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ICT in Business and the Public Sector

Traditional BI vs. advanced analytics competency centers

Analysing and comparing two types of Business Intelligence & Analytics Competency Centers

Name: Martijn Klaver
Student-no: S2162032

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1st supervisor: Dr. W. Heijstek
2nd supervisor: Drs. B. Kruiswijk

MASTER'S THESIS

Leiden Institute of Advanced Computer Science (LIACS)
Leiden University
Niels Bohrweg 1
2333 CA Leiden

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Martijn Klaver
S2162032
MSc. Thesis

Supervisors
Dr. Werner Heijstek
Drs. Bas Kruiswijk

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ABSTRACT

Recent years have seen a significantly increased interest in the potential of business intelligence & analytics (BI&A). The times have passed that a debate on the importance of BI&A existed. Instead, the debate centers on how to make the best out of the opportunities they have to offer. Organizational structure decides to which extent BI&A reaches its full potential and can flourish (Gartner 2015). Organizational models for BI&A include those making use of a shared service center for BI&A, offering their services centrally for the whole organization. Two types of BI&A shared service centers are identified: traditional BI competency centers and advanced analytics competency centers (Schüritz, Brand, Satzger, & Bischhoffshausen, 2017). This research aims to contribute to the understanding of organizing business intelligence and analytics, and specifically competency centers. On first sight, the centers seem similar. However, separate organizational entities are spotted in literature (Schüritz et al. 2017; Duncan 2016) and in practice. Therefore, a comparison is drawn between the two types of competency centers (CCs), based on the characteristics, objectives, structure, roles, processes, and governance.

In addition to desk research, a qualitative study with an interpretive exploratory research design was used for finding, collecting, and analysing data. Nine semi-structured interviews were conducted to collect data. These were analysed using the thematic analysis method, including open coding, and identifying themes in the data.

A clear distinction between traditional BI CCs and advanced analytics CCs is present in practice. In literature, this distinction is less apparent. Hence, the comparison between the two types of CCs is mainly based on interviews.

Both types of center have main objective: gain business value from data and helping the organization becoming more data-driven. Both try to reach this objective in a centralized way, resulting in an organization-wide overview and prioritization of BI&A activities, but a challenge on securing decentral (business) expertise. The way they aim to reach the objective differs. Traditional BI CCs focus on descriptive and diagnostic analysis and make use of historical, internal data to build reports and dashboards. Advanced analytics CCs focus on predictive and prescriptive analysis, are explorative in nature and make use of internal and external data to build models that help the business improve their products or services.

The described difference is expressed by the way both types of center look at data. While for the traditional BI CC data quality is of the highest importance, advanced analytics CCs mainly need volume. Here, it is important to know the quality, but it must not be very high. Traditional BI CCs are mainly reporting on business operations. These reports must

be 100% true, making quality very important. Advanced analytics CCs are modelling for business improvements. Hereby, they are more explorative in nature and quality is less important.

The contrasting views on data results in other differences. Although the roles over the two CCs have similar names (data engineer, architect), their day to day work differs much because of the underlying techniques. Furthermore, while the development process of traditional BI CCs has a structured, systematic approach, the development process of advanced analytics CCs is more explorative and opportunistic in nature.

Besides the shared objective, more overlap between the two types of centers is found. Both cope with the advantages and challenges of being a shared service center. Both need leadership, work in multidisciplinary teams and prefer the agile way of working. Furthermore, for both types of centers, it is recommended to place them outside of IT and organize them together under one organizational unit 'Business intelligence & analytics'.

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LIST OF ABBREVIATIONS

- Business Analytics (BA)
- Business Intelligence (BI)
- Business Intelligence & Analytics (BI&A)
- Center of Excellence (CoE)
- Competency Center (CC)
- Data Mining (DM)
- Enterprise Resource Planning (ERP)
- Information Technology (IT)
- Proof of Concept (PoC)
- Shared Service Center (SSC)

1 INTRODUCTION

1.1 BACKGROUND & RESEARCH QUESTION

Recent years have seen a significantly increased interest in the potential of big data and analytics. With "Competing on Analytics The New Science of Winning", Davenport & Harris (2007) opened up a new chapter of research on analytics. The times have passed that a debate on the importance of big data and analytics existed: Organizational performance can be enhanced by business analytics, creating a sustainable competitive advantage (Davenport and Harris 2007). Nowadays, the (strategic) relevance of collecting and analysing large amounts of data is widely recognised (Manyika et al. 2011).

Instead, the debate centres on how to make the most of the countless opportunities analytics has to offer. In particular, research stresses the importance of organizational factors in obtaining performance gains and competitive advantage from IT applications (Thurow 1991; Sharma, Yetton, and Zmud 2008).

Organizational structure influences to which extent analytics reaches its full potential and can flourish. Without proper structure, analytics cannot keep up with the demanded speed and rapid changes in this environment (Gartner 2015).

Several ways exist to structure analytics in an organization: Decentralized, where the analytics team resides in the business function/unit; Centralized, where the analytics team resides in a Shared Service Center (SSC) used by the entire organization; Hybrid, where the analysts are deployed both in a SSC and in business units (Anderson 2015; Grossman and Siegel 2014; Hernandez, Berkey, and Bhattacharya 2013; Khalil and Wood 2014; Lismont et al. 2017). These different ways are displayed in Figure 1.

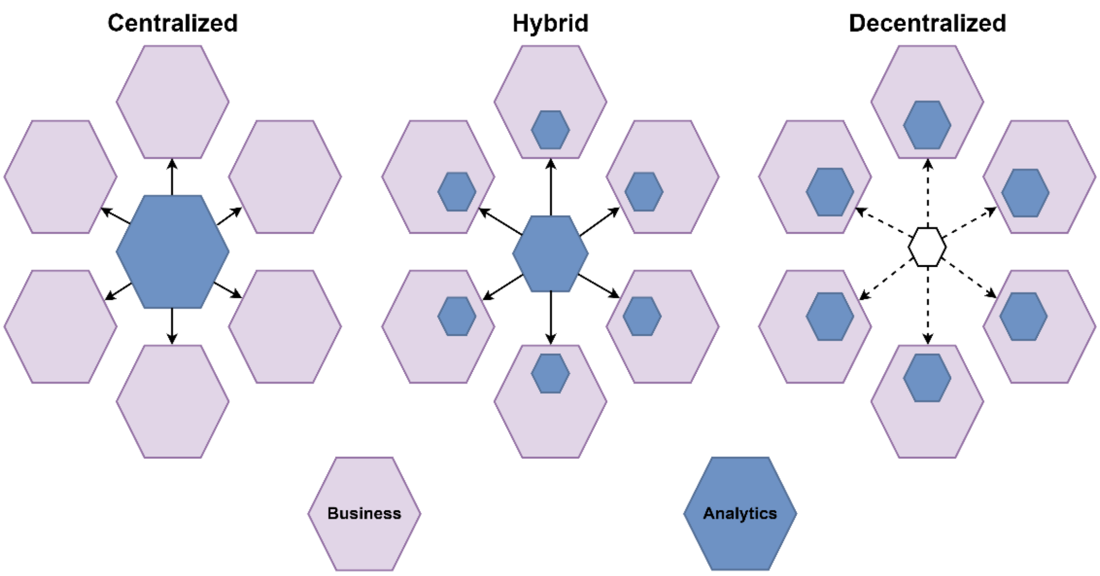


Figure 1: Centralized, Hybrid and Decentralized model

SSCs have existed in many places in the organization such as HR, finance and legal and are also present in the field of Business Intelligence & Analytics (BI&A); here often called Center of Excellences (CoEs) or Competency Centers (CCs). Such centers in the field of what we will define as traditional BI have been around since the early 2000's and are generally defined as a "group of business, IT and information analysts, working together to define the business intelligence strategies and needs of the entire organization" (Hostmann 2007). Research has been performed on establishing and maintaining such traditional BI competency centers in various contexts (Hostmann 2007; Miller, Bräutigam, and Gerlach 2006; Laursen and Thorlund 2010; Marcinkowski and Gawin 2017).

Schüritz, Brand, Satzger, & Bischhoffshausen (2017) acknowledge a division between two types of SSCs made by Goold, Pettifer, & Young (2001) and apply this to the field of BI&A: those focussing on the future and those focusing on the presence. Schüritz et al. (2017) argue that advanced analytics competency centers (focusing on future) are a different organizational entity from traditional BI competency centers (focusing on presence). In their research they identify "strategic and structural design options, common processes, best-practices and potential future development paths" for advanced analytics competency centers. They claim previous research focuses on traditional BI competency centers and characteristics of advanced analytics competency centers have not been researched before.

Apart from Schüritz et al., (2017) and some grey literature, the distinction between traditional BI competency centers and advanced analytics competency centers is rarely recognized in literature. However, explorative conversations with field experts indicated the distinction is very much present in practice. Multiple companies have both types of competency centers in place.

Although traditional BI and advanced analytics work with different methods and maybe even have different goals, at first sight, they share multiple important characteristics: both collect, analyse and visualize (large amounts of) data, identify pain points and need proper IT infrastructure to be in order to carry out analyses. Therefore, the question rises in which ways the two types of BI&A competency centers are similar to and different from each other. While Schüritz et al. (2017) define different types of advanced analytics competency centers, a comprehensive comparison with traditional BI competency centers is missing.

Consequently, the following research question is drafted:

How do traditional business intelligence competency centers differ from advanced analytics competency centers and how is that reflected in its objectives, structure, roles, processes, and governance?

To answer the research question and reach the research objective, two guiding questions have been defined. These questions describe the context to answer the main research question.

1. Which ways are there to organize business intelligence & analytics?
2. What are traditional BI CCs and what are advanced analytics CCs?

1.2 Objective

The objective of this research is to contribute to the understanding of organizing business intelligence and analytics, and specifically competency centers. Two types of these centers seem to exist: traditional BI CCs and advanced analytics CCs. As described, the two seem to have differences and similarities. This research aims to make a cross-industry comparison between the two, as to come to a better understanding of the nature of both centers and develop insights for organizational structure purposes. Using this research, better organizational decisions can be made regarding setting up and maintaining BI&A competency centers.

1.3 Thesis overview

The thesis is structured as follows: Chapter 2 discusses the research design and process. Chapter 3 aims to answer the first guiding question, resulting in a context to answer the main research question. The second guiding question aims to explore the nature of the two types of BI&A competency centers and is answered chapter 0 and 5. Chapter 4 discusses the desk research on the two types of BI&A competency centers. In chapter 5, a direct comparison is made between the two centers based on interviews with participants. In chapter 6, the research question is answered, conclusions are drawn, and limitations and suggestions for future research are given.

2 RESEARCH METHODOLOGY

In this section, the steps taken towards answering the research question will be elaborated on. The goal of this chapter is to give a clear, detailed overview of how this study has been executed.

This chapter is based on the research onion of Saunders, Lewis, & Thornhill (2007) and the research project book of Thomas (2017).

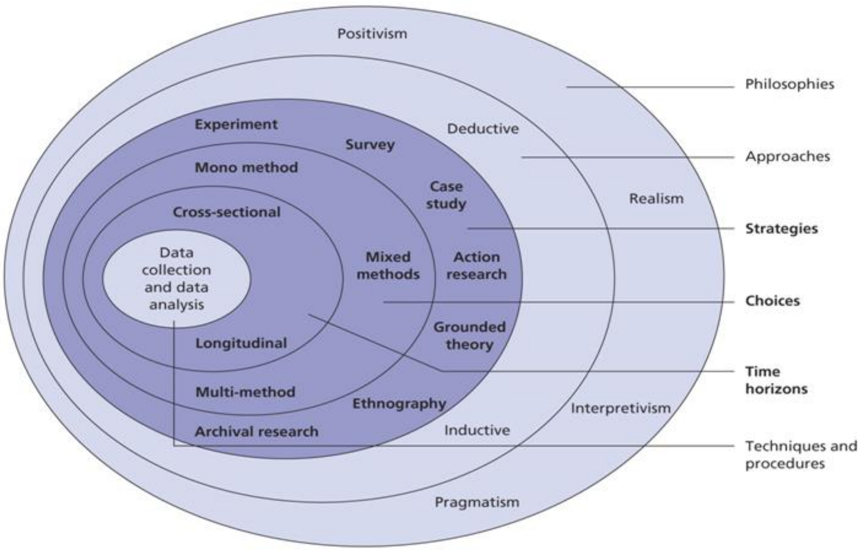


Figure 2: Research onion (M. Saunders, Lewis, and Thornhill 2007)

2.1 RESEARCH DESIGN & METHODOLOGY

The research compares two types of business intelligence and analytics competency centers to create a better understanding of both, if and how they are connected and gain insights for organizational structure purposes. Using this, better organisational decisions can be made regarding setting up and maintaining BI&A competency centers. The advanced analytics competency center is a relatively new research subject and is rarely covered in research. The comparison between the types of BI&A competency centers is to the best of the researcher's knowledge, not been researched. In addition to earlier named research objectives, this study aims to contribute to this lack in knowledge by comparing predetermined characteristics of the two centers.

