Furthermore, teams should consist of specialists whose skills are complementary to other team members.	Davenport and Harris, 2007.
		People Capability Area	Business Skills and Knowledge	Combined skills and knowledge of people throughout the organisation that are involved in the business side of BA initiatives including; (i) fundamental business principles, and (ii) depth of domain knowledge of the organisation's key products, services, processes, value chain and industry in general. It also includes the ability to; (i) network, (ii) seek out opportunities and threats, and (iii) develop and drive an agenda. Some level of technical expertise is necessary to understand the data available to them and communicate with BA technical specialists.	Anderson-Lehman et al., 2004.

		People Capability Area	Management Skills and Knowledge	Combined skills and knowledge of people in BA related management roles throughout the organisation to (i) prioritise and manage BA projects, (ii) redesign business processes as a result of implementing BA, and (iii) translate, communicate and sell the potential values and benefits of BA to senior executives (e.g. senior executives and general managers). Some level of technical expertise is necessary to understand the data available to them and communicate with BA technical specialists.	Davenport and Harris, 2007.
		People Capability Area	Entrepreneurship and Innovation	Combined skills and knowledge of BA managers and other BA users throughout the organisation to (i) continually challenge the status quo, (ii) manage new innovation as a separate activity to continuous improvement, (iii) create and promote a technical innovation team, as well as (iv) an innovation forum made up of innovation teams from other business units. It is characterised by an entrepreneurial mindset and vision and the ability to rationally assess risks and benefits. It is enhanced through the provision of some authoritative autonomy and financial independence, which provides BA managers with a degree of freedom to pursue value-creating actions.	Sharma et al., 2010.
		Technology Capability Area	Data Management	Mechanism for (i) sourcing data for BA initiatives from multiple channels, including operational/transactional systems and third-party sources, (ii) ensuring its quality e.g. consistency, accessibility, flexibility, integrity, timeliness and availability and (iii) integrating it with existing data in a central repository e.g. enterprise data warehouse. It also includes master data management and metadata management to ensure data definitions are consistent across organisational units to encourage common usage and understanding of the data.	Watson and Wixom, 2007.

		Technology Capability Area	Systems Integration	Seamless integration of BA systems with operational/transactional systems at the process, technology and data levels in order to exploit the capabilities of both. Systems integration is important for leveraging value from BA and is facilitated by the flexible design of technology infrastructure and systems architecture. It also introduces a degree of complexity and therefore should be done with care and careful consideration of the need.	Sharma and Shanks, 2011.
		Technology Capability Area	Reporting BA Technology	Ability to develop and utilise self-service analysis applications e.g. reports, dashboards, scorecards, online analytical processing (OLAP) and data visualisation technologies, which display output in a user-friendly format that is readily understood by non-technical users. These applications are particularly useful for addressing structured problems and facilitate the visual manipulation and exploration of data.	Watson and Wixom, 2007.
		Technology Capability Area	Discovery BA Technology	Ability to develop and utilise quantitative and qualitative analysis tools (e.g. statistical analysis, data mining, text mining and predictive analysis) to facilitate the semi-automated analysis of numerical, semi-structured and unstructured data to; (i) discover new actionable insights from patterns in the data, and (ii) extrapolate patterns found in the data to predict what is likely to occur in the future. These tools are particularly useful for addressing less structured problems.	Negash, 2004.
24	(Ramakrishnan et al., 2020)	BI&A Innovation Infrastructure capability	BI&A Technology	The degree to which an organization implements BI&A technology, which includes business intelligence, collaboration, distributed learning, discovery, mapping, opportunity recognition, generation and aspects related to data/analytics security and privacy.	Multiple, inductively created
		BI&A Innovation Infrastructure capability	BI&A Culture	The norms by which an organization uses BI&A for decision making.	Multiple, inductively created

		BI&A Innovation Infrastructure capability	BI&A Governance	The degree to which an organization defines BI&A-related rules, policies, procedures, processes, and report patterns.	Multiple, inductively created
		BI&A Customer Process Capability	BI&A Customer Orientation	The way an organization orients BI&A to meets its customer needs and serve them.	Multiple, inductively created
		BI&A Customer Process Capability	BI&A Customer Application	The way an organization uses BI&A to absorb customer-related intelligence.	Multiple, inductively created
		BI&A B2B Process Capability	BI&A B2B Orientation	The way an organization orients BI&A to address supply chain-related needs.	Multiple, inductively created
		BI&A B2B Process Capability	BI&A B2B Engagement	The way an organization uses BI&A to engage new B2B partners and improve coordination with existing B2B partners.	Multiple, inductively created
		BI&A B2B Process Capability	BI&A B2B Compatibility	The degree to which BI&A has contributed towards process coordination and operational capability improvement through increased compatibility.	Multiple, inductively created
		BI&A Integration Capability	BI&A Acquisition	The degree to which an organization uses BI&A to procure and share intelligence.	Multiple, inductively created
		BI&A Integration Capability	BI&A Conversion	The degree to which an organization uses BI&A to make the intelligence gathered use.	Multiple, inductively created
25	(Işık et al., 2013b)	Technological BI capabilities	Data Quality	Data quality refers to the consistency and comprehensiveness of the data. It is estimated that more than half of BI projects fail due to data quality issues and that customer data quality issues cost U.S. businesses over $600 billion dollars a year. Poor data handling processes, poor data maintenance procedures, and errors in the migration process from one system to another can cause poor data reliability.	Multiple, inductively created
		Technological BI capabilities	Integration with other systems	Integration involves linking various systems and their applications or data together, either physically or functionally, so that value can be created above and beyond that provided by each individual system. While much of the discussion of integration in BI speciffcally on data integration and its associated tools, the integration of both related systems and data stores presents a signiffcant challenge in many sectors. For example, a recent survey of the energy utility sector found that this	Multiple, inductively created

				integration was one of the top two challenges they faced in moving forward with BI.	
		Technological BI capabilities	User Access	One size does not fit all with BI; different BI tools have different capabilities and serve different purposes. Because organizations have multiple purposes for and user groups within BI, they may need to employ different BI applications with different access methods. Some organizations deploy a BI that provides unlimited access to data analysis and reporting tools to all its users, while others offer relatively restricted access. Although most web-centric applications are relatively easy to use, especially for non-technical users, desktop applications are mainly dedicated to speciffc users and provide specialized functionalities for more effective analysis. In this study, we define user access according to users' perceptions of their access to their BI, including such factors as the overall quality, scope, and support of their decision making.	Multiple, inductively created
		Organizational BI capabilities	Flexibility	Flexibility is the organizational capability of BI to provide decision support when variations exist in business processes, technology or the business environment in general. To achieve the competitive advantages provided by BI, organizations must select the underlying technology to support the BI operations carefully; flexibility is one of the most important factors to consider. Ideally, the system must be compatible with the existing tools and applications to minimize cost and complexity.	Multiple, inductively created
		Organizational BI capabilities	Risk Management Support	Risk management support refers to the organizational BI ability to support decisions under conditions of uncertainty when not all the facts are known. People, processes, technology and external events can present risks to an organization. Risk	Multiple, inductively created

				management is crucial to organizational success, and risk management support by BI applications is important, especially for organizations operating in high-risk environments.	
26	(Arunachalam et al., 2018)	Data Generation (DG) capability	-	-	Multiple, based on thematic analysis
		Data Integration and Management (DIM) capability	-	-	Multiple, based on thematic analysis
		Advanced analytics capability	-	-	Multiple, based on thematic analysis
		Data visualisation capability	-	-	Multiple, based on thematic analysis