2.1.1 RESEARCH PHILOSOPHY AND APPROACH

The key to all research is describing, interpreting, and analysing. However, it is needed to determine in which way this research will carry out the aforementioned: the approach (Thomas 2017). The research question aims for a deeper understanding of a construct that has multiple point of views. Accordingly, this research uses an interpretivist philosophy. Interpretivism enables the researcher to look at the research subjects in a way that enables an understanding to take place of how the BI&A centers have been implemented and what motives underlie the observed behaviours. The aim of the approach on this research is to look at the world from the subject's point of view and interpret their thoughts on the characteristics of BI&A competency centers. Further, the interpretivist philosophy can be used for testing or building a theory (Thornhill, Saunders, and Lewis 2009), which is suitable for this research as not much information on the subject is available.

Some elements of positivism exist in the research question. The characteristics of the two types of BI&A centers could be studied using a more straightforward, descriptive approach. The positivist approach would provide answer but no depth of reasoning. As the nature of the answer is more ambiguous, dependent of perception and has a contingency approach, interpretivism was chosen as a philosophy.

An inductive reasoning approach was used to form conclusions in this research. As explained, due to the contingency and interpretivism approach, the data of this research is to be interpreted by the researcher. As the inductive approach is likely to be particularly concerned with the context in which such events were taking place, this is the right fit for this research (Smith, Thorpe, and Jackson 2008). For this reason, qualitative data tends to be fit for inductive reasoning (Sun 2009).

2.1.2 Research strategy, choices and time horizons

This research uses a qualitative, exploratory research methodology. Qualitative research has its roots in social sciences and is primarily concerned with finding out why people behave as they do. The nature of the data in this research is not numeric. Qualitative studies provide rich, contextualized understanding of human experience through the intensive study of particular cases. A qualitative methodology was chosen as the findings in this research are ambiguous and dependent of perception and therefore always embedded within a context. Generalization by quantitative research is thus not needed (Sun 2009).

Thematic analysis

To ensure a valid and reliable process of analysis, a data processing and analysis method is chosen. Many methods exist. For our research question, after comparing the goal of the research and the goal of the methods, it was concluded a grounded theory-minded method is most relevant. After researching the goal of grounded theory, it became clear that a full grounded theory would only be achievable in a large (1 year+) research project, and is rarely used, even when a grounded theory method is claimed (Pidgeon and Henwood 1997).

Furthermore, Thomas (2017) notes that grounded theory is a very difficult method for inexperienced researches. Hence, other methods were considered.

Content analysis and thematic analysis are two similar, commonly, and interchangeably used approaches in data analysis. The methods search for patterns and themes in and across data. The main difference between the two is that content analysis is more focused on quantifying the qualitative data (Vaismoradi, Turunen, and Bondas 2013), while thematic analysis "moves beyond counting explicit words or phrases and focuses on identifying and describing both implicit and explicit ideas within the data, that is, themes" (Guest, MacQueen, and Namey 2012)

Thematic analysis was chosen as the data processing and analysis method. This method shows similarities to 'grounded theory-lite' method, which involves coding and the generation (and interpretation) of broader patterns in data (Pidgeon and Henwood 1997). It involves using the techniques of grounded theory for the development of categories and concepts, and an understanding of the relationship between the various categories and concepts. Thematic analysis is most popularly described by Braun & Clarke (2006) and has been proven inside and outside of psychology.

Time horizon

The time horizon set for this research is cross sectional as the time horizon is already (somewhat) established. The research does not focus on examining change over time but is rather investigating the phenomenon of BI&A competency centers at a specific time.

2.2 Research Process

Each research needs data to answer the research question. Data can be collected using (various types of) instrumentation. The instrumentations used in this research are desk research and semi-structured interviews.

2.2.1 Initial phase

Firstly, a literature review was performed to create an understanding and identify what has been going on in the field of organizing business intelligence and analytics, and particularly the BI&A competency centers. The literature review was performed by searching keywords on Google Scholar and the Leiden University Library, Scopus and Web of Science.

SUBJECT	KEYWORDS
Organizing business intelligence and analytics	- *"Organizing data science"* - *"Organizing analytics"* - *"Organizing business intelligence"*

	- *"Data governance"* - *"Analytics governance"* - *"Analytics governance maturity"* - *"Organization of data"* - *"Analytics organization" & "structure"* - *"Organizational design" & "big data"*
Business intelligence & analytics competency centers	- *"Center of excellence"* - *"Center of excellence" & "analytics"* - *"Shared Service Center" & "analytics"* - *"Business analytics competency centers"* - *Business intelligence competency centers* - *"BICC"* - *"BACC"* - *"Analytic Competency Center"*
Business intelligence & Analytics	- *"Big data"* - *"Business Intelligence"* - *"Business analytics"* - *"Business intelligence" vs "business analytics"*

Table 1: Desk review subjects and keywords

Grey literature

Grey literature includes sources outside of the traditional academic publishing. For this research, grey literature from the consulting firms like Accenture, Bain, and McKinsey was used, as well as material from research and advisory company Gartner. Furthermore, non-academic reports written by (business) experts on subjects were used. Although these sources are not scientific, including them is valuable to us as the academic material on this topic is scarce. A more holistic view could be created using grey literature.

2.2.2 INTERVIEWS

More knowledge is required about the topic. Expert interviews generate specific knowledge about the situation that is investigated and are accordingly well suited (Pfadenhauer 2009). "An interview is a discussion with someone in which you try to get information from them" (Thomas 2017). During the interview, participants can share their stories and experience. The researcher can collect in-depth answers that focus on the participant's knowledge and opinion related to the research topic (Murtezaj 2011).

Interviews can be structured, unstructured or semi-structured of nature. For this research, semi-structured interviews are used. Semi-structured interviews can offer the best of both worlds, combining with structure in the interview questions with the freedom to follow up points when necessary (Thomas 2017). The questions that were not answered during the interview were asked afterwards via email to ensure each participant has had the same questions. The first interview served as a test interview after which some questions were altered, added, or deleted. The first (test) interview did contain valuable content and was used in the analysis.

At the end each interview, the participants are asked if the topic was covered fully and if something was missing during the interviews.

2.2.3 Procedure

After drafting the research question and finishing the literature review, the interview questions were drawn up. The research question was divided in parts. For each part, separate interview questions were derived. Together with generic questions, these were included in the interview questionnaire so that the answers to all the parts would provide enough data to answer the research question properly. The parts are: Introduction, BI&A competency centers, Objectives, Structure & Roles, Processes, Governance and Other questions. The interview starts with introducing the topic, the research question, and the used definitions for traditional BI and advanced analytics. Letting the participant accustom to answering questions, it continues with introductory, straightforward fact-based questions and follows up with questions about the different parts of the research question.

Bücker (2015) recommends making these questions interpretive and descriptive, based on the observation of a natural setting and in-depth description of a situation or views of "natural setting". Most questions are descriptive and describe the as-is situation of an organization's BI&A center. Dependent on participants' attitude during answering, questions are asked about the participants' opinion on how aspects 'should' work in a to-be situation. It is of interest to see how the centers are meant by the organization and how the centers turn out to be in practice. Here, possible discrepancies between theory and practice can come to light. The interview questions are given in Appendix A.

Ethical considerations

The interview participance is voluntary and agreement is asked to record. The interviewees will be made anonymous, as will company names and names of clients. As the interviewees are mostly consultants, their experience is based on their work with or at clients. The interviewee's described situation at the client is naturally part of the data. However, if this described situation contains privacy or otherwise sensitive/confidential content, the information is censored.

2.2.4 Setting up and participants

Most of the interviewees were approached via email, the others face-to-face. After initial contact where the purpose, terms of confidentially, format and length of the interview were made clear, an appointment was scheduled via email. The interviews were planned with 1 hour estimated time. The interviews are held in Dutch and English, as the mother tongue of most participants and the researcher is Dutch. Some technical terms were expressed in English. The interviews were recorded and transcribed in their respective languages. The interviews were transcribed within 3 workdays of the interview. The transcriptions can be found in Appendix C. For anonymity and confidentiality purposes, the transcriptions will not be presented outside of university purposes.

All interviews with exception of interview I were held face-to-face. Face-to-face interviews enable the researcher to connect and interact better with the participant and are preferred when social cues are essential to the research (Opdenakker 2006). Seven out of nine participants work(ed) at Capgemini, so most interviews could be conducted at the Capgemini office. Others required travelling for the researcher. All interviews were conducted in a confined space, benefiting the safety to answer freely and practical considerations like audio quality.

Sample size

In the case of inductive, exploratory research, which by definition looks to explore phenomena of which key themes cannot be identified in advance, defining sample size a priori is inherently problematic. In such an approach, specifying a priori how many participants will be needed to create enough understanding of what is yet unknown is, in essence, illogical (B. Saunders et al. 2018; Slevitch 2011). However, as a cut-off must be made at some point, the point of lessening return is considered. In qualitative samples, as the study progresses more data does not necessarily lead to having new information (Mason 2010).

To identify participants, multiple selection questions exist: "Who has relevant information? Who is able to give precise information? Who is willing to provide information? Who is available?" (Gorden 1975). Relevant information in the case of this research would be when the participant has extensively worked with or for one of the two types of BI&A competency centers. It would be a big plus if the participant has experience with both types of centers, as they would be able to compare them.

Via the network of Capgemini and the researcher's own network, the first participants were identified. Subsequently, snowball sampling was used for identifying the potential participants, involving the participant telling the researcher who the next participant might be, that participant doing the same, and so on (Thomas 2017). The snowballing process of this research is displayed in Figure 3.

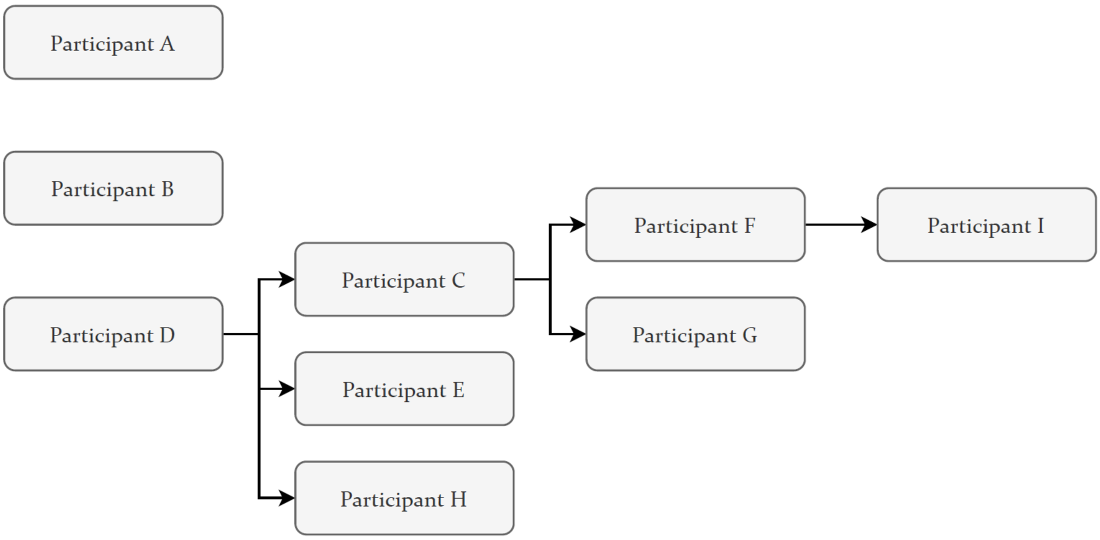


Figure 3: Participant snowball tree

2.2.5 Data processing and analysis

As said, data is gathered through interviews. The interviews have been transcribed and analysed. To provide knowledge and understanding of the phenomenon under study, the documents were thematically analysed. Below, the phases of thematic analysis are displayed.

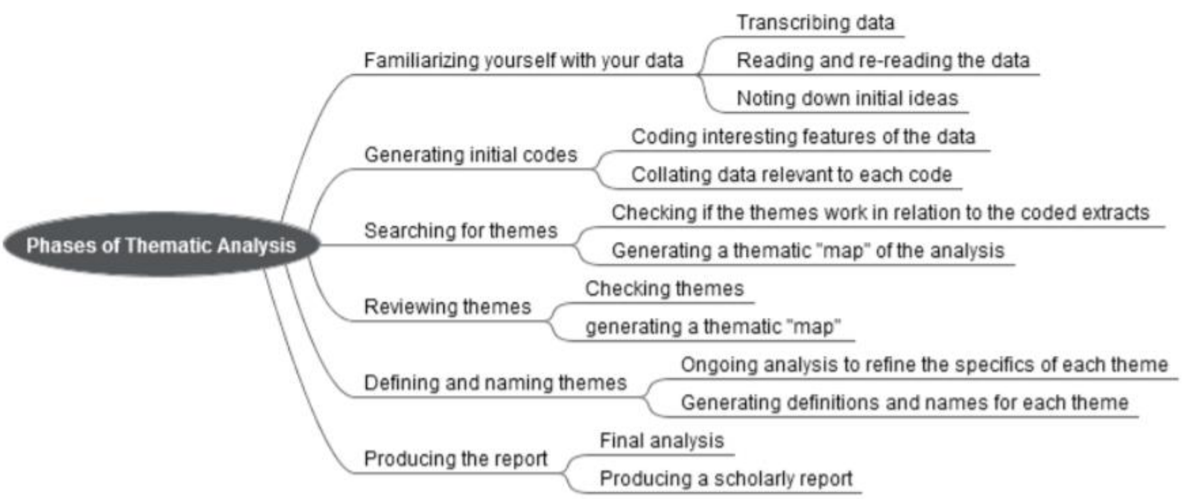


Figure 4: Phases of thematic analysis (Braun and Clarke 2006)

The phases described by Braun & Clarke (2006) are integrated in the research. During the second phase, the researcher is required to generate initial codes. Due to the explorative design of the research, this is done through open coding of the data. Sasldaña (2015) Was used as a guide for coding. Furthermore, the program MaxQDA was used as a tool to support the coding, searching, and reviewing phases of the process. A list of codes in given in Appendix B

3 Organizing Business Intelligence & Analytics

Functions like marketing, human resources or finance have been around for such a long time that standards have been developed. Most of the functionally structured organizations include higher functional management (e.g. CFO, CMO, Vice president of HR). For HR, the function is subdivided into among others customer service, advertising, and product planning. With each subdivision employing its director, governance is ensured, and roles are clear. Given the maturity and pervasiveness of these functions, standards have risen. The 'problem' for the field of business intelligence & analytics is that this discipline does not have the luxury of being around for such a long time in its current form, so has yet to become standardised.

This chapter contains a literature review on the meaning and importance of BI&A and ways to formalize the function within the organizational structure. Both are underlying important factors when looking at BI&A competency centers. This chapter aims to answer the first guiding question.

3.1 Big data, Business Intelligence & Analytics

The terms '(big) data analytics', 'business intelligence', 'data mining', '(business) analytics', 'data-driven insight' and others are often used interchangeably. As said, Davenport & Harris (2007), paved the way for research on how to successfully exploit the potential of 'big data' and 'analytics' by providing several managerial strategies. However, the idea of leveraging data to improve business performance is not new. For example, operations research uses mathematical and statistical techniques to solve business problems and made its appearance during WWII as a concept to optimise military operations. The term 'Business Intelligence' (BI) was first composed by Luhn (1958) and made concrete later as an umbrella term introduced by Howard Dresner of the Gartner Group in 1989 to "describe a set of concepts and methods to improve business decision making by using fact-based computerised support systems" (Nylund 1999). As means by which data could be collected increased in the 2000s, the possibilities and need for analysing and reporting on this data increased with it. The rising interest in this subject is also reflected in literature, covering multiple domains (Y. Chen et al. 2016). The focus in scholars on the subject of business intelligence and analytics evolved from operational excellence and hindsight information to leveraging statistical and mathematical models to predict behaviour of underlying business drivers and optimising business outcomes (Davenport 2006; H. Chen, Chiang, and Storey 2012; Sharma et al. 2010).

3.1.1 BIG DATA

Laney (2001) identified challenges and opportunities in (big) data management. Laney specifies these challenges and opportunities using the 3Vs model, i.e., the increase of Volume, Velocity and Variety. This model has emerged as a common definition for *big data* in many scholars (H. Chen, Chiang, and Storey 2012; Kwon, Lee, and Shin 2014; McAfee et al. 2012; Grossman and Siegel 2014). While the 3Vs is still the most used definition, others expanded the 3Vs model with new Vs (Mikalef et al. 2018). Owais & Hussein (2016) go as far as defining big data using 9 Vs: Velocity, Variety, Volume, Validity, Veracity, Variability, Visibility, Verdict and Value. The six extra Vs add to the existing model a more semantic meaning (relationship of data, BI and statistics).

3.1.2 BUSINESS INTELLIGENCE & ANALYTICS

Business intelligence, business analytics, traditional BI and advanced analytics

In practice and in most academic literature, Business Intelligence (BI) and Business Analytics (BA) are used interchangeably. At some point, 'analytics' was added to the jargon and integrated in business intelligence scholars. The definitions of BI and BA not being MECE (mutually exclusive, collectively exhaustive) too contributes to the confusion. However, while doing desk research and having non-formal conversations with experts, it became clear that meaning of the umbrella term 'business intelligence' changed over time. Although some authors argue a hard, formal distinction between the terms Business Intelligence and Business Analytics exists (Ramirez Linares 2019; Ahmed and Ji 2013), the choice was made to attribute these differences to the terms 'traditional BI' and 'advanced analytics'. Experts agree a distinction can be made between the two, but some note that the two may not be so different as they seem. Following the distinction made by Ahmed & Ji (2013) and Ramirez Linares (2019), they are defined as:

- Traditional BI: focusses on telling *what happened* by creating the ability to comprehend presented information and then use it to guide business actions to achieve planned strategic goals successfully.
- Advanced analytics: helps to tell what *is going to* happen by using data, statistical and quantitative analysis, explanatory and predictive models.

Traditional BI has been described in relation to BI that is non-traditional in different contexts: Traditional BI vs. real time BI (You 2010; Dobrev and Hart 2015; Dasgupta and Vankayala 2007), vs. agile BI (Muntean and Surcel 2013), vs. predictive analytics (Koch 2015) and vs. advanced analytics (Bose 2009). All agree on traditional BI being an information processing system or workflow that presents historical data to users for analysis. This historical data is processed into reports from which business executives devise strategic decisions and plans (Yang and Fong 2010).

When the velocity of Big Data changed traditional BI (2003 and onwards), predictive and prescriptive analytics started to emerge (Larson and Chang 2016). Advanced analytics focusses on these and makes use of a combination of tools to gain information, analyse that information and predict outcomes of the problem solutions. Data integration and data mining are the basis for advanced analytics. Pattern recognition and relationship idenfitication based on statistical analyisis is key to advanced analytics (Bose 2009).

Business Intelligence & Analytics

To speak collectively about both traditional BI and advanced analytics and stay away from the confusion to unite them under 'Business Intelligence', the term Business Intelligence & Analytics (BI&A) is used (following H. Chen et al. (2012)). Holsapple, Lee-post, & Pakath (2014) list 18 different definitions for business intelligence & analytics and summarise: "we adopt a general core characterization of business analytics as being concerned with evidence-based problem recognition and solving that happen within the context of business situations". A more frequently referred to definition for the collective term BI&A is: "*techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand its business and market and make timely business decision*" (H. Chen, Chiang, and Storey 2012). In this research, sometimes scholars using a different term are paraphrased. Unless stated otherwise, these paraphrased scholars agree with the identified definition of H. Chen et al., (2012).

Goals & Objectives

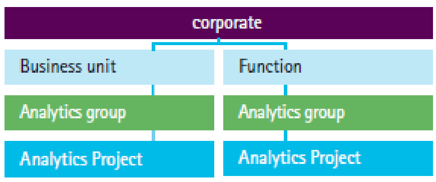
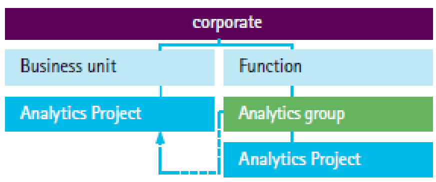
The goal of BI&A is optimisation. BI&A optimises both *speed* and *quality* of business decisions to improve business performance (Davenport and Harris 2007). Data is transformed into insight and subsequently into actions (Sharma, Mithas, and Kankanhalli 2014). Disregarding the specific application, organizations that exploit their data using BI&A seem to outperform competitors, creating a competitive advantage (LaValle et al. 2011).

Optimisation by BI&A can be both internal and external. Internally by raising process efficiency or creating additional insights into a company's customer base (Manyika et al. 2011). Externally by applying data and analytics to offer completely new data-driven services (Schüritz and Satzger 2016). As a result of the maturing cloud technologies, scalable processing power, and user-friendly applications is enabled, allowing a wide range of departments to benefit from data and analytics (Satzger, Holtmann, and Peter 2015).

3.2 ORGANIZATIONAL MODELS FOR BI&A

Already thirty years ago, Tushman & Nadler (1991) highlighted that “Different organisational structures have different capacities for effective information processing”. Several structures (models) exist to determine where the BI&A function resides within the organization, divided into three main categories: centralized, decentralized and hybrid. These models are visualized in Figure 1.

Different forms with different nuances on these three categories are described in various pieces of research (Grossman and Siegel 2014; Lismont et al. 2017; Khalil and Wood 2014; Anderson 2015). Hernandez et al. (2013) summarises the various possibilities in six models which differ on three characteristics: BI&A governance (project pipeline resource allocation and budget management), Analyst location (where analysts reside) and Project Management Support (coordination of analytic activity).

MODEL	BI&A GOVERNANCE	ANALYST LOCATION	PROJECT MANAGEMENT SUPPORT
DECENTRALIZED 	Resources allocated only to projects within their silos with no view of BI&A activities or priorities outside their function or business unit	BI&A is scattered across the organization in different functions and business units	Little to no coordination
FUNCTIONAL 	Resource allocation driven by a functional agenda rather than an enterprise agenda	Analysts are located in the functions where the most analytical activity takes place, but may also provide services to rest of the corporation	Little coordination

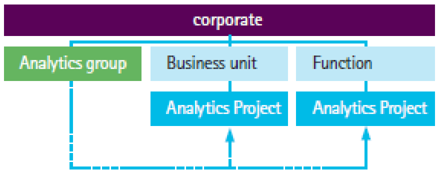
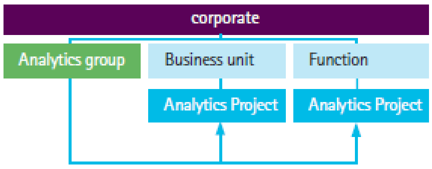
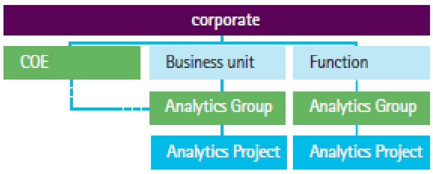
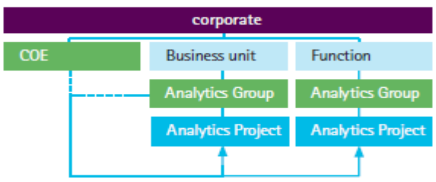
CONSULTING 	Resources allocated based on availability on a first-come-first-served basis without necessarily aligning to enterprise objectives	Analysts work together in a central group but act as internal consultants who charge “clients” (business units) for their services	No centralized coordination
CENTRALIZED 	Stronger ownership and management of resource allocation and project prioritization within a central pool	Analysts reside in central group, where they serve a variety of functions and business units and work on diverse projects	Coordination by central analytic unit
CENTER OF EXCELLENCE 	Better alignment of BI&A initiatives and resource allocation to enterprise priorities without operational involvement	Analysts are allocated to units throughout the organization and their activities are coordinated by a central entity	Flexible model with right balance of centralized and distributed coordination
FEDERATED 	Same as ‘Center of Excellence’ model with need-based operational involvement to provide SME support	A centralized group of advanced analysts is strategically deployed to enterprise-wide initiatives	Flexible model with right balance of centralized and distributed coordination

Table 2: BI&A organizational models (Hernandez, Berkey, and Bhattacharya 2013)

3.2.1 Decentralized Models

The Decentralized and Functional model highlighted by Hernandez et al. (2013) are both decentralized typed models. The largest difference between the two is that in a Decentralized model, BI&A is scattered over the whole organization while in a Functional model, BI&A is subdivided by business function. The distinction between the two is not made in most literature so generic conclusions over the two models are drawn. The decentralized model is the most common in practice (Davenport, Harris, and Morison 2010). At the same time, this model is considered to be less mature than its centralized or hybrid counterparts (Davenport, Harris, and Morison 2010; Griffin and Davenport 2011; LaValle et al. 2011). A large contributor to this immaturity is the challenge to excel at high-level BI&A without having centralized coordination, expertise and overview (Khalil and Wood 2014). The decentralized model entails that a group of data scientists are placed in each business unit or business function. The data scientists report to individual business unit leaders and perform work under their leadership.

Khalil & Wood (2014) and Anderson (2015) describe several important advantages, challenge and focus points of the decentralized model:

Advantages

- The analysts share the goals of the business unit. They live the goals, reports and metrics.
- Teams can quickly react to high-priority business unit needs
- Data science teams learn the organization's data and its context resulting in a diminishing of project spin-up. Further, it helps the teams in becoming equal partners in both solving problems and identifying possibilities
- Data scientists know the business unit better and can, through this deepened understanding, ask new, hard questions.

Challenges

- The data science team can be removed from other analysts. This can lead to 'silo-thinking' and limited motivation to collaborate and integrate.
- Potential for redundancy of effort, divergence of tools, skills, metric definitions and implementation.
- There can be a lack of communication and sharing among analysts from different teams
- Business units with more money can staff more data scientists. This may not contribute to the greatest organizational impact.
- The work may become dull for the data scientist.

Focus points

- "**Governance**: It is recommended to establish cross-functional group(s) responsible for guiding organization-wide analytics standards, to include data, tool selection, and means of prioritizing analytics efforts.

- **Peer Collaboration**: Establish forums such as data science communities of practice and mentorship circles to share best practices and lessons learned (e.g., trends, algorithms, methods)
- **Creative Outlets**: Fund analytics competitions, crowdsourcing, and conference attendance that allow data scientists to exercise their minds, solve new problems, and explore techniques" (Khalil and Wood 2014).

3.2.2 CENTRALIZED

The above described Centralized and Consulting model are both forms of centralized typed models. This model centralizes BI&A by placing all data scientists in a single unit. They are in service of the entire organization and report to a Chief Data Officer. The largest difference between the Centralized and Consulting model is the respectively solid vs. dotted line reporting to the BI&A project. In the consulting model, the analysts work together in a central group but act as internal consultants who charge 'clients' (business units) for their services. In the Centralized model, analysts also reside in a central group and serve business units, but the budget comes from the central group. Further, there is more centralized coordination on projects in the Centralized model than in the Consulting model.