Appendix F: Data Extraction Form – DA Business Value Typologies

Table F1

ID	Reference	DA Business Value Construct	Definition/understanding	Adapted from, if applicable
1	(Wang & Hajli, 2017)	IT infrastructure benefits (Operational business value)	Items: • Reduce system redundancy • Avoid unnecessary IT costs • Transfer data quickly among healthcare IT systems Process standardization among various healthcare IT systems • Simplify IT management • Reduce IT maintenance costs regarding data storage	-
		Operational benefits (Operational business value)	Items: • Improve the quality and accuracy of clinical decisions Process a large number of health records in seconds Enable proactive treatment before the condition worsens • Reduce the number of unnecessary treatments • Shorten the time of diagnostic test • Meaningful use of EHRs • Reduce the rate of readmission • Reduce the time of patient travel • Reductions in surgery-related hospitalizations • Immediate access to clinical data for analysis • Explore inconceivable new research avenues	-
		Organizational benefits (Strategic business value)	Items • Deliver a seamless, coordinated, and consentient patient experience across all of its facilities • Improve cross-functional communication and collaboration among administrative staff, researchers, clinicians, and IT staff • Detect interoperability problems much more quickly than traditional manual methods • Drive full adoption of EHRs across organizational boundaries • Enable to share data with other institutions and add new services, content sources and research partners	-
		Managerial benefits (Operational and potentially strategic business value)	• Gain insights quickly about emerging trends • Provide members of the board and heads of department with sound decision-support information on the daily clinical setting • Optimization of business growth-related decisions	-

		Strategic benefits (Strategic business value)	• Provide a comprehensive view of treatment delivery for meeting future need • Use business analytics as a competitive differentiator	-
4	(Wang et al., 2018)	Operational benefits (Operational business value)	The benefits obtained from the improvement of operational activities. Sub-dimensions: • Cost reduction • Cycle time reduction • Productivity improvement • Quality improvement • Customer service improvement	-
		Managerial benefits (Operational and potentially strategic business value)	The benefits obtained from business management activities which involve allocation and control of the firms' resources, monitoring of operations and supporting of business strategic decisions. Sub-dimensions: • Better resource management • Improved decision making and planning • Performance improvement	-
		Strategic benefits (Strategic business value)	The benefits obtained from strategic activities which involve long-range planning regarding high-level decisions. Sub-dimensions: • Support for business growth • Support for business alliance • Building for business innovations • Building cost leadership • Generating product differentiation • Building external linkages	-
		Organizational benefits (Mainly strategic business value)	The benefits arise when the use of an enterprise system benefits an organization in terms of focus, cohesion, learning, and execution of its chosen strategies. Sub-dimensions: • Changing work patterns • Facilitating organizational learning • Empowerment • Building common vision	-
5	(Bordeleau et al., 2018)	Operational Business Value	Several dimensions have been included in the measurement of IT effect on strategic performance, notably financial impacts, competitive impacts, and market performance. We adopt the most recent definition for BI&A strategic business value, which includes all of the above in addition to the ability to meet strategic objectives.	Fink et al., 2017
		Strategic Business Value	We define BI&A operational value as subjective efficiency assessment by a senior manager and objective performance indicator variation.	Lönnqvist and Pirttimäki, 2006.

6	(Gupta & George, 2016)	Operational Performance (Operational business value)	Items / measures of firm performance with regards to their market: • Our productivity has exceeded that of our competitors • Our profit rate has exceeded that of our competitors. • Our return on investment (ROI) has exceeded that of our competitors. • Our sales revenue has exceeded that of our competitors.	Ravichandran and Lertwongsatien, 2005. Wang et al., 2012.
		Market Performance (Strategic business value)	Items / measures of firm performance with regards to their market: • We have entered new markets more quickly than our competitors. • We have introduced new products or services into the market faster than our competitors. • Our success rate of new products or services has been higher than our competitors. • Our market share has exceeded that of our competitors.	
8	(Popovič et al., 2018)	Operational and Strategic Benefits (Operational and strategic business value)	Echoing extant studies in operations literature, we find that when firms utilize more BDA, they better forecast previously unpredictable outcomes, and improve process performance. As a result, firms realize operational process benefits in the form of cost reductions, better operations planning, lower inventory levels, better organization of the labor force and elimination of waste, while they leverage improvements in operations effectiveness and customer service.	-
13	(Torres et al., 2018)	Firm performance (Strategic business value)	Firm performance is the firm's ability to use its assets to generate revenues, measured in monetary terms. According to the dynamics capabilities literature, the effect of dynamic capabilities on firm performance is mediated by functional performance, i.e. the efficiency and effectiveness of a firm's ordinary capabilities.	Helfat et al., 2007.
		Functional performance (Operational business value)	Functional performance is defined as the operational efficiency and effectiveness of the firm's business processes, and as such it reflects the degree to which the firm's ordinary capabilities are optimized for the current environment.	Frei and Harker, 1999. Ramirez et al., 2010.
16	(Yasmin et al., 2020)	Financial / operational performance measures (Operational business value)	Performance measures: • Product development • Cost saving • Number of new product and service projects Return on sales - profit/total sales	
		Market-related performance measures (Strategic business value)	Performance measures: • Sales growth • Market share	
20	(Grover et al., 2018)	Strategic business value	Four distinct targets of value creation: • Organization performance such as the quality of decision making	

			• Business process improvement (e.g., the greater efficiency of business processes through automation) • Product and service innovation • Customer experience and market enhancement (e.g., improved consumer satisfaction, retention, and customer-firm relationships)	
22	(Fink et al., 2017)	Operational business value	Operational value represents improvements in the efficiency of business processes, including cost reduction and productivity enhancement.	Melville et al., 2004.
		Strategic business value	Strategic value represents the ability to meet organizational objectives, including improvements in financial performance and competitiveness.	Melville et al., 2004.

Appendix G: IoT Analytical Capabilities

Table G1: IoT Analytical Capability Categories by Siow et al. (2018)

Capability Category	Definition/description	Adapted from
Descriptive Analytics	It helps us to answer the question, “What happened?” It can take the form of describing, summarizing, or presenting raw IoT data that has been gathered. Data are decoded, interpreted in context, fused, and then presented so that it can be understood and might take the form of a chart, a report, statistics, or some aggregation of information (Siow et al., 2018).	Bertolucci et al., 2013.
Diagnostic Analytics	It is the process of understanding why something has happened. This goes one step deeper than descriptive analytics in that we try to find out the root cause and explanations for the IoT data. Both descriptive and diagnostic analytics give hindsight on what and why things have happened (Siow et al., 2018).	Kart, 2012. *Gartner*. Chandler et. al, 2011. *Gartner*.
Discovery Analytics	Through the application of inference, reasoning, or detecting nontrivial information from raw IoT data, the capability of Discovery in Analytics is created. Given the acute problem of volume that IoT data presents, Discovery in Analytics is also valuable in narrowing down the search space of analytics applications. Discovery in Analytics on data tries to answer the question of what happened that we do not know about, and the outcome is insight into what happened. What differentiates this from the previous types of analytics is using the data to detect something new, novel, or different (e.g., trends, exceptions, or clusters) rather than describing or explaining it (Siow et al., 2018).	Corcoran, 2012.
Predictive Analytics	Predictive Analytics move past hindsight and insight to foresight. It tries to answer the question, “What is likely to happen?”, and uses past data and knowledge to predict future outcomes and provides methods to assess the quality of these predictions (Siow et al., 2018).	Bertolucci et al., 2013.
Prescriptive Analytics	It looks at the question of what be done about what has happened or is likely to happen. It enables decision-makers to not only look into the future about opportunities (and issues) that are potentially out there, but it also presents the best course of action to act on foresight in a timely manner with the consideration of uncertainty. This form of analytical capability is coupled with optimization and answering “what if” questions to evaluate and present the best solution (Siow et al., 2018).	Bertolucci et al., 2013.

Appendix H: IoT Analytics Themes

Table H1: IoT domains and potential application areas (Siow et al., 2018)

Domain	Potential Areas
Health	Healthcare, e.g. Ambient Assisted Living
Transport	Smart Transportation / Logistics / Traffic Control
Living	Smart City / Smart Buildings / Cultural Behavior
Environment	Smart Energy System / Environmental Monitoring such as Wind Forecasting
Industry	Smart Factory / Smart Farming / Chemical Process Monitoring

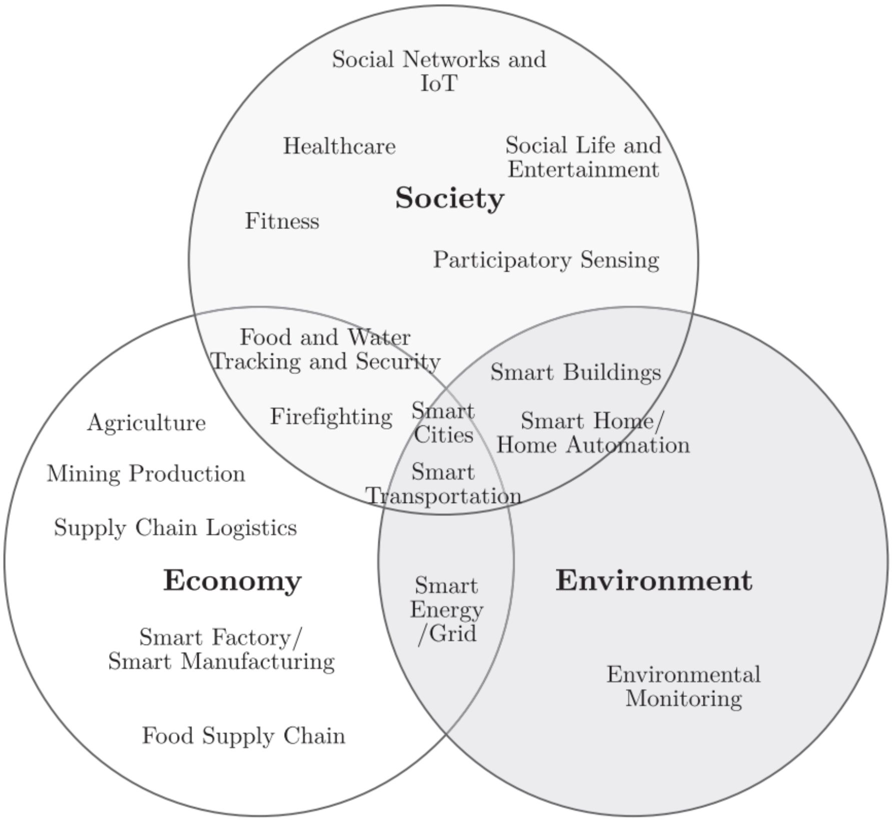

Figure H1: IoT themes and potential application areas (Siow et al., 2018)