According to Saxena & Srinivasan (2012), if a company wants to create a data-driven decision making culture, *entirely* centralizing an BI&A team is nearly impossible. However, this model is one of the "easiest ways to achieve critical mass, obtain necessary data, drive an integrated infrastructure and gain the required expertise to efficiently test and deploy data science models" (Grossman and Siegel 2014).

Khalil & Wood (2014) and Anderson (2015) describe several important advantages, challenge and focus points of the centralized model:

Advantages

- The team can standardize skills, training and tooling. Resources and software license costs can be shared
- More easily promote the use of BI&A within the organization
- Analysts can communicate easily, learn from and mentor each other, feel like they are part of a like-minded team.
- Perception of greater objectivity as their success or reward is unlikely to be aligned with the success of the projects that they are analyzing
- Project diversity motivate data science teams and contributes to strong retention

Challenges

- Can be removed from business owners and their goals
- Tend to be reactive to request for work
- Different team compositions need to be arranged for every new challenge

- Business units must provide another organization (i.e., the data science unit) with access to their data, which they might be reluctant to do
- They lack intimate domain knowledge
- A challenge that counts specific for the consulting model is to add to the enterprise-wide objective as incoming service requests are not prioritized by a central analytic unit but by the first come-first served principle.

Focus points

- "**Selling Analytics**: Demonstrate tangible impacts of analytics to business unit leaders—they are the customers and need to buy-in
- **Portfolio Management**: Create transparency into how the organization will identify and select data science projects, including criteria to prioritize opportunities and align resources
- **Teamwork**: Establish early partnerships between data science teams and business units, which will be integral to framing problems and translating analytics into business insights
- **Education:** Train business unit leaders on the fundamentals of data science and the characteristics of a good data science problem, so people across the organization can recognize opportunities" (Khalil and Wood 2014).

Centralized vs decentralized

Anderson (2015) summarizes the pros and cons of the centralized and decentralized model in the below-shown table. 'Greater domain knowledge' could go either way, as data scientists in decentralized organizations can better understand the voice of customer data, analytical processes and metrics. However, there is a larger risk for losing the relevant knowledge when data scientists leave. In a centralized organization, data scientists switch often among different lines of business, so domain knowledge is more likely to be redundant.

Pro	Centralized	Decentralized
Clear career path	✓	
Direct, full-time access		✓
Faster turnaround time		✓
Greater redundancy of domain knowledge	✓	
Standardized toolset and training	✓	
Standardized metrics: numbers that agree	✓	
Less bureaucracy		✓
(Perceived) objectivity	✓	
Greater domain knowledge	?	?

Figure 5: Pros and cons of centralized versus decentralized BI&A structure
(Anderson 2015)

3.2.3 Hybrid

The Center of Excellence and the Federated model are both hybrid typed models. The hybrid model combines the centralized and decentralized approach by placing data scientists both in a central unit as well as distributing them throughout the organization. Most of the time, the central unit is organized as a 'Center of Excellence' (CoE) or 'Competency Center' (CC). The center of excellence and the federated model are very similar. The federated model adds to the center of excellence model deed-based operational involvement to provide subject matter support (Hernandez, Berkey, and Bhattacharya 2013). In literature, when discussing the hybrid model, the notion of operational involvement (thus the federated model) is included most of the time (LaValle et al. 2011).

Khalil & Wood (2014) describe a different kind of hybrid model: The Deployed model. Here, as with the two decentralized models, data scientists are embedded in the business units. However, these data scientists report to a Chief Data Officer as opposed to business unit managers.

Although the deployed model differs from the federated or center of excellence model, it shares (most) of its important advantages, challenges, and focus points. These are described by Anderson (2015) and Khalil & Wood (2014).

Advantages

- Combining advantages from the decentralized and centralized model: Knowledge is developed across business units, but central overview for enterprise-wide issues is ensured by the chief data scientists or the center of excellence

Challenges

- Data science teams in the business unit are reporting to two bosses. This may lead to conflicting priorities and accountability.
- Resource allocation may still feel competitive. Data science teams risk alienating business unites whose proposed projects are not selected.
- Risk of being 'stuck in the middle' between two approaches: experiencing the challenges of both models but not the full potential of its advantages.

Focus points

- "**Conflict management:** The chief data scientist should proactively engage business unit leaders to prevent competing priorities from becoming the data science teams' responsibility to resolve
- **Formal Performance Feedback:** Agree to performance goals at the onset of each project, and collect feedback during the life of project, including at its conclusion
- **Rotation:** Allow data science teams to work on projects across different business units, rather than within a single business unit—take advantage of one of the main benefits this model affords
- **Pipeline:** Regularly communicate the data science project pipeline, allowing business units to see how their priorities are positioned" (Khalil and Wood 2014).

3.2.4 Which model to choose?

There is no answer as to "which model is the best?". In general organizational design, there is no best design as the organizational model is dependent on the organization's current contingencies (Donaldson 2001). Many factors go into choosing one of the models. The leading contingency is organizational strategy, but also the organization's size, products and services or utilising technologies may be of influence on the decision (Blarr 2012; Venkatraman 1989). Contingency theory claims that when the composition of attributes *fit* its contingencies, the organization achieves higher performance (Van de Ven and Drazin 1985).

Specific for organizational design of BI&A, Grossman & Siegel (2014) claim that managers must recognise the trade-offs associated with each model and make their choice accordingly. This might be true but still gives little direction for these managers. Harris, Craig, & Egan (2009) and Khalil & Wood (2014) specify that organization size, diversity of its business or missions sets, culture and strategic goals and its ability to hire and retain data scientists are factors to consider when choosing a model. According to Pearson & Wegener (2013), "companies with deep analytics capabilities and an emphasis on experimentation can rely on a generally decentralized approach". When engaging analysts is the primary goal, centralization of the BI&A organization would be the best approach (Harris, Craig, and Egan 2009).

Most common model

Although nine years ago, the decentralized model was the most common model (Davenport, Harris, and Morison 2010), in 2017, a different distribution was found: 47% of 73 respondent organizations organize their BI&A centrally (centralized team or CC) and 23% choose for the hybrid option meaning that 70% of the organizations choose for some form of centralization (Lismont et al. 2017). The same authors conclude that several formats of organizing BI&A are used and that companies frequently combine models. This shift is recognized by Hernandez et al. (2013) and is contributed to its flexibility to allocate capabilities to maximize effectiveness, easier governance and increased resource engagement.

On an employee level, the centralized and hybrid models offer the greatest potential too, showing significantly higher levels of engagement, job satisfaction, perceived organizational support and resources and intention to stay than decentralized analysts or those working in consulting units (Davenport, Harris, and Morison 2010).

Governance

To add on the choice of a model, “an organization must not only choose a model, but also establish mechanisms needed to ensure communication and collaboration between the various BI&A teams, and between BI&A and business leaders. Regardless of the model, the data science teams must be proactive” (Khalil and Wood 2014). Miranda (2018) also argues that any of these models can work effectively, as long as governance is established to prevent the various units from becoming islands. ‘Analytics governance’ helps in overcoming challenges regarding identifying and resourcing analytics opportunities, obtaining the data and deploying the models (Grossman and Siegel 2014). The same article discusses a set of parameters for designing a governance structure.

Staying up to date

Several studies about organizational models for analytic teams end with the note that organizing data science is not a one-time activity (Khalil and Wood 2014; Miranda 2018; Griffin and Davenport 2011; Hernandez, Berkey, and Bhattacharya 2013). As organizations and markets change, their arguments for choosing a specific model can become outdated. Its organizational model must not be permanent. It is necessary to re-evaluate the validity of the arguments and modify the model. The consolidation and reviewing can be performed by a centralized BI&A organization and/or a steering committee. They recognize the importance of opportunities based on a defined set of criteria and will prioritize them accordingly (Hernandez, Berkey, and Bhattacharya 2013).

4 Business Intelligence & Analytics Competency Centers

Traditional BI competency centers and advanced analytics competency centers are different types the collective term business intelligence & analytics competency centers (BI&A CCs). These BI&A CCs are type of Shared Service Center (SSC). The difference between traditional BI and advanced analytics was earlier explained in 3.1.2. In this chapter, the two types of centers are analysed by a literature review. The two centers are described based on the earlier named characteristics objectives, structure, roles, processes, and governance.

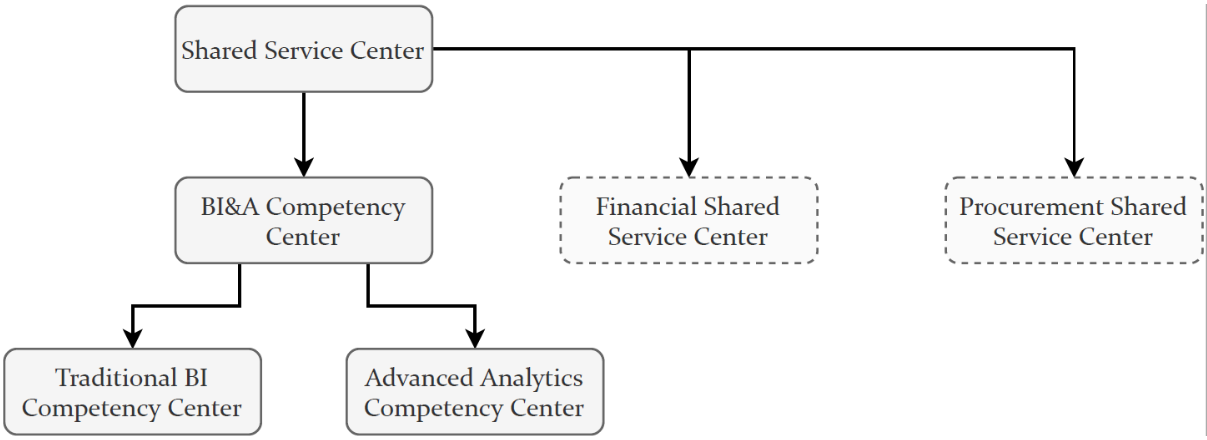


Figure 6: Shared Service Center Breakdown

4.1 Shared service center

Shared Service Centers (SCCs) have been around for a while but gained popularity during the trend to centralize organizational design, targeting to better leverage internal skills (Singh and Craike 2008). While there is no formal definition in academic literature for a SSC (Singh and Craike 2008; Schulz and Brenner 2010), it can be described as a business model of a semi-autonomous business unit consolidated out of similar business functions or roles. This unit offers defined services to internal clients (Bergeron 2003).

In the past, such centers have been used in IT related matters for enterprise resource planning (ERP) and business intelligence systems too (Schüritz et al. 2017). The central and hybrid typed organizational models described in 3.2 incorporate SSCs. The Consulting and Centralized models are the most prominent examples of an SSC use, but the Center of Excellence and Federated model too have a centralized hub for their BI&A.

4.2 Two types of SSCs

According to Schüritz et al. (2017), the earlier described contingency theory is one not regularly applied in regards to designing a Shared Service Center. With exception of Goold, Pettifer, & Young (2001) existing research does not cover contingencies or attributes of SSCs.

Goold et al. (2001) make a contingency distinction between SSCs, focusing on transaction-oriented processes on the one hand and complex, knowledge-oriented processes on the other hand. This distinction is a relevant one for us.

The most significant difference, described by Schüritz et al. (2017), between transaction-oriented and knowledge-oriented SSCs is that the first focusses on the presence while the second focusses on the future. Transaction-oriented SSCs serve processes that aim for economies of scale by consolidating skills and resources. Knowledge-oriented SSCs serve processes that aim to reduce time-to-value (Goold, Pettifer, and Young 2001). Further, the same authors argue that transaction-oriented processes are standard, process driven. Knowledge-oriented processes are more complex, professionally-driven expert services. Schüritz et al. (2017) recognise this distinction in the field of BI&A.

4.2.1 Traditional BI competency center vs advanced analytics competency center

Traditional BI CCs

To bridge the gap between business users and data scientists organizations can "employ analytic applications that blend data analysis technologies with task-specific knowledge" (Kohavi, Rothleder, and Simoudis 2002). Centralization of these applications have contributed a great deal to implement enterprise resource planning and business intelligence systems. These centers "placed emphasis on reporting, historical analysis and dashboards" (Schüritz et al. 2017). Such organizational entities have often been named business intelligence competency centers (BICC) or business intelligence centers of excellence (BI CoE) (Dresner et al. 2002). The historical focus is acknowledged by Berndtsson et al. (2018), who add that such BICCs deliver reports on a monthly or quarterly basis and any requests for ad hoc reports are added to their to-do lists. As a result of the focus on historical analysis and reporting, Schüritz et al. (2017) characterise such centers as transaction-oriented SSCs. Such centers fit the earlier provided description of 'traditional BI' (3.1).

Advanced Analytics CCs

The last years have seen an emergence of SSCs that focus on providing analytics and data mining as an internal service across the organization (Watson 2015). These SSCs focus on predictive and prescriptive analysis and are thus focusing on the future, rather than on the presence (Schüritz et al. 2017). Hereby, they are characterised as knowledge oriented SSCs. Such knowledge-oriented SSCs have different names in different organizations, such as (Big data) Competency Center (CC), (Big) Data Lab, Analytics Competency Center, Analytics Center of Excellence, Analytics Service Center (Schüritz et al. 2017).