Appendix I: DA Capabilities coding network

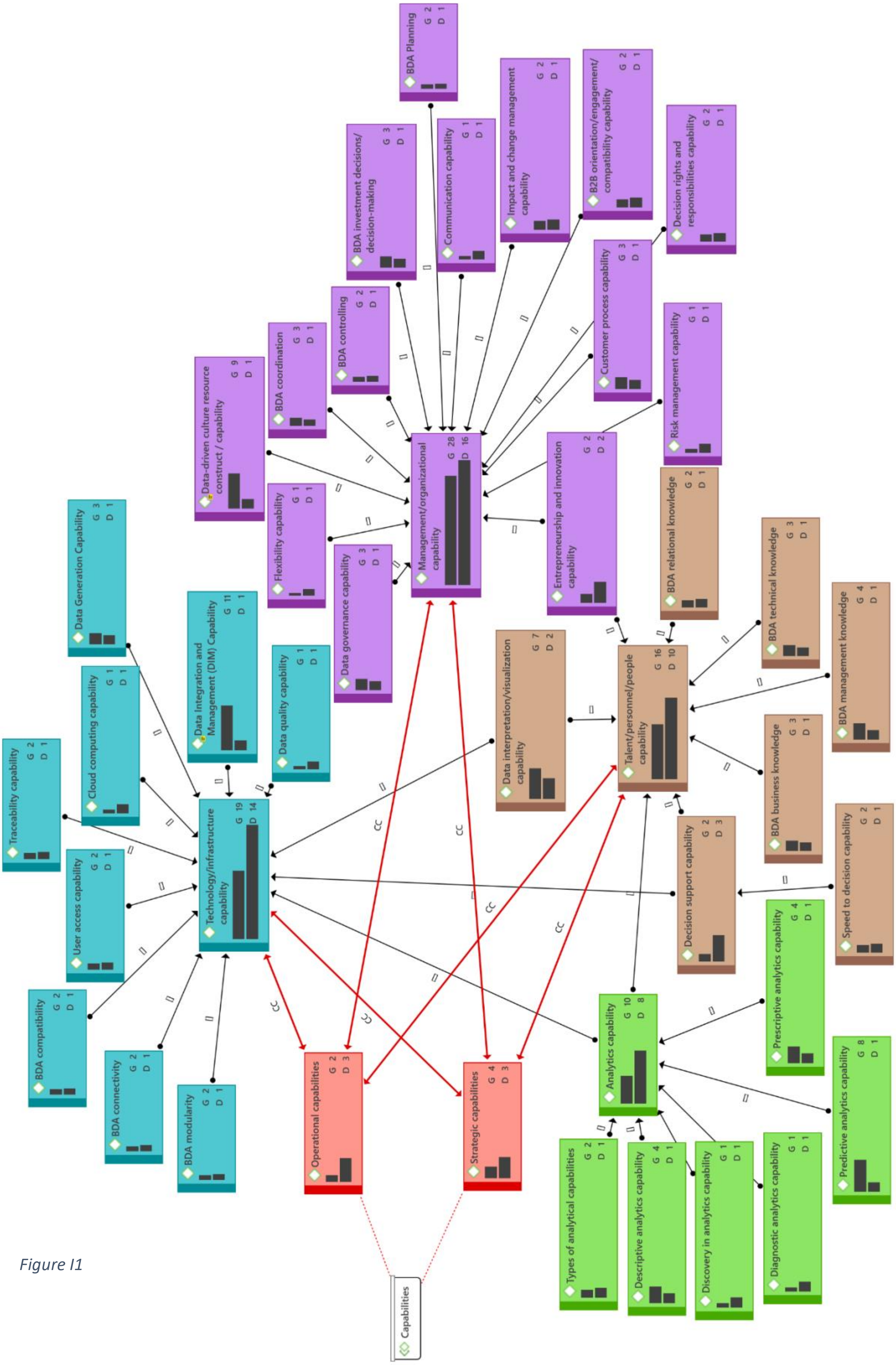

Figure I1

Appendix J: DA Business value coding network

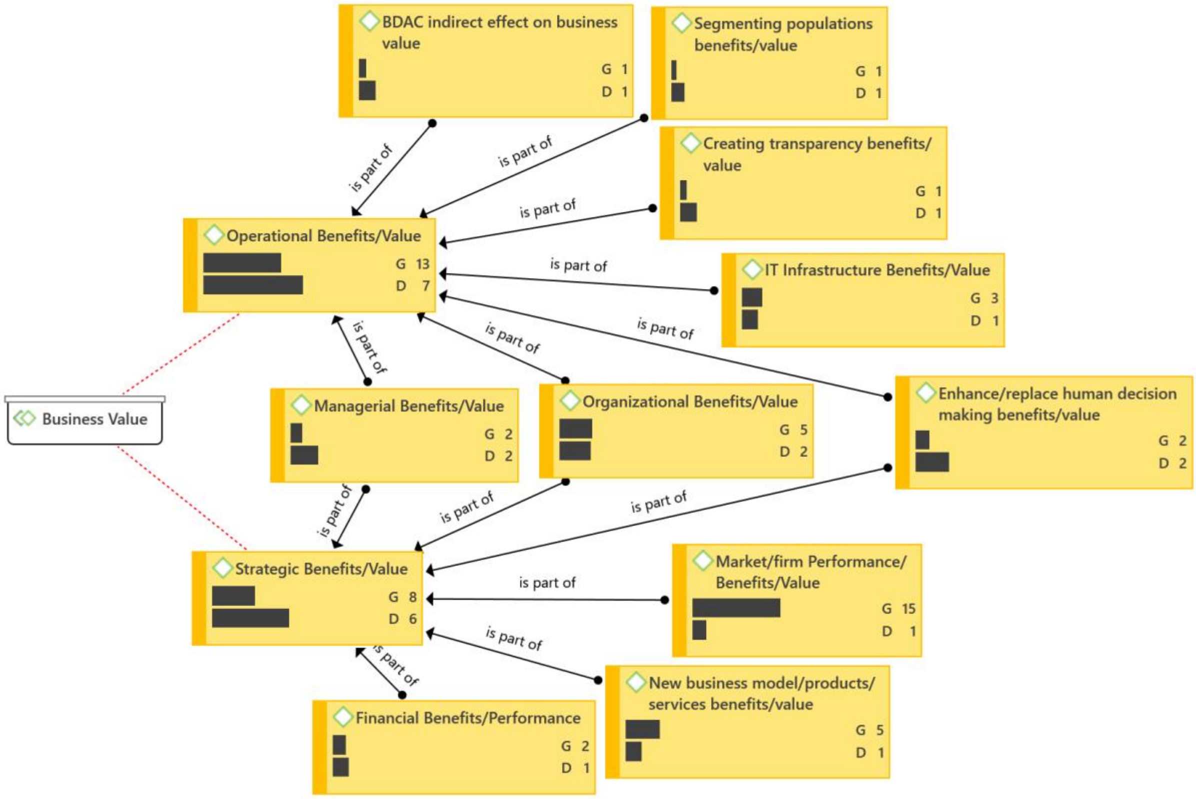

Figure J1

Appendix K: Literature Review Codes from Atlas.ti

Table K1

Code	Groundedness	Density	Code Groups
Operational Benefits/Value	13	6	Business Value
Strategic Benefits/Value	8	3	Business Value
Market/firm Performance/Benefits/Value	15	1	Business Value
New business model/products/services benefits/value	5	1	Business Value
Organizational Benefits/Value	5	1	Business Value
Enhance/replace human decision making benefits/value	2	1	Business Value
Managerial Benefits/Value	2	1	Business Value
Financial Benefits/Performance	2	1	Business Value
Creating transparency benefits/value	1	1	Business Value
Segmenting populations benefits/value	1	1	Business Value
IT Infrastructure Benefits/Value	3	0	Business Value
Sources of value from analytics	1	0	Business Value
Value creation mechanisms	1	0	Business Value
Intangible value	1	0	Business Value
Tangible value	1	0	Business Value
Management/organizational capability	28	16	Capabilities
Technology/infrastructure capability	19	14	Capabilities
Talent/personnel/people capability	16	10	Capabilities
Analytics capability	10	6	Capabilities
Strategic capabilities	4	3	Capabilities
Decision support capability	2	3	Capabilities
Operational capabilities	2	3	Capabilities
Data interpretation/visualization capability	7	2	Capabilities
Entrepreneurship and innovation capability	2	2	Capabilities
Data Integration and Management (DIM) Capability	11	1	Capabilities
Predictive analytics capability	6	1	Capabilities
BDA management knowledge	4	1	Capabilities
BDA technical knowledge	3	1	Capabilities
BDA business knowledge	3	1	Capabilities
Data governance capability	3	1	Capabilities
Data Generation Capability	3	1	Capabilities
BDA coordination	3	1	Capabilities
Customer process capability	3	1	Capabilities

BDA investment decisions/decision-making	3	1	Capabilities
Prescriptive analytics capability	2	1	Capabilities
Descriptive analytics capability	2	1	Capabilities
BDA relational knowledge	2	1	Capabilities
BDA modularity	2	1	Capabilities
BDA compatibility	2	1	Capabilities
Traceability capability	2	1	Capabilities
Speed to decision capability	2	1	Capabilities
BDA connectivity	2	1	Capabilities
BDA controlling	2	1	Capabilities
Impact and change management capability	2	1	Capabilities
Decision rights and responsibilities capability	2	1	Capabilities
Types of analytical capabilities	2	1	Capabilities
B2B orientation/engagement/compatibility capability	2	1	Capabilities
BDA Planning	2	1	Capabilities
User access capability	2	1	Capabilities
Risk management capability	1	1	Capabilities
Communication capability	1	1	Capabilities
Cloud computing capability	1	1	Capabilities
Flexibility capability	1	1	Capabilities
Data quality capability	1	1	Capabilities
DA Capability Definition	19	0	Capabilities
How capabilities are built	9	0	Capabilities
Literature overview - capabilities	7	0	Capabilities
Overview of 16 BA Capabilities	3	0	Capabilities
31 DA capability constructs/challenges	1	0	Capabilities
Data-driven culture resource construct / capability	9	1	Capabilities Miscellaneous
DA Capability research history	2	0	Capabilities Miscellaneous
Limited empirical research on DA capability	1	0	Capabilities Miscellaneous
Sensors	38	0	IoT
Internet of Things	30	0	IoT
IoT frameworks/figures	1	0	IoT
Methodology - approach	3	0	Methodology
Content Analysis	1	0	Methodology
Methodology - case selection	1	0	Methodology
BDAC indirect effect on business value	1	1	Miscellaneous
Framework/model overview	30	0	Miscellaneous
Research Questions/Objectives	28	0	Miscellaneous

Conclusion/main findings	26	0	Miscellaneous
Future studies recommendations	7	0	Miscellaneous
Contextual variables	2	0	Miscellaneous
Data types	2	0	Miscellaneous
Lack of exploratory research	1	0	Miscellaneous
For literature review	1	0	Miscellaneous
Summary of studies BDAC and firm performance	1	0	Miscellaneous
BDA & Management Research Clusters	1	0	Miscellaneous
Data Security	1	0	Miscellaneous
Orchestration	1	0	Miscellaneous
RBT/Resources	10	0	Resources
Technology resources construct	6	0	Resources
Human resources	6	0	Resources
Data resources construct	5	0	Resources
Tangible resources	4	0	Resources
Intangible resources	4	0	Resources
Technical human skills resources construct	4	0	Resources
Process resources construct	3	0	Resources
Organizational resources construct	3	0	Resources
People resources construct	3	0	Resources
Managerial human skills construct	3	0	Resources
RBV vs Resource Orchestration Theory	2	0	Resources
Types of resources	1	0	Resources
Basic resources construct	1	0	Resources
Organizational learning resources construct	1	0	Resources

Appendix L: Interview protocol

Interview protocol and operationalization based on the capabilities identified in the literature review. Before each question, the definition of the construct is explained. For clarity, the research questions are posted again below.

SRQ4: What capabilities are needed for IoT Analytics and how are they built?

SRQ5: What are the most important IoT analytics capabilities and what types of business value do they lead to?

Table L1

Category	Questions and clarifications	Time in minutes
Consent	Explain data processing and purpose Ask for consent to record audio and process data in the form of a transcript and coding	**2**
Introduction	*Briefly explain purpose of the study.* *Explain what is understood by a capability in the context of IoT Analytics:* *"An IoT Analytics Capability is the transformation of resources (e.g. knowledge, hardware, software, financial means, etc.) into the ability to get something specific done. The orchestration of capabilities results in business value."* Can you tell me about your role and experience in the company, role, and industry? What department do you work in? (Who does what in the IoT projects?) Can you tell me more about the IoT (Analytics) initiatives that you have worked on? How do you think IoT Analytics projects differ from other analytics applications, or data analytics in general?	**5**
IoT Analytics Business Value	*Explain what is understood by business value from IoT Analytics and give some examples if needed* What (business) value has [organization] gained from IoT Analytics? Can you classify the business value in different categories or types? (E.g., operational and strategic business value)	**10**
IoTA Analytics Capabilities	What are the first things that come to mind which have been crucial in your IoT Analytics initiatives? What success factors have you observed in your IoT Analytics initiatives? What barriers and challenges have you observed in your IoT Analytics initiatives?	**15**
	Explain each core and sub-construct capability and its definition. What is your understanding of [capability construct] in IoT Analytics? How is it similar and different from general Data Analytics capabilities? Can you give examples of how [capability construct] were built at [organization]? How does [capability construct] add to the creation of business value? What capabilities or other topics would you add to the ones discussed now that you have an overview of the conceptual framework?	**25**

Closing	*Verify the answers and notes of all constructs.* Do you have any last remarks or questions? Do you think IoT analytics capabilities and business value as we discussed is useful for implementation of IoT in your organization? And why? Thank participant and explain again what will be done with the data as well as any follow-up communication needed.	**5**

Appendix M: List of organizations and research participants

Table M1

Organizations and Case Studies				
Anonymized Organization Name / Case Study	**Organization Domain (Siow et al., 2018)**	**Organization Employee Size**	**Years of experience with IoT Analytics (maturity)**	**Number of participants**
OrgA	Transport	5,000-10,000	7+	2
OrgB	Industry	20,000+	2+	2
OrgC	Transport	10,000-20,000	6+	2
OrgD	Industry	1,000-5,000	4+	2
OrgE	Environment	1,000-5,000	12+	2
OrgF	Transport	20,000+	3+	2
OrgG	Transport	5,000-10,000	7+	2
OrgH	Industry	20,000+	3+	1
OrgI	Environment	500-1,000	2.5+	1

Table M2

Research Participants						
Number	**Anonymized Organization Name**	**Anonymized Participant Name**	**Participant responsibility**	**Participant role/title**	**Years of experience in function**	**Interview date**
1	OrgA	ParAA	IoT Analytics	Senior Data Scientist	3.5	29/Nov/21
2	OrgA	ParAB	IoT Architecture	IoT Solution Architect	3+	07/Dec/21
3	OrgB	ParBA	IoT Platform	Information Technology Manager	11	01/Feb/22
4	OrgB	ParBB	IoT Architecture	Business Information Designer	10	22/Dec/21
5	OrgB	ParCA	IoT Platform	Connected Product Strategy	6	25/Feb/22
6	OrgC	ParCB	IoT Analytics	Data Analyst	3.5	07/Mar/22

7	OrgD	ParDA	IoT Analytics	Head of Data & AI	2.7	28/Jan/22
8	OrgD	ParDB	IoT Platform	Product Manager Digital Platform	2.9	13/Apr/22
9	OrgE	ParEA	IoT Architecture	Corporate enterprise architect	5+	25/Feb/22
10	OrgE	ParEB	IoT Platform	Chief Technology Officer	5+	20/May/22
11	OrgF	ParFA	IoT Platform	Product Owner IoT	5+	10/Mar/22
12	OrgF	ParFB	IoT Analytics	Lead Data Scientist	2	15/Apr/22
13	OrgG	ParGA	IoT Platform	Client Delivery Executive	2+	06/May/22
14	OrgG	ParGB	IoT Architecture	Senior Solution Architect	12+	20/Apr/22
15	OrgH	ParHA	IoT Analytics	Lead Data Scientist	2.5+	18/Mar/22
16	OrgI	ParIA	IoT Analytics	Innovator BI & Data Management	2+	29/Apr/22

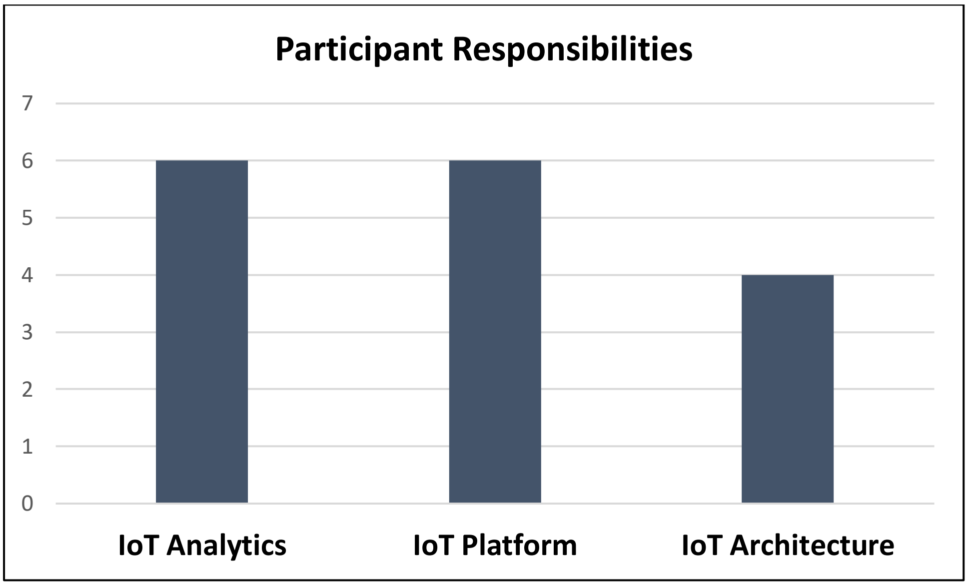

Figure M1

Appendix N: Coding framework

This coding framework has its purpose of documenting the data analysis process and ensuring consistency during the detailed analysis, which consists of the following parts.

- Preliminary codebook
    - Pre-existing themes, or code groups in Atlas, and codes, or subthemes in Atlas
    - Descriptions of each theme and subtheme adopted from the conceptual framework and edited to fit within the IoT Analytics focus of this study
    - Themes and subthemes including preliminary descriptions by skimming the interview transcripts, which improves rigor
- Data analysis process and reflection
    - Methodological notes during analysis and action in Atlas
    - Audit trail of coding history in Atlas

Table N1

Preliminary codebook			
Theme [Code group in Atlas]	**Subtheme [Code in Atlas]**	**Description**	**Source**
Technology Capability		The ability of the Data Analytics technology (e.g., applications, infrastructure, data, and networks) to enable staff to quickly develop, deploy, and support necessary system components (Akter et al., 2016).	Conceptual framework
	Data Generation	The ability of organizations to seek, identify, create, and access data from heterogeneous data sources across organizational boundaries. This capability facilitates the availability IoT data to an organization's disposal by establishing data sources, procedures and policies to generate required data for decision-making (Arunachalam et al., 2018).	Conceptual framework
	Data and Systems Integration	The ability to transform diverse types of data into a data format that can be read and analyzed by analytics platforms, so that data is consistent, visible, accessible and interoperable for analysis (Wang et al., 2019).	Conceptual framework
	Data Management and Security	The ability to manage data from different perspectives, such as data quality, flexibility, availability, and integrity, including the ability to ensure the IoT data, networks, and systems are secure.	Conceptual framework
	Analytics	The ability to drive decisions and actions through the extensive use of data and different analytical techniques, based on the specific mechanisms used for analytics, thus addressing the various needs of users and other stakeholders (Grover et al., 2018). Other important elements of this capability are user access, data visualization, and interpretation. Five categories of IoT Analytics can be found, namely Descriptive, Diagnostic, Discovery, Predictive, and Prescriptive Analytics (Siow et al., 2018).	Conceptual framework
Human Capabilities		The relevant professional ability of all employees involved in IoT Analytics (e.g., skills or knowledge) to	Conceptual framework

		undertake assigned tasks or generate new ideas (Wamba et al., 2017a).	
	Technical Knowledge	The ability of technical knowledge elements, including operational systems, networks, statistics, programming languages, and database management systems (Akter et al., 2016).	Conceptual framework
	Business Knowledge	The ability to understand other business functions and the overall business environment. For example, analytics professionals can be nurtured to develop their feel for business issues and empathy for customers (Akter et al., 2016).	Conceptual framework
	Relational Knowledge	The ability of analytics professionals to communicate and work with people from other business functions (Akter et al., 2016).	Conceptual framework
	Entrepreneurship and Innovation	The ability to mobilize and deploy IoT Analytics functionalities to support innovation in the organization through infrastructure, culture and technological improvements (Ramakrishnan et al., 2020).	Conceptual framework
Organizational Capabilities		The ability to plan, invest, organize, and control all IoT and Analytics resources and capabilities in accordance with business needs and priorities through a thriving data-driven culture (Wamba et al., 2017a).	Conceptual framework
	Planning and Investment	The ability to identify business opportunities, do cost-benefit analyses of IoT Analytics initiatives, make investments, and determine how they can create business value.	Conceptual framework
	Process and Coordination	Represents a form of routine capability that structures the cross-functional synchronization of analytics activities across an organization and ensures processes are in place for each step in the project (Akter et al., 2016).	Conceptual framework
	Control	The ability of controlling functions, which are performed by ensuring proper commitment and utilization of resources, either implicit or explicit through documentation, including budgets and human resources (Akter et al., 2016).	Conceptual framework
	Data-driven Culture	The set of collective values, beliefs, norms and principles that embrace and guide an evidence-based and data-driven culture (Wang et al., 2019).	Conceptual framework
Business Value and Outcomes		All positive business outcomes as part of IoT Analytics initiatives, resulting in operational and strategic business value.	Conceptual framework
	Operational Business Value	Operational value represents improvements in the efficiency of business processes, including cost reduction and productivity enhancement (Fink et al., 2017).	Conceptual framework
	Strategic Business Value	Strategic value represents improvements such as business transformation, corporate performance management, customer relations optimization, business activity monitoring. High-level outcomes also include positive financial or market performance (Fink et al., 2017).	Conceptual framework
	Business challenge	Any challenge that is coming from the business or organization as perceived by a group of people or individual part of a business process.	Skimming the interview transcriptions
	Technical Challenge	Any challenge that is coming from the technical implementation phase of IoT and analytics.	Skimming the interview transcriptions