Confusingly enough, the terms previously used for transaction-oriented SSCs (BICCs or BI CoEs) are nowadays predominantly referring to units that fit the definition of knowledge-oriented SSCs. Schüritz et al. (2017) argue however that knowledge-oriented SSCs are "still rarely covered in research". Knowledge-oriented centers fit the earlier provided description of 'advanced analytics (3.1). Schüritz et al. (2017) provide an overview of what we will call advanced analytics CCs design options in terms of objectives, functions, structure, roles, processes, and governance.

Duncan (2016) describes some distinction between traditional BI and advanced analytics Competency Centers too. Here is argued that the traditional BI CC needs to evolve into "some kind of Analytics Community of Excellence", as the world of BI is changing and the importance of prescriptive analysis increases.

Concluding, Schüritz et al. (2017) identify two types of BI&A centers: traditional BI competency centers (which they call *transaction-oriented CCs or* BICCs) and advanced analytics competency centers (which they call *knowledge-oriented CCs or* ACCs). The first focuses the presence (traditional BI, described as reporting and historical analysis) and the second on the future (advanced analytics, described as predictive and prescriptive analysis).

4.3 Traditional BI Competency center

Schüritz et al. (2017) is the first in academic research to make a clear distinction between the two types of BI&A SSCs. All other performed research thus far describes a single type of BI&A SSC, most often referred to as a Business Intelligence Competency center (BICC). As said, Schüritz et al. (2017) indicate that literature about advanced analytics CCs (knowledge-oriented CCs) is rare. Most existing literature about competency centers is thus about traditional BI CCs (transaction-oriented CCs).

4.3.1 Objectives

According to Healy (2010), the unique issues associated with BI projects are often underestimated by traditional IT deployment efforts and can thus not be handled by an internal IT department. Hostmann (2007) backs up this claim by adding that organizations treat data quality and accessibility problems as an IT issue. Many organizations have recognised that without business user involvement, BI problems cannot be solved. Moreover, analysts are often scattered around different departments of an organization, resulting in little coordination between the analysists and local, department-level problem solving (Laursen and Thorlund 2010).

To involve the business more and provide a shared forum for analysts, companies can choose to establish traditional BI competency centers. The traditional BI CC is defined as a "group of business, IT and information analysts, working together to define the business intelligence strategies and needs of the entire organization" (Hostmann 2007).

The Gartner Group is generally contributed with opening the discussion about the traditional BI CC concept and state: "Their role is to champion the BI technologies and define standards, as well as the business-alignment, project prioritization, management and skills issues associated with BI projects" (Strange and Hostmann 2003).

In their book '*Business intelligence competency centers: a team approach to maximizing competitive advantage',* Miller, Bräutigam, & Gerlach (2006) describe a traditional BI CC as a cross-functional team with a permanent, formal organizational structure; the CC supports and promotes effective use of BI across the organization by defining BI tasks, roles, responsibilities and processes. This definition explicitly states BI as a process, as opposed to it just being analytical tools and techniques. They name five reasons to establish a traditional BI CC:

1. "Preserve and exploit the full value of technology investments.
2. Integrate and consolidate business and analytical intelligence processes and initiatives.
3. Reduce overall risk of implementation projects and project realization.
4. Support business users in fully understanding data and acting properly on analyses.
5. Ensure that BI knowledge (BI value, concepts, and technology) is shared throughout the organization." (Miller et al., 2006)

Laursen & Thorlund (2010) acknowledge reasons 1 and 4 and add that a traditional BI CC can be established to make business analytics a business process rather than an IT process. Gray (2011) summarizes the idea of a traditional BI CC from an organizational structure perspective: "The idea is to provide the people with these competencies with an organizational structure that allows them to overcome the inter-organizational barriers that would otherwise exist"

4.3.2 Structure and roles

As organizations form a dedicated unit, the question arises how to set up such a unit in terms of its structure and roles.

All below-described roles form a unit that dependent of the place in the organization, reports either to the Chief Technology Officer, the Chief Information Officer, the Chief

Financial Officer, or the Chief Operating Officer. Some companies have identified a Chief Data Officer or Chief Analytics Officer, who reports to the Chief Executive Officer.
There is no “best” solution to where the traditional BI CC reports to, as long as it reports into a division that has strategic and enterprise influence (Burton et al. 2006).

Miller et al. (2006) identifies 15 core job roles that are needed in a traditional BI CC. The roles are ordered by importance and the authors claim that roles 1-4 are essential. Note that one individual could fulfil several of these roles. Also note that the term BICC is used, this corresponds to traditional BI CC.

1. BICC Manager
2. Business Analyst
3. Chief Data Steward
4. Technical Consultant
5. Project Manager
6. Warehouse Architect
7. Administrative Assistant
8. Knowledge Officer BICC
9. Internal Communicator
10. Application Designer/Developer
11. Warehouse Consultant
12. License Administrator
13. Statistician/Data Miner
14. Training Consultant.

Hostmann (2007) acknowledges the need for a formal organization construct and displays the competencies and skills needed in a traditional BI CC, displayed in Figure 7. Here too, emphasis lies on a wide variety of roles and domains, covering different skills.

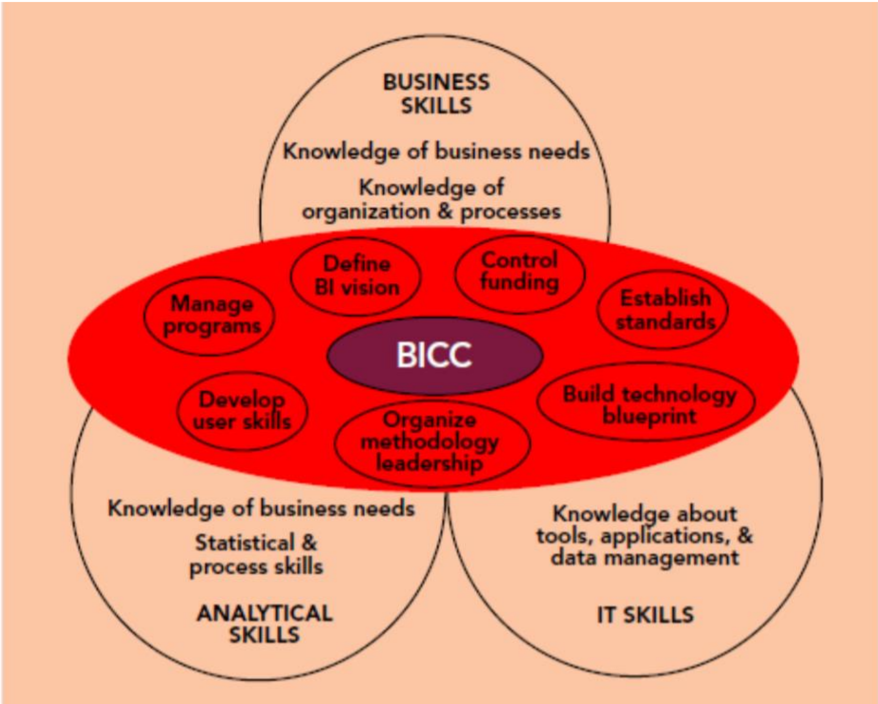


Figure 7: Essential BI Competencies and Skills integrated with traditional BI CCs
(Hostmann 2007)

4.3.3 Processes and governance

Governance is part of every organizational entity. BI governance is an increasingly popular field of study. Organizing BI initiatives centrally is a form of BI governance by itself, but questions remain on governance within the traditional BI CC. BI governance is defined as "a framework that helps identify, deliver and maintain the BI strategy" (Larson and Matney 2007). Furthermore, it is the assembly of procedures, rules and policies to sustain the BI value chain in order to support decisions made by managers (Muntean, Muntean, and Liviu 2013).

Type of traditional BI CC

Two types of traditional BI CCs exist: virtual and fully staffed traditional BI CCs exists. In a virtual traditional BI CC, representatives from different departments take place in a virtual center. In a fully staffed traditional BI CC, the center is set up as its own functional unit. In a virtual CC, representatives from the entire organization are involved in creating information and knowledge based on available tools while the IT department itself manages the IT solution development process. A virtual CC takes strategic decisions and focuses more on processes, architectures, services and technology vendors, technology development as well as integration (Marcinkowski and Gawin 2017).

Pros and cons were derived from Miller et al. (2006) for both the virtual and fully staffed traditional BI CCs:

Virtual

Pros

- Less disturbing to organizational structure
- Members stay close to day-to-day business

Cons

- Limited accountability, communication, and alignment between members → Increases knowledge sharing difficulties
- Priorities, goals, and objectives lie at direct management → objectives could be in conflict
- Management buy-in and support from individual business units needs to be high

Fully staffed

Pros

- Members will be more independent and less prone to act in the interest of any particular business unit.
- Clearly defined roles. Responsibilities, reporting lines and place in organization
- High visibility in organization

Cons

- Internal reorganization and shifting budgets
- Members are alienated from day-to day business activities

Processes

There is much literature on the process of establishing a traditional BI CC (Hitachi Consulting 2015; Miller, Bräutigam, and Gerlach 2006; Anderson 2015), but not much has been written on process flows for projects within a traditional BI CCs as the BI CC has been established.

This process flow gives structure to the selection and application, the execution, and the maintenance of new traditional BI projects. These are all areas that fall under the category of project management. The combination of a project management within a traditional BI (or advanced analytics for that matter) CC has not been researched explicitly. Zimmer, Baars, & Kemper (2012) have researched the need for agility and thus 'agile project management' in many different BI departments, some of which are traditional BI CCs. They conclude there is a certain need for the agile way of working in BI projects.

Laursen & Thorlund (2010) describe the information wheel as guidance to deliver the right information and right knowledge to the right people at the right time. The traditional BI CC is in the center of this wheel, keeping it turning.

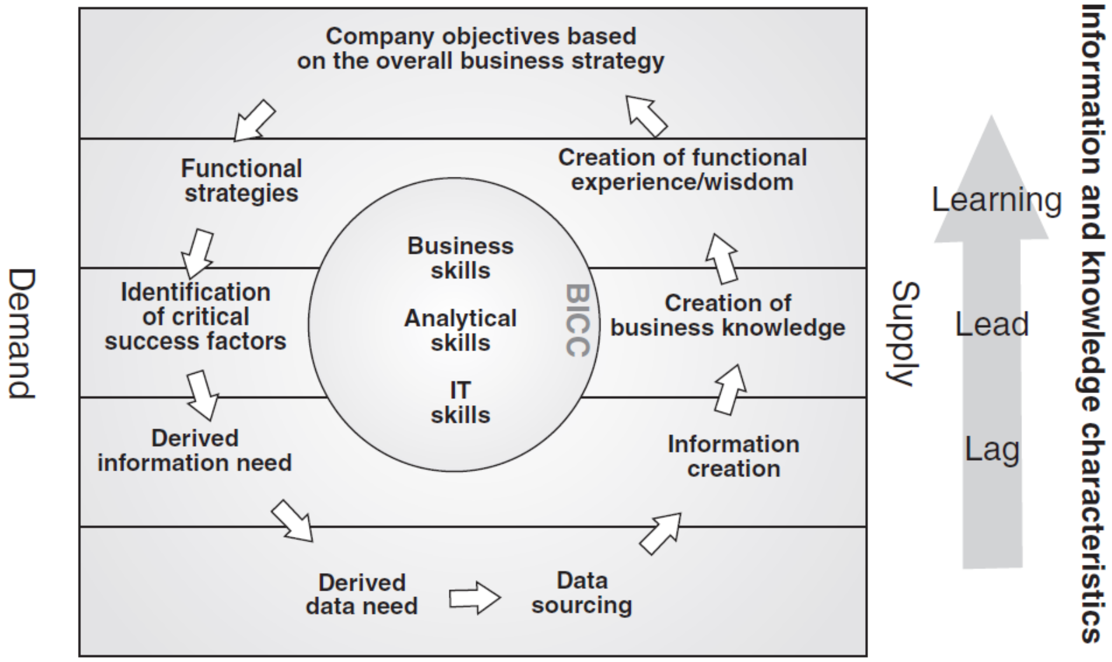


Figure 8: The information wheel (Laursen and Thorlund 2010)

Funding models

Different funding models exist. Specifically for traditional BI CCs, Miller et al. (2006) describe three main funding models:

- *Pay per use model*
  Users of BI services are charged for projects or help based on an internal billing system. Shares costs fairly over users but has a higher entry barrier for new users.

This model where the business units pays for the services received is commonly used in shared service centers (Schmidt 1997).

- *Overhead costs model*
  Department costs are treated as overhead costs and all other departments or users can use the BI services. This is a straight-forward method but it may be difficult to see the economic value of the traditional BI CC.
- *Subscription-based billing model*
  Assigns costs across user groups based on anticipated usage of services. Reduces barriers for use but subscription fees must be compared to actual usage regularly.

Place in the organization

As said, virtual and fully staffed traditional BI CCs exist. Regardless of this distinction or any other structure in the organization, Miller et al. (2006) recommend that the traditional BI CC has executive sponsorship of higher management, e.g. the CEO or CIO. One of the main objectives of the traditional BI CC is alignment between traditional BI goals between various functional areas. This can only be realized by placing the traditional BI CC 'close' to the people who actually oversee these different functional areas in the organization.