	Cost Challenge	Any challenge that is coming from the business or organization directly relating to costs and expenditures. This could also be a challenge in the implementation phase of IoT and analytics.	Skimming the interview transcriptions
IoT analytics terms and characteristics		All relevant and specific IoT terms, trends, unique traits and other interesting points or IoT analytics specific potential capabilities which can later be distributed among the above themes.	Skimming the interview transcriptions
	Predictive / Advanced Analytics	Advanced analytics through algorithms and machine learning models which make predictions of a process, product, asset, or otherwise. This varies from predicting maintenance to predicting how to tweak parameters enabling improved process or product design. It is also important the factor of time, where predictions can be done near real-time, per hour, per day, or on a longer term. Taking it one step further, this notion also enables giving recommendations or automating processes based on predictions and smart business logic.	Skimming the interview transcriptions
	Connectivity	Connectivity seems to be unique to IoT Analytics as in many other data analytics applications this is not as important, already taken care of, or not a prerequisite at all. In the case of Internet of Things Analytics, the name already suggests that the internet is one of the main components, connecting the physical world with a centralized infrastructure.	Skimming the interview transcriptions
	Edge and Hardware	The edge and hardware development seem to be unique to IoT Analytics as in other data analytics applications this less of a concern, or not relevant at all. This concept has to with planning, developing, maintaining, and organizing the hardware and software to be placed in the physical world, or the 'edge' as many participants referred to.	Skimming the interview transcriptions

Table N1

Data analysis process and reflection	
Date	**Notes**
5 June 2022	Created document groups per organization to allow for easier cross-comparison between participants in an organization and between organizations and cases.
5 June 2022	Created 3 code groups to reflect the three core capabilities technology, human, and organizational including their sub capabilities as codes.
5 June 2022	Edits have been made in the methodology to improve adherence with design science research methodology.
5 June 2022	Data analysis and evaluation chapter edited to conform with the six phases of analysis.
6 June 2022	Read through Nowell et al.'s thematic analysis phases (2017).
6 June 2022	Created coding manual based on conceptual framework and descriptions.
6 June 2022	Re-read six phases by Nowell and cross-check them with the adopted phases for this study for proper alignment.
6 June 2022	Added code group Business Value, Use Cases, and Challenges which includes the codes for business value outcomes, use cases, as well as any challenges that are mentioned during the interviews. A first skim through transcripts showed that this also includes technical and cost challenges during the implementation of the IoT analytics. These have been added to the codes in the preliminary codebook.
6 June 2022	Added code group IoT Analytics terms and characteristics, where all relevant and specific IoT terms, trends, unique traits and other interesting points or potential capabilities go into which are mentioned during the interviews. Some of these codes might be reorganized to fit into the

	capabilities themes later in the thematic analysis. For example, I added Predictive Maintenance as well as Connectivity as two codes because I see them as two interesting concepts specifically relating to IoT.
7 June 2022	Started detailed coding analysis with three techniques: • A priori coding, codes derived from the conceptual framework constructs • In-vivo coding, where participants' actual terms will guide the name for the code • Label coding, where the researcher creates code names that best describe the unit of data For example, one participant mentioned tactical business value which is between operational and strategic business value. Perhaps this should be a separate business value construct, or it will be consolidated into the other two.
10 June 2022	After having coded half of the interviews, I noticed the participants talked about clear differences in the capabilities. From a broader 'hardware' capability to data generation, connectivity, data management, storage, and security capabilities, all these should be seen as distinct technology capabilities.
11 June 2022	I'm realizing that codes are added that I might've missed in the other documents, because the level of detail in the initial coding varies depending on what the participants said explicitly. However, there are many instances where codes apply to passages in the interviews which are more implicit. For example, one participant explicitly mentioned change management as an important needed capability while others implicitly described what is essentially change management.
11 June 2022	Changed the code 'initial phase' to reflect a broader concept in the interviews relating to 'IoT analytics maturity'. The needed capabilities depend on the maturity of the IoT analytics program, and business value in turn depends again on the maturity.
11 June 2022	Many participants mention that human capabilities are not only about knowledge but also skills. Therefore, these capabilities have been changed to Skills and Knowledge it's more encompassing of the actual capability. Alternatively, to better fit within the definition of a capability, it could be renamed to something that organizations need to be able to do instead of just skills and knowledge. For example, Relational Skills and Knowledge could be renamed to (1) Interdisciplinary Collaboration and (2) Networking. Business Skills and Knowledge could be renamed to for example (1) Effective Business Communication. Technical Skills and Knowledge could be renamed to (1) Hardware and (2) Software Development, although these are also partially Technology Capabilities. A decision on this should be made through further analysis.
12 June 2022	Created three more document groups to reflect the responsibilities of the participants. Participants can be categorized in roughly three categories and document groups in Atlas. (1) Responsibility: IoT platform refers to a full responsibility for both technology and business. (2) Responsibility: IoT Architecture mainly refers to the technology architecture as well as business architecture and responsibility. (3) Responsibility: IoT Analytics refers to solely analytics and data science responsibilities, the people who create data aggregations, visualizations, including machine learning development for advanced analytics. It is important to note that in reality there is a bit of overlap between these responsibility groups as not all companies have dedicated roles for each step in the IoT analytics initiative.
12 June 2022	Changed the code Executive Support to Top Management Support & Vision to better reflect the full scope of the capability.
13 June 2022	Changed the code Hardware Capability to Edge and Hardware Development Capability, as eventually, every company and participant needed some degree of capabilities on 'the edge', that is the locations and hardware where the IoT is being deployed in the physical world. Some companies did have to develop their own hardware, while some procured hardware to be embedded in their own edge locations and products or assets.
13 June 2022	Many participants mention Security as a separate capability from data management because it's not only technical security, but also organizational security and compliance. Therefore, the analysis should investigate the option to create Security and Compliance as a dedicated capability.
15 June 2022	Finished coding all interviews.
17 June 2022	Started organizing the codes and placing codes in the code groups, which enables a structured data analysis process. First, the core capabilities will be analyzed one by one, including their sub-constructs. Then business value will be analyzed and categorized, and then any codes relating to IoT analytics as well as challenges, success factors, and more will be analyzed. These could provide information for the capabilities and business value findings as well.