There is a trend in organizations wanting to become 'data driven'. Many definitions exist but essentially it entails making decisions based on (proven) data rather than on gut feeling. Previously the top data position was filled by the CTO or CIO. According to Anderson (2015) a Chief Data Officer (CDO) and/or a Chief Analytics Officer (CAO), one of whom is often the head of a traditional BI CC, must be part of the 'C-suite' to enable data driven decision making.

4.4 Advanced Analytics Competency center

As Schüritz et al. (2017) are the first and only ones in academic literature to make a clear distinction between traditional BI CCs and advanced analytics CCs, claiming that advanced analytics CCs are still rarely covered in research, literature about advanced analytics CCs is mostly limited to the research of Schüritz et al. (2017).

4.4.1 Objectives

Objectives are generally seen as something that you plan to do or achieve; the end-goal. Schüritz et al. (2017) summarize the objectives (and functions) of an advanced analytics CC in Table 3.

Objective	Functions
Transformation towards a data driven company	• Identify potential for data-driven business models • Establish awareness for analytics • Provide leadership for analytics project
Analytics expertise	• Act as the single point of contact for analytics • Achieve economies of scale by centralizing skills • Connect ACC experts, business units and external service provider • Testing and advising on suitable technologies and process improvements
Data strategy	• Gain data access (e.g. for data lake strategy) • Develop, test and maintain of a data lake • Integrate and migrate data
Use cases	• Optimize business processes • Improve products and services • Evaluate and estimate of data usefulness • Provide project management and communication for analytics projects
Platform Management	• Select tool set, manage security, control versioning, manage load and performance • Develop, test and maintain platform • Integrate in enterprise architecture
Knowledge Management	• Share best practices • Ensure management and transfer of knowledge • Define standards (methodology, notation, tools, etc.) • Comply with industry standards
Broad adoption of analytics within organization	• Drive end-user deployment • Offer trainings to create higher sensibility and awareness for analytics effort
IT governance for analytics	• Conduct risk & change management • Request funding • Manage vendors and external service provider • Handle license management for analytics software

Table 3: Objectives and functions of an advanced analytics CC (Schüritz et al. 2017)

4.4.2 Structure and roles

Schüritz et al. (2017) summarize the structure and roles advanced analytics CC in Figure 9. Note that the term ACC translates to advanced analytics CC.

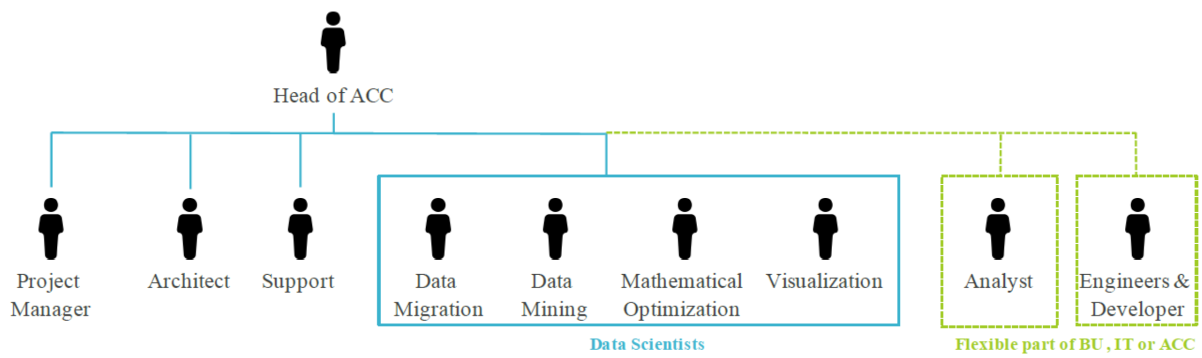


Figure 9: Roles in an advanced analytics CC

In the context of advanced analytics, governance generally refers to a set of structures, rules, policies and controls established for data analytics (Avery and Cheek 2015; Espinosa and Armour 2016).

Type of advanced analytics CC

For advanced analytics CCs as well, a difference in fully staffed and virtual CCs is noted. Fully staffed CCs are set up as centralized on-site collaboration teams and virtual CCs are dispersed over business units and interact on a virtual basis (Schüritz et al. 2017).

Processes

When the advanced analytics CC is up and running, use cases are created, tested and implemented. Schüritz et al. (2017) researched different advanced analytics CCs and derived a standard procedure. Each step in the process is assigned with a description and alterations in the process are indicated by adding options (e.g. A or B).

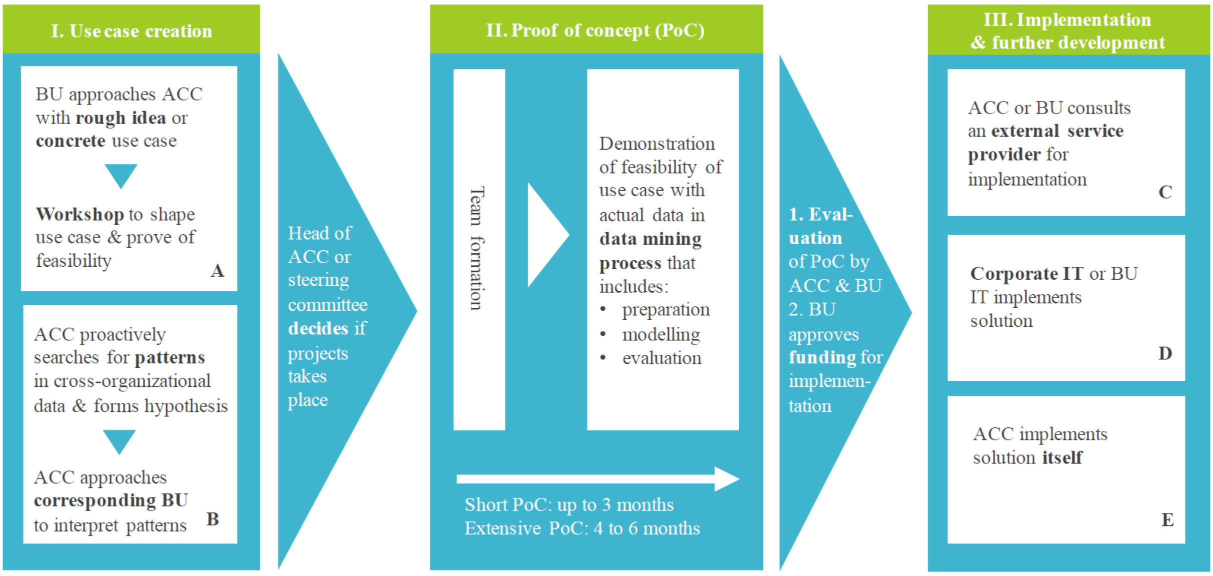


Figure 10: General process of advanced analytics CCs use cases (Schüritz et al. 2017)

Ideas to apply analytics are conceptualized and elaborated in the use case phase. These ideas either come from a business unit or are identified by the advanced analytics CC themselves. After the center has identified the complete use case, the use case enters a so called 'use gate'. This stage gate functions as a 'go, no-go' moment where (dependent of the organization's governance) someone decides whether a project enters the next phase.

In the proof of concept (PoC) phase the advanced analytics CC works with the available data to prove feasibility of the use case. Often a data mining process like CRISP-

DM is used. After this phase, a stage gate is entered again where someone decides on the feasibility of the project (Schüritz et al. 2017).

The third stage is the implementation & further development stage. Here, the concept solution from the second stage is implemented. Also, scaling or other implementation features might need further developing performed by the advanced analytics CC (Schüritz et al. 2017).

Funding models

Schüritz et al. (2017) identifies three different funding models for advanced analytics CCs:

- *Business units to pay for services*
  Here, the business unit pays for services provided by the advanced analytics CC. This entails that the number of uses cases presented to the CC is limited by the BU's budget. Furthermore, this model creates a certain organizational distance between the BU and the CC, as the BU might see the CC only as a 'costly' service provider, instead of a same-level organizational entity.
- *Advanced analytics CC is covering the cost*
  Here, the advanced analytics CC is acting independently. The CC is motivated to see the bigger picture, benefiting the company as a whole, instead of the single BU. There are no delays due to budget approval on the BU side. Acting on its own budget, the advanced analytics CC can prioritize themselves and act with higher speed and agility. BU's might present a massive amount of use cases which the CC has to prioritize themselves.
- *Hybrid financing model*
  To overcome cons and maintain pros of the models, organizations have come up with a hybrid approach. Here, the CC has an own budget and takes financing from BU's. It has a dedicated budget for certain parts of the project (e.g. use case creation), for proactive, cross-organizational projects and for short term cash flow issues. Other financing comes from specific projects for BU's.

Place in the organization

No information about the advanced analytic CC's place in the organization is present in current literature. However, the advanced analytics CC and the traditional BI CC share the objective to make organizations more data driven. To achieve this objective, Anderson (2015) recommends to include a CDO or a CAO in the 'C-suite'.

5 Findings & Analysis

This chapter contains the findings derived from the literature and the data gathered in the interviews. The findings are described and analysed. This chapter aims to draw a direct comparison between the two types of competency centers through the literature and interviews. In this chapter, quotes of participants are displayed. These quotes are translated from Dutch to English and serve to illustrate conclusions.

5.1 Desk research

Literature presented in chapters 3 and 0 provides us with different insight regarding organizing BI&A and the difference between traditional BI CCs and advanced analytics CCs. These findings are presented and summarized below.

5.1.1 Organizing Business intelligence & analytics

Business Intelligence & Analytics (BI&A) is the collective term for the use of data to improve decision making. Traditional BI and advanced analytics both do this in their own way. Where traditional BI focuses on telling what happened, advanced analytics helps to tell what is going to happen.

Three main ways to organize BI&A exist. The decentralized model, the central model, and a best of both worlds solution: the hybrid model. The decentralized model places BI&A people in a functional department. This ensures BI&A experts have local business unit knowledge from their domain as they operate in it. However, decentralization might cause silo thinking.

Centralized models place BI&A people in a single unit, providing services to the whole organization. This offers standardization in skills training and tooling and enables central units to oversee the whole organization. Members do not share the business owners' goals and expertise and BU's must provide data to another organizational unit.

The hybrid model aims to combine the advantages from decentralization and centralization. Knowledge is developed across business units but central overview for enterprise wide initiatives is ensured. However, team members are reporting to two bosses, making it prone to internal conflicts. Resource allocation may feel competitive.

5.1.2 Two types of BI&A Competency Centers

A shared service center offers defined services to internal clients. Two types of shared service centers for BI&A exist: traditional BI competency centers and advanced analytics competency centers. Research has been performed on both type of centers, but mainly on the traditional BI CC. Differences and similarities for both type of centers are identified from literature:

Objectives

Traditional BI CCs and Advanced analytics CCs share the objective 'transformation to a data driven company'. Although not specifically named in traditional BI CC literature, when reading between the lines, 'transformation to a data driven company' is the main objective for these centers. Many named objectives contribute directly to this higher objective.

- To integrate business with BI&A processes.
- To support business users in fully understanding data and act properly on analyses.
- To ensure BI knowledge is shared throughout the company.

Furthermore, as both are types of shared service centers, naturally they share the objective to centralize BI&A activities. Either in a completely central or in a hybrid form.

Structure and roles

The roles business analyst and project manager directly overlap. Furthermore, the BICC manager and head of ACC are similar roles. The same applies to warehouse architect and architect, administrative assistant + internal communicator and support. Some technical roles like statistician and mathematical optimization may also overlap in basic role description, but looking deeper at the techniques and skills required, they will not overlap.

Process and governance

The definitions of (traditional) BI governance and (advanced) analytics governance are very similar. Both take the general definition for governance (i.e. assembly of procedures, rules policies, controls, structures, etc.) and apply it to their field.

Both the traditional BI as the advanced analytics CC can make use of either a virtual or fully staffed CC. The virtual CC as a unit in which people from different business units virtually unite in a center in which they discuss and solve business unit transcending, enterprise wide issues.

Not much is known about a project process in a traditional BI CC. The described information wheel overlaps somewhat with the advanced analytics CC project process. Identification of critical success factors and derive information + data need can be linked to the use case creation phase. Data sourcing, information creation can be linked to the proof of concept phase. Creation of business knowledge and creation of functional experience can be linked to the implementation & further development phase.

The financing models are mostly similar. The pay per use model in traditional BI CC literature corresponds to the business units to pay for services model in advanced analytics

CC literature. The overhead costs model corresponds to advanced analytics CC is covering the costs. The subscription-based model is not addressed to in advanced analytics CC literature. The hybrid financing model is not addressed to in traditional BI CC literature.

For the place in the organization, no literature has been written for the advanced analytics CC. However, as this CC shares one of the main objectives with the traditional BI CC; to help organizations becoming data driven, it is concluded that the recommendation to include a CDO or CAO in the 'C-suite' also deems fitting for organizations with an advanced analytics CCs.

Literature on advanced analytic CCs is scarce. This means no extensive comparison between the two centers could be drawn from literature. Furthermore, literature does not make a direct comparison between the two type of centers. In the parts below, this extensive, direct comparison is made.

5.2 Participants

The participants are almost all business-IT consultants. Most of them work for Capgemini. The consultants who work in the consulting sector have been seconded to an organisation in a certain industry, at which they have experience with the BI&A competency center(s).