	The exact way codes are analyzed in Atlas is as follows: • First, the Code Manager is used to filter the codes per code group, e.g., Technology Capabilities. • In the Code Manager, the codes are sorted by groundedness, i.e., by the number of quotations. • First, codes with the fewest quotations are analyzed through reading the quotations individually and in context. Then, they are evaluated to potentially be part of higher-level order constructs or other codes that encompass the same concept. • The quotations of each of the codes are opened in the Quotation Manager to be read and analyzed within their own construct meaning. For example, the Analytics Capability quotations were analyzed which showed that many respondents distinguish between two categories of analytics, Business Intelligence, which is more descriptive, and Data Science, which is more predictive. Such analyses and synthesis are written down in the code comments in Atlas with the relevant quotations. • It is important to further analyze potential relationships between codes, which is the last step in the process of the code analysis. Through the code co-occurrence table these relationships are uncovered and noted down once again in the comments of that particular code. For example, looking at the Analytics Capability again, we can see that it is mentioned very often in the context of data management as well as data and systems integration. • A constant back and forth between the above three steps allows for the creation of Atlas networks per higher-order capability and business value.
17 June 2022	Started with analysis of the codes through code group analysis and code co-occurrence analysis in Atlas.
18 June 2022	Added Appendix N: Basic Code Analysis to validate all constructs have been sufficiently discussed per organization. This validates the framework at the highest construct order level.
20 June 2022	The coding analysis has almost been finalized. Reflecting upon this process, several codes which had less than five quotations were reviewed for merging into other codes. Some codes were also split and renamed to better reflect the answers of the participants. => merged <> split = renamed **Technology** System Architecture => Solution Design and Planning = Solution Architecture Data Processing / Refinement => Data Processing and Standardization Data Management and Security <> Data Management as a separate capability and Security and Compliance as a separate capability Data Storage => Data Management = Data Management and Storage Data Governance => Data Management Storage = Data Storage, Management, and Governance Field Service => into Edge and Hardware Predictive Analytics => Data Science Solution Architecture => IoT Platform = Design Platform Architecture Data Visualization => Business Intelligence **Organizational** Data-Driven Culture => Change Management Customer Collaboration => Interdisciplinary Collaboration Business Synergy => Interdisciplinary Collaboration = Business and Ecosystem Synergy Creativity => Entrepreneurship and Innovation Recruitment => Knowledge Management Training and Enablement => Knowledge Management and Training Trust => Top Management Support Strategic Alignment => Top Management Support = Management Support and Vision Control => Process and Coordination Agile Workflow => Process and Coordination Planning and Investment => Scalability = Scalability and Planning Investment => Management Support and Vision

	Human Relational Skills and Knowledge = Interdisciplinary Collaboration International Collaboration => Interdisciplinary Collaboration
21 June	Reflecting upon the research questions in the context of answers from the participants, it has become clear that the ‘how’ part of the research question is subject to many differences within and among organizations. The ‘how’ behind a capability is far too much of a detailed matter to incorporate in this research. Therefore, the research questions have been amended as seen below. SRQ1: What DA capabilities can be found in the literature ~~and how are they built~~? SRQ2: ~~How do DA capabilities create business value and what types of business value?~~ What types of business value do DA capabilities create? SRQ3: How can DA capabilities and business value be integrated in a conceptual framework for IoTA? SRQ4: What capabilities are needed for IoT Analytics ~~and how are they built~~? SRQ5: What are the most important IoT Analytics capabilities and what types of business value do they lead to?

Appendix O: Cross-case analysis

In this appendix a cross-case analysis of the research themes is visualized in tables which supports the findings and discussion. It follows the same structure as the main report, namely the following cross-case analysis tables can be found:

- Table O1: Differences between IoT Analytics and general Data Analytics
- Table O2: Business Value
- Table O3: Technology Capabilities
- Table O4: Organizational Capabilities
- Table O5: Human Capabilities

The number in the tables is the number of quotations of that table dimension. For example, in the table below, in case OrgA there are three quotations that relate to Organizational Differences and six that relate to Technical Differences. 'Gr' refers to the groundedness of Codes (number of quotations coded by a code) or Case (quotations created for a case).

Furthermore, tables are presented that facilitate the cross-case synthesis in the discussion. The quotations in these tables have been normalized to account for the differences in participant size per characteristic. The following tables are included:

- Table O6: Cross-case analysis by domain
- Table O7: Cross-case analysis by company size
- Table O8: Cross-case analysis by maturity in years

Differences between IoT Analytics and general Data Analytics

The following table is an overview of the organizational and technical differences of IoT Analytics compared to general Data Analytics.

Table O1

Differences	OrgA Gr=150	OrgB Gr=117	OrgC Gr=118	OrgD Gr=125	OrgE Gr=129	OrgF Gr=123	OrgG Gr=99	OrgH Gr=59	OrgI Gr=62	Totals
Organizational Difference Gr=43	3	4	7	8	3	9	3	3	3	43
Technical Difference Gr=60	6	7	8	11	7	8	7	3	X	60
Totals	9	11	15	19	10	17	10	6	6	103

Business Value

The undermentioned table is an overview of the Operational and Strategic Business Value constructs. Both were validated across all case organizations.

Table O2

Business Value	OrgA Gr=150	OrgB Gr=118	OrgC Gr=121	OrgD Gr=126	OrgE Gr=129	OrgF Gr=123	OrgG Gr=99	OrgH Gr=59	OrgI Gr=62	Totals
Operational Business Value Gr=78; GS=9	14	10	14	3	10	11	6	7	3	78
Strategic Business Value Gr=70; GS=12	10	7	5	8	13	11	10	3	3	70
Totals	24	17	19	11	23	22	16	10	6	148

Technology Capabilities

The following table is an overview of all Technology Capabilities. All capabilities were validated with a majority support across all organizations.

Table O3

Technology Capabilities	OrgA Gr=150	OrgB Gr=118	OrgC Gr=121	OrgD Gr=126	OrgE Gr=129	OrgF Gr=123	OrgG Gr=99	OrgH Gr=59	OrgI Gr=62	Totals
Business Intelligence Gr=24	2	5	2	2	3	4	1	3	2	24
Connectivity Gr=30	1	3	5	4	3	6	3	2	3	30
Data Accessibility Gr=7	1	1	1	1	1	1	✗	✗	1	7
Data and Systems Integration Gr=46	6	11	6	4	6	5	2	2	4	46
Data Generation Gr=18	2	3	2	1	2	3	✗	4	1	18
Data Processing and Standardization Gr=16	3	4	✗	4	2	2	✗	1	✗	16
Data Science and Automation Gr=58	10	6	5	6	6	15	3	5	2	58
Data Storage, Management and Governance Gr=46	4	8	7	6	10	3	✗	1	7	46
Platform Architecture and Design Gr=39	1	4	4	2	5	8	8	4	3	39
Edge and Hardware Development Gr=36	2	2	2	6	9	8	5	2	✗	36
Operational Maintenance and Monitoring Gr=16	✗	✗	✗	5	3	2	3	✗	3	16
Security and Compliance Gr=22	3	4	1	1	6	3	3	✗	1	22
Software Development Gr=19	1	2	3	4	✗	5	4	✗	✗	19
Totals	36	53	38	46	56	65	32	24	27	377

Organizational Capabilities

The table below is an overview of all Organizational Capabilities. All capabilities were validated with a majority support across all organizations.

Table O4

Organizational Capabilities	OrgA Gr=150	OrgB Gr=118	OrgC Gr=121	OrgD Gr=126	OrgE Gr=129	OrgF Gr=123	OrgG Gr=99	OrgH Gr=59	OrgI Gr=62	Totals
Process and Coordination Gr=58	14	9	5	11	6	3	5	1	4	58
Business and Ecosystem Synergy Gr=34	3	2	5	7	8	3	3	2	1	34
Change Management Gr=33	4	4	4	6	4	5	✗	3	3	33
Knowledge Management and Training Gr=44	4	4	9	3	8	5	2	6	3	44
Management Support and Vision Gr=45	5	7	6	4	4	6	4	3	6	45
Product and Service Development Gr=25	✗	2	5	10	1	3	4	✗	✗	25
Scalability and Planning Gr=67	12	7	7	7	11	8	6	5	4	67
Totals	42	35	41	48	42	33	24	20	21	306

Human Capabilities

The next table is an overview of all Human Capabilities. All of the capabilities were validated across all case organizations with all nine organizations validating each capability.