Most of the participants have a technical educational background; physics, computer science or a business-IT combination. Two of the participants have a non-technical educational background. All participants have seen both types of BI&A CCs in companies they worked with or for. Furthermore, they all have experience with multiple BI&A CCs (in traditional BI, advanced analytics, or both). Participants are asked to take one typical example in mind for each of the two types of BI&A competency centers and apply the questions to these centers. In Table 4, the participants and their relative experience with the BI&A competency centers are displayed.

Participant	Role	Experience with BI&A Competency Centers	Described Traditional BI Competency Center and function	Described Advanced Analytics Competency Center and function
A	Consultant	3 years	-	Retail A *Lead Data scientist*
B	Consultant	10 years	Public Sector A *Program manager - Setting up CC*	Public Sector B *Program manager -Setting up CC*

C	Consultant	13 years	Insurance A *BI Developer*	Public Sector C Project manager
D	Consultant	23 years	Banking A -	Banking A *Various roles - Setting up CC*
E	Consultant	15 years	Public Sector D *Service delivery manager intelligence*	Public Sector D *Service delivery manager intelligence*
F	Consultant	6 years	-	Banking A *Business analyst*
G	Consultant	13 years	Public Sector E *Various roles*	Public Sector D *Strategy consultant & business analyst*
H	Consultant	6 years	Banking A *Various roles* Telecommunication A *Project manager*	-
I	Lead Advanced Analytics CC	6 years	Banking A	Banking A *Lead Advanced Analytics CC*

Table 4: Participants and their experience

All participants are Dutch and living in the Netherlands. Interviews A through H were held face to face. Due to the coronavirus outbreak, interview I was held via video calling.

5.3 BI&A Competency Centers found

The participants were approached on having experience with BI&A CCs, so naturally all 9 participants acknowledged the existence of BI&A CCs. Furthermore, all participants acknowledged experiencing a formal difference between the two types of BI&A CCs. Participants A through H all recognized some form of BI&A CC in multiple organizations. These organizations differ over various markets like retail, the financial industry, telecommunication, and the public sector.

Definition

When asked about the definition for traditional BI and advanced analytics CCs, many participants started to chuckle, after which they explained many definitions exist. The organizations they work for often have little idea what certain terms entail.

One of the most prominent distinction in the two definitions was the concept of looking back (reporting) vs looking ahead (predicting). This distinction is one made by all participants and supported by literature. First of all, (Schüritz et al. 2017), whose work this research builds on distinguishes reporting and predicting. Others go a step further and classify 4 types of data analytics: descriptive, diagnostic, predictive and prescriptive analytics. It is not entirely clear where this classification originated, but it is widely used in grey literature and mentioned by 6 out of 9 participants. Also, the descriptions of the other three participants for traditional BI and advanced analytics are in line with this classification. Figure 11 shows how the classification can be leveraged along two axis: value proposition and computational sophistication (Delen and Ram 2018). The blue dotted line indicates the cut-off point of traditional BI and advanced analytics. Participant and C, H and I too emphasize that further up the complexity axis does not mean that this type of analytics is better. An organization needs both traditional BI and advanced analytics.

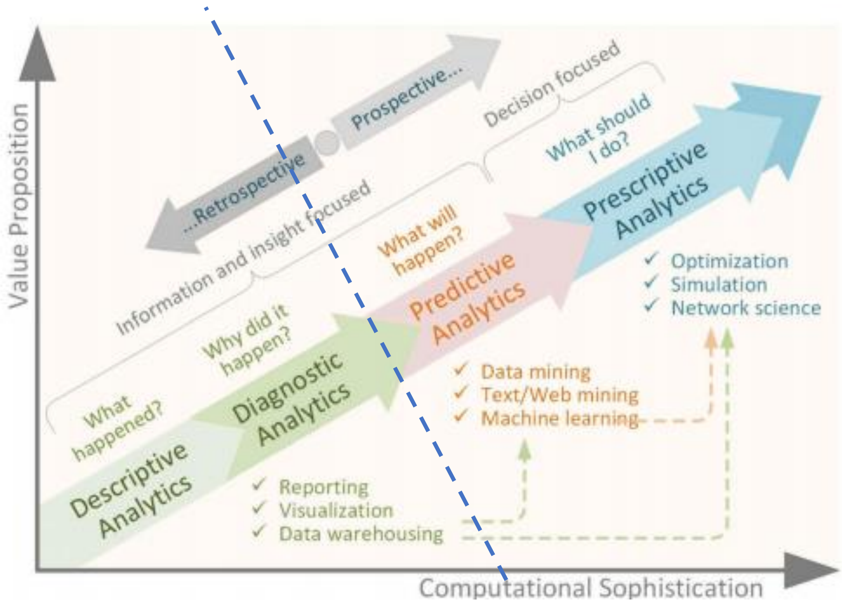


Figure 11: 4 types of BI&A. Edited from Delen & Ram (2018)

Names for BI&A CCs

The earlier noticed inconsistency in names for BI&A reflect in the names of the researched BI&A CCs. The centers have different names like Management Insight Room (advanced analytics CC at Retail A) and Data Lab (advanced analytics CC at Banking A).

Definition	Traditional BI CC	Advanced Analytics CC
Focus	Reporting on business operation (C, D) Being reliable (B, G, I)	Exploring business value (A, C, G, I)
Type of analytics	Retrospective → Descriptive and diagnostic (C, D, E, F, H, I)	Prospective → Predictive and prescriptive (C, D, E, F, H, I)

5.3.2 MATURITY

BI&A CC starting point

Participant D, who has 23 years of experience in the field of organizing BI&A indicated that centralizing BI&A is happening since the late 1990's. Back then, it was a bunch of young applied mathematicians who were working on predictive models. A few years later, he had his first experience with what he would now call traditional BI CC, where databases from all over the company were put together. Participant B, who also has many years of experience indicated that traditional BI CCs scarcely existed up and until 10 years ago:

> *"Before 10 years ago, datacenters did not really exist. Some people were doing something with data, but these data had way more potential… Those people working with data were loners who operated by themselves. There was no organizational structure to support them." (Participant B, Pos 12)*

Advanced analytics CCs have only been recognized for a few years now.

Appearance and centralisation

The centers could not have been established if it were not for the technique being apparent. As noted earlier, traditional BI and advanced analytics make use of different mathematical techniques and IT components. Mainly because of the predictive nature of advanced analytics, statistics plays a larger role in advanced analytics (Bose 2009).

The activities for the two types of CC are further compared below, but relevant for the maturity of the centers is the maturity of the underlying technique. The techniques behind traditional BI have been present for a longer time than the techniques behind advanced analytics. Many participants acknowledged this and deemed it as one of the main reasons advanced analytics CCs have been present for +- 4 years, while 'it's a given' that there is a traditional BI CC.

On the question why advanced analytics CCs have been popping up in the past few years while traditional BI CCs have been around longer, participant I answered the following:

"For a large part, technology. Technology has been developing rapidly over the past 2, 3 years. It has enabled us in doing so much more. On the other hand, there was much value to be created using simple analytics. … Simple statistics. So there was not really a demand for data science. So I think for a part technology, for a part that the organization was not ready for it yet." (Participant I, Pos. 28-29)

Besides the technology maturing, another reason for the difference in how long the two types of centers exist was found: 'organizational readiness'. As organizations are getting more and more used to advanced analytics being around, the value of advanced analytics is more recognized. Miller et al. (2006) too describe a factor of organizational readiness before setting up a traditional BI CCs: "It is important that everyone in the organization has a common understanding of what a BICC is and the purpose it serves". Furthermore, two participants stated that the moment the business proceeds to formalize a center, it also means the value that traditional BI/advanced analytics has to offer is truly recognized.

Participant H: "And, advanced analytics needs also adoption from the organization. The organization needs to be ready for it. Businesses need to be able to embed it in their business processes and organization."

Martijn Klaver: "With this, are you saying that before, advanced analytics was already present, but the business was not ready for it yet?"

Participant H: "Indeed, I think the capability was already present. But the business did not know very well how to get it into production." (Participant H, Pos. 27-29)

It is worth noting that traditional BI and advanced analytics CCs are going through a similar phase when it comes to business supporting the technique and formalizing its organizational structure. Both were 'new' techniques that change the way of doing business and subsequently are subject to innovation resistance (Sheth 1981).

BI&A maturity model

Gartner developed a maturity model for BI&A, displayed below (Howson and Duncan 2015). Note that in level 3, the BICC (traditional BI CC) is established. Level 5, the highest level of maturity establishes a Chief Analytics Officer (CAO) and a mindset of transforming the business with BI&A. Most researched organizations estimated to be in level 4. Sophisticated program management was started, as traditional BI CCs and advanced analytics CCs were present and promoted. However, many organizations do not have a CAO (Or Chief Data Officer) yet and the recognition of value is inconstant. The business is not yet driven by data.

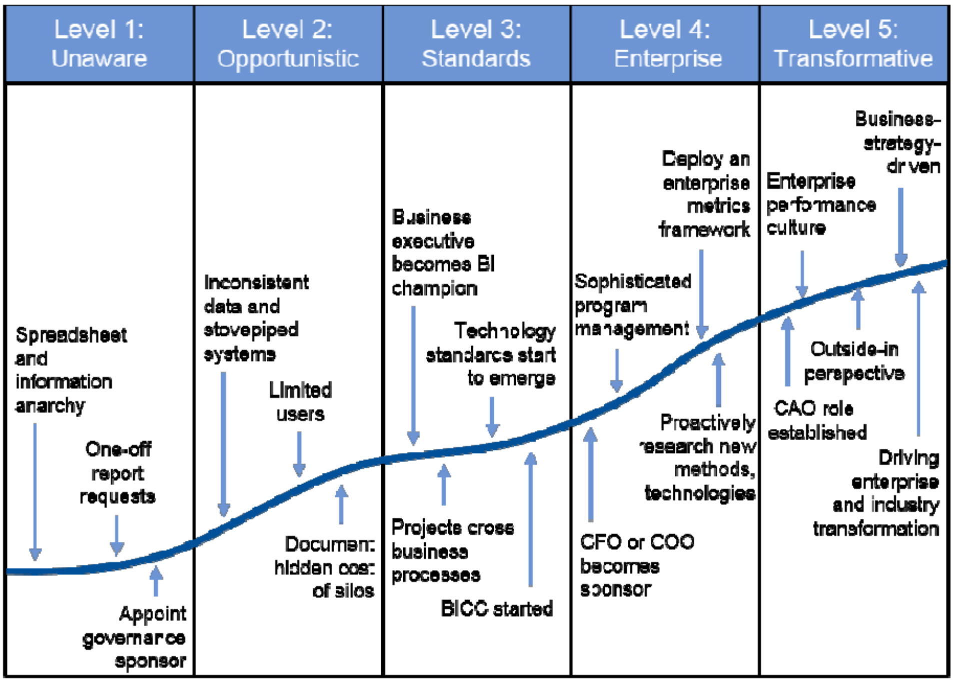


Figure 12: BI&A Maturity – from Howson and Duncan (2015)

	Traditional BI CC	**Advanced Analytics CC**
Maturity		
General technique (traditional BI vs advanced analytics technique)	A - 15 years D – 20 years	B – 8 years D – 10 years E – 4 years
Years since establishment of center.	B - 10 years C, D, H, I – Long, it's a given G – 12 years	A - 3 years B, D, H, I – 2 years C – 5 years G – 5 years

Table 5: Traditional BI CC vs Advanced Analytics CC – Maturity

5.4 Objectives

5.4.1 Objectives

During the study, various reasons for setting up a competency center are identified. Roughly, they can be divided into two categories: Organizational reasons and substantive reasons.

Centralization

Centralization of a business unit enhances cooperation between business units and their people according to Participant E, H and I. This view is supported by Anderson (2015). The same participants indicate centralization increases the impact BI&A can have on the entire business. This is explained by the ability to more easily promote BI&A in the company, making it more used, making people recognizing added value (Khalil and Wood 2014; Anderson 2015). These reasons apply to Shared Service Centers in general and are thus true for both types of CC.

> *"At first, the idea was that each department would employ one or two data scientists by themselves. We indicated that this was not going to work. Frist of all, you will not retain the data scientists. Second of all, you will not succeed to deliver value. Because you will never bring models to production from there. That is too much work. You need data engineers for that, and they need each other. You need a team to do that." (Participant I, Pos. 59)*

Furthermore, centralization enables organizations to have an overview over all projects and prioritize accordingly (Participant H & I).

"When you are at the risk department, you are only working on risk business cases. But a finance business case may be more relevant on that moment. There is no way of exchange that information. We can do that. We have the overview over the products and teams. I think that enables us most in reaching our objectives." (Participant I, Pos 67)

Lastly, Participant H indicates that centralization helps giving attention to treating data as an asset. It always has been an asset, but to treat it this way, it must be organizationally formalized in a way. This is supported by Khalil and Wood (2014) and Hernandez et al. (2013).