Table O5

Human Capabilities	OrgA Gr=150	OrgB Gr=118	OrgC Gr=121	OrgD Gr=126	OrgE Gr=129	OrgF Gr=123	OrgG Gr=99	OrgH Gr=59	OrgI Gr=62	Totals
Business Skills and Knowledge Gr=48	3	12	6	4	6	6	9	1	1	48
Entrepreneurship and Innovation Gr=43	7	7	4	6	4	5	6	2	2	43
Interdiscipinary Collaboration Gr=70	11	11	9	6	10	8	5	3	7	70
Technical Skills and Knowledge Gr=54	7	8	10	4	4	6	9	4	2	54
Totals	28	38	29	20	24	25	29	10	12	215

Cross-case analysis by domain (Siow et al., 2018)

T-CAP = Technology Capabilities, O-CAP = Organizational Capabilities, H-CAP = Human Capabilities O-VAL = Operational Business Value, S-VAL = Strategic Business Value, IOT = Differences IoTA and DA

Table O6

Cross-case analysis by domain	Environment Gr=191	Industry Gr=303	Transport Gr=493	Totals
H-CAP: Interdisciplinary Collaboration Gr=70	40	29	33	103
O-CAP: Scalability and Planning Gr=67	36	28	33	97
O-VAL: Operational Gr=62	29	22	35	86
IOT: Technical Difference Gr=60	24	31	29	84
O-CAP: Process and Coordination Gr=58	24	31	27	82
T-CAP: Data Science and Automation Gr=58	19	25	33	77
T-CAP: Data Storage, Management and Governance Gr=46	40	22	14	76
S-VAL: Strategic Gr=47	29	22	20	71
H-CAP: Technical Skills and Knowledge Gr=54	14	23	32	70
T-CAP: Data and Systems Integration Gr=46	24	25	19	68
H-CAP: Business Skills and Knowledge Gr=48	17	25	24	66
O-CAP: Management Support and Vision Gr=45	24	21	21	65
O-CAP: Knowledge Management and Training Gr=44	26	19	20	65
H-CAP: Entrepreneurship and Innovation Gr=43	14	22	22	58
IOT: Organizational Difference Gr=43	14	22	22	58
T-CAP: Platform Architecture and Design Gr=39	19	15	21	55
T-CAP: Edge and Hardware Development Gr=36	21	15	17	53
O-CAP: Business and Ecosystem Synergy Gr=34	21	16	14	52
O-CAP: Change Management Gr=33	17	19	13	49
T-CAP: Connectivity Gr=30	14	13	15	42
T-CAP: Business Intelligence Gr=24	12	15	9	36
T-CAP: Security and Compliance Gr=22	17	7	10	34
O-CAP: Product and Service Development Gr=25	2	18	12	32
T-CAP: Operational Maintenance and Monitoring Gr=16	14	7	5	27
T-CAP: Data Generation Gr=18	7	12	7	26
T-CAP: Data Processing and Standardization Gr=16	5	13	5	23
T-CAP: Software Development Gr=19	✗	9	13	22
T-CAP: Data Accessibility Gr=7	5	3	3	11

Cross-case analysis by company size

T-CAP = Technology Capabilities, O-CAP = Organizational Capabilities, H-CAP = Human Capabilities
O-VAL = Operational Business Value, S-VAL = Strategic Business Value, IOT = Differences IoTA and DA

Table O7

Cross-case analysis by company size	500 – 1,000 employees Gr=62	1,000 - 5,000 employees Gr=255	5,000 – 10,000 employees Gr=249	10,000 – 20,000 employees Gr=121	20,000+ employees Gr=300	Totals
H-CAP: Interdisciplinary Collaboration	37	20	25	24	22	128
O-CAP: Scalability and Planning Gr=67	21	23	28	19	20	111
O-VAL: Operational Gr=62	16	15	25	35	18	109
O-CAP: Process and Coordination Gr=58	21	22	30	13	13	99
IOT: Technical Difference Gr=60	16	23	21	21	18	99
T-CAP: Data Storage, Management and Governance Gr=46	37	20	6	19	12	94
H-CAP: Technical Skills and Knowledge	10	10	25	27	18	91
O-CAP: Management Support and Vision	31	10	14	16	16	88
T-CAP: Data Science and Automation	10	15	21	13	26	86
T-CAP: Data and Systems Integration	21	13	13	16	18	80
O-CAP: Knowledge Management and Training Gr=44	16	14	9	24	15	78
S-VAL: Strategic Gr=47	10	22	19	13	11	75
IOT: Organizational Difference Gr=43	16	14	9	19	16	74
H-CAP: Business Skills and Knowledge	5	13	19	16	19	72
H-CAP: Entrepreneurship and Innovation	10	13	21	11	14	68
T-CAP: Platform Architecture and Design	16	9	14	11	16	66
O-CAP: Change Management Gr=33	16	13	6	11	12	57
T-CAP: Connectivity Gr=30	16	9	6	13	11	55
O-CAP: Business and Ecosystem Synergy	5	19	9	13	7	54
T-CAP: Edge and Hardware Development	✗	19	11	5	12	48
T-CAP: Business Intelligence Gr=24	10	6	5	5	12	39
O-CAP: Product and Service Development	✗	14	6	13	5	39
T-CAP: Security and Compliance Gr=22	5	9	9	3	7	33
T-CAP: Operational Maintenance and Monitoring Gr=16	16	10	5	✗	2	33
T-CAP: Software Development Gr=19	✗	5	8	8	7	28
T-CAP: Data Generation Gr=18	5	4	3	5	10	28
T-CAP: Data Processing and Standardization Gr=16	✗	8	5	✗	7	19
T-CAP: Data Accessibility Gr=7	5	3	2	3	2	14

Cross-case analysis by maturity in years

T-CAP = Technology Capabilities, O-CAP = Organizational Capabilities, H-CAP = Human Capabilities
O-VAL = Operational Business Value, S-VAL = Strategic Business Value, IOT = Differences IoTA and DA

Table O8

Cross-case analysis by maturity in years	0-3 years Gr=180	3-5 years Gr=308	5-10 years Gr=370	10+ years Gr=129	Totals
H-CAP: Interdiscipinary Collaboration Gr=70	30	18	25	25	98
O-CAP: Scalability and Planning Gr=67	18	21	25	28	92
O-VAL: Operational Gr=62	18	14	29	23	83
IOT: Technical Difference Gr=60	17	23	21	18	78
O-CAP: Process and Coordination Gr=58	22	16	24	15	76
T-CAP: Data Science and Automation Gr=58	13	27	18	15	73
T-CAP: Data Storage, Management and Governance Gr=46	25	10	11	25	72
S-VAL: Strategic Gr=47	15	11	17	25	69
H-CAP: Technical Skills and Knowledge Gr=54	17	15	26	10	67
H-CAP: Business Skills and Knowledge Gr=48	22	11	18	15	66
T-CAP: Data and Systems Integration Gr=46	25	11	14	15	66
O-CAP: Knowledge Management and Training Gr=44	12	15	15	20	61
O-CAP: Management Support and Vision Gr=45	22	14	15	10	60
H-CAP: Entrepreneurship and Innovation Gr=43	15	14	17	10	56
IOT: Organizational Difference Gr=43	12	21	13	8	53
T-CAP: Platform Architecture and Design Gr=39	12	15	13	13	52
T-CAP: Edge and Hardware Development Gr=36	3	17	9	23	52
O-CAP: Business and Ecosystem Synergy Gr=34	5	12	11	20	49
O-CAP: Change Management Gr=33	12	15	8	10	44
T-CAP: Connectivity Gr=30	10	12	9	8	39
T-CAP: Security and Compliance Gr=22	8	4	7	15	35
T-CAP: Business Intelligence Gr=24	12	9	5	8	34
O-CAP: Product and Service Development Gr=25	3	14	9	3	28
T-CAP: Data Generation Gr=18	7	8	4	5	24
T-CAP: Operational Maintenance and Monitoring Gr=16	5	7	3	8	23
T-CAP: Data Processing and Standardization Gr=16	7	7	3	5	22
T-CAP: Software Development Gr=19	3	9	8	✗	21
T-CAP: Data Accessibility Gr=7	3	2	2	3	10

Appendix P: Data Extraction Form – Interview results

Interview dataset is available at request.