> *"In an organization, certain processes are assigned to certain business departments. A BI&A CC is by definition a unit that serves a company-wide purpose. So every department or division wants to use it. To establish a BI&A CC, a certain capability is secured. Responsibility is assigned and attention for this capability is created. Synergy is created in organizing it in this way". (Participant H, Pos. 45)*

Becoming data driven

This brings us to the following substantive reasons for centralizing BI&A initiatives. BI&A has a substantial benefit for the business. Every participant named using BI&A to become 'data driven' as the main objective, independent of the type of center. Organizations often have no idea what becoming data driven exactly entails (Participant C, F, G). However, almost every organizations nowadays sees the added value BI&A has to offer. The value of big data analysis and visualization tools is that they transform raw data, providing business managers and analysts with appropriate information to improve decision making (Wixom, Watson, and Werner 2011)

"Naturally, the largest similarity is that they need to solve business problems, and that they are there to solve these problems with data. Both want to gain insights from data." (Participant G, Pos 75)

Right to exist

Another substantive reason to give more attention to BI&A is the 'right to exist', in the interviews sometimes referred to as being 'fit to purpose'. This works in two ways:

- The right to exist relative to the **internal** business operation. Traditional BI CCs have a large responsibility to the internal business as it comes to reporting. They report on the internal business, for instance on Key Performance Indicators (KPI's). These reports give guidance for decisions. As organizations strive to make more data driven decisions, it is important to present and interpret the data in a way that these decisions can be made. This is the primary task of the traditional BI CC (Participant B, C, D, F).
- The right to exist relative to the **external** forces. This can be for commercial reasons: When a better model of the outside world can be created using data, the internal operations can be adjusted according to the model (e.g. sales forecasting). Also, information about the outside world can be sold. Furthermore, in many cases external end users (customers/civilians) expect a certain intelligence from organizations (Participant B). In the example of the company Banking A, they need to report certain information to the bank regulator. The traditional BI CC team has an automatic exchange with the bank regulator for this (Participant D).

"Advanced analytics does not focus on giving insight to govern your company, but on giving insight to improve products or services to increase the value proposition. It is focusing more externally on the outside world." (Participant B, Pos 38).

Efficiency

A larger focus on efficiency can also be an objective for BI&A CCs. According to Participant A and C, organizations certainly have cost-efficiency in mind when investing in traditional BI or advanced analytics CCs. With all types of BI&A displayed by Delen and Ram (2018), cost efficiency can be reached. Traditional BI focusses on reporting of internal processes. Here, bottlenecks can be identified by using data. Advanced analytics can contribute to cost efficiency by e.g. making forecasting models so that less inventory has to be in store (Participant A).

Objectives	Traditional BI CC	Advanced Analytics CC
Centralization		
- Cooperation	✓	✓
- Impact on business	✓	✓
- Treat data as an asset	✓	✓
Becoming data driven	✓	✓
Right to exist		
- Internally	✓	
- Externally	✓	✓
Efficiency	✓	✓

Table 6: Traditional BI CC vs Advanced Analytics CC – Objectives

The participants were confronted with the objectives and functions described by Schüritz et al. (2017), also referred to in 4.4.1. All participants indicated that they only recognize 'becoming data driven' to pursue as an end goal. The others, such as analytics expertise and platform management are enablers for becoming data driven, but not stand-alone objectives.

5.4.2 TYPE OF BUSINESS PROBLEMS

As mentioned above, both traditional BI and advanced analytics have the same overarching goal: deliver value from data. Apart from the later recognition of value in advanced analytics, traditional BI and advanced analytics add value in a different way. This difference can be contributed to two factors: Firstly, the type of BI&A they use and secondly, the way they look at of data and aim to solve business problems.

Type of BI&A

As described above, BI&A can be categorized in 4 types of analytics: descriptive, diagnostic, predictive and prescriptive analysis. Traditional BI mostly operates in the first two types, advanced analytics in the last two. As can be seen in Figure 11, the first two are classified as 'retrospective', while the last two are classified as 'prospective'. This means that although traditional BI CCs and advanced analytics CCs can work on the same business question, they are involved in different parts. Often a problem starts at a descriptive analysis and continues with having the insight and wanting to know where it originated. This is diagnostic work. Subsequently, if this insight is interesting, a predictive model can be made so that there can be action in an early phase. Then, there is a desire for prescriptive action, so that a person does not have to act on its own, but it is taken care of automatically (Participant B, E & I). These four different steps in the business problem are divided over the two types of BI&A CCs.

View on data and solution for business problems

Because of the type of BI&A, the nature of the analysis is different and requires a different view on data. Also, it requires a different view on solutions to solve problems. As mentioned before, the technology and tools for traditional BI were longer present then those for advanced analytics. This is because the 4 different types of BI&A each require its own technology and tools (Participant G).

For traditional BI, the following principles apply:

- Data quality must be as good as possible. What is displayed in the reports must be 100% true. Much time and effort is spent on data refinement and cleaning (Participant B, E & F).
- Has a small scope, analyses a business process and reports on it (Participant B).
- Works on reports that need to be done (e.g. reporting on business KPI's or reports for the bank regulator) and on semi-finished products. Does not directly deliver value, but insight on which decisions can be made that deliver value (Participant I).

For advanced analytics, the following principles apply:

- Volume is critical. Because of the volume, data quality is less important. Works with raw data. Predictive analysis is about trend analysis, getting a global overview of complex issues. Therefore, there must be insight in the data quality, but it does not have to be perfect (Participant B & E).
- Large scope. Besides the company's own data, third party data can be very useful. Potentially using worldwide data (Participant B & D).
- Works on predictive and prescriptive models that directly deliver value (Participant I). Less focus on internal business operation but improvement of products or services to the outside world (Participant B & C).

Damhof Quadrant Model

The distinction on how data is viewed and handled to solve business problems is one that is more often recognized. Ronald Damhof developed a model in which he describes four quadrants (Damhof 2016). This model is mentioned by Participant B, E and H. The four-quadrant model is used to develop data strategy, share concerns about data and substantiate investments in data. The quadrants indicate four different ways of looking at and handling of data. The x-axis indicates the data push/pull point. "Push systems are aimed at achieving economies of scale as volume and demand increase, while the quality of the product and the associated data remains guaranteed. On the other hand, there are pull systems which are demand driven. Different types of users want to work the data to produce 'their' product, their truth, on the basis of their own expertise and context" (Damhof 2016).

The y-axis indicates the developments style. The first is systematic, in which the developer and user are often two different persons. Defensive governance is applied, focussing on control and compliance. The second is opportunistic, in which the developer and user are often the same person. Offensive governance is applied focussing on flexibility and adaptability.

Quadrant I and II describe the way traditional BI CCs looks at data. Facts appear (descriptive, push) and need to be interpreted (diagnostic, pull). As the quality of data and reporting is very important, the development style is systematic.

Quadrant III and IV describe the way advanced analytics CCs look at data. As the volume is high, the quality of the data does not have to be perfect. The development style is opportunistic. Most of the advanced analytics CC's activities fall in quadrant IV, which is characterized by innovation and prototyping (Damhof 2016).

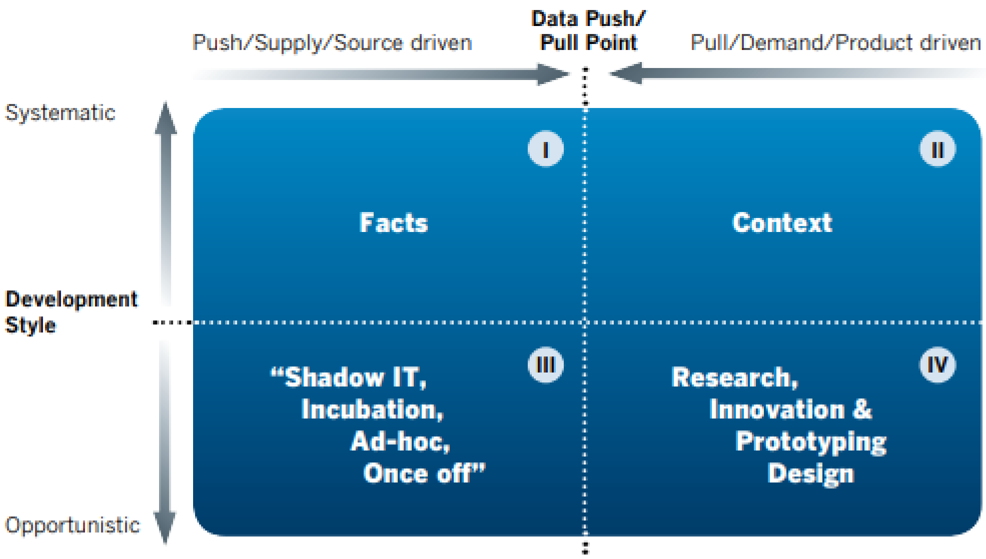


Figure 13: Damhof Quadrant model (Damhof 2016)

Responsibility & Innovation

Because of the above described nature of the work, another substantive difference between the deliverables of the two centers exist. In short, the traditional BI CC has a responsibility to deliver, the advanced analytics CC does not (Participant D, F, H). Because the traditional BI CC reports on internal business operations, delivering it to e.g. interpret KPI's or accountability for the bank regulator, there is a large responsibility for this center. When they fail to deliver, banks can lose their licence, yearly reports are not produced, and businesses will come to a standstill.

In contrast, advanced analytics CCs try to discover patterns in data, improving their products and services. This is of a more innovative nature. As such, when advanced analytics CCs do not deliver, innovation comes to a standstill. On the long term, this is problematic, as competitors will not stand still, but on the short term, the business will not collapse. More on the innovative development culture is described below.

"I think it has to do with the fact that the advanced analytics CC was doing all sorts of proof of concepts at the time. And they were not bringing anything to production. We (traditional BI CC) had the responsibility to bring products to production and maintain it. Hence, administrators were also part of the 200 employees of the center. At a certain time, it is needed to keep products up and running. That asks for people who are available day and night because a product did not load in the system. They (advanced analytics CC) did not have that." (Participant H, Pos. 61)

Type of business problem	Traditional BI CC	Advanced Analytics CC
Gain business value from data	✓	✓
Type of BI&A		
- Retrospective	✓	
- Prospective		✓
View of data		
- Quality	Must be high	As long as we know what the quality is, it is ok
- Scope	Report on internal business	Use third party data to your advantage
- Deliverables	Reports and dashboards where decisions are based on	Models that deliver direct value. Improvement of products / services
Responsibility	Keep business running	Innovation

Table 7 : Traditional BI CC vs Advanced Analytics CC – Type of business problem

5.5 Structure & Roles

5.5.1 Size, Teams & Leadership

Size

The exact size of the BI&A CCs obviously varies over organizations. In our small subset of organizations, the traditional BI CC often had around 30-60 people in it (± 5000 people in the organization). Normally about 2% of the organization works for the traditional BI CC (Participant C). In every interviewed organization, the traditional BI CC is at least 5 times larger than the advanced analytics CC. This can be explained by its maturity, and coherently, the needs of the company.

Teams

Every interviewed organization worked with multidisciplinary teams, meaning that people from the BI&A CC are part of a team from different departments, working together to solve an overarching business problem. Dependent on the size of the CC, they work in formal teams within the CC as well. As traditional BI CCs are often larger in terms of FTE, these are subdivided in functional teams like finance, retail, marketing, etc.

No general way of working was found over the interviewed organizations. The choice of working in teams, duo's or alone depends per organization and its current way of working.

Leadership & reporting structure

In each of the interviewed organization, independent of the type of center, they have a head of the center. This role has different names, such has Head of center X, Lead of center X. The CIO of the organization was never the head of the center. However, most of the organizations followed the advice of Miller et al. (2006) to have sponsorship of the CIO (Participant A and C). Anderson (2015) goes a step further and recommends making the head of the center part of the 'C-suite'. In none of the organizations this was the case. However, in Bank A, the CDO was part of the C-suite. This CDO is responsible for the whole of the data-organization. The head of the advanced analytics CC directly reports to this CDO.

> *"It is a conscious choice to let the CDO not be part of the business, or worse, be part of ICT. The ICT department is not present in this discussion. BI could have been there, but it is not. The advanced analytics CC could have been there too, but it is not. So that was a conscious decision to make data important for the whole company. Then, the CDO must answer directly to the CEO". (Participant D, Pos. 94)*

5.5.2 Employee background & roles

Employee background

The people working in the two type of centers often have different backgrounds. The traditional BI CC mainly exists out of people with a background in business, who have learned some IT (Participant A, B & I). The advanced analytics CC mostly employs people with a strong mathematical or statistical background (Participant A, B & I)

Roles

For the advanced analytics CC, most of the respondents agreed with the general layout of roles made by Schüritz et al. (2017), displayed in Figure 9. This layout is specifically for advanced analytics CCs but can for a large part be translated to a traditional BI CC (Participant B, C, E). For advanced analytics CCs, all roles but the 'support' and 'data mining' role were acknowledged. Data mining is an outdated term and can be covered by the other roles (Participant D). For traditional BI CCs, the blue bordered data scientist cluster can be renamed to like 'BI developer'. This role however exists out of data visualization and migration too. Furthermore, as the focus in traditional BI CCs is more on developing reports, they employ more modellers and ETL developers (data engineer for advanced analytics CCs). Mathematical optimization is a lesser prominent role but not to be excluded.

Participant E and G emphasize that although in words the role description may be the same over the two types of CC, they are doing very different activities. This has for the largest part to do with the underlying technique for their activities. To develop an ETL flow from a data warehouse or preparing data from a data lake on a data platform are essentially the same things: extracting data from a source, adjusting it and displaying it in a different place. However, the goal is different; for traditional BI, the goal is to get the data in the information model of the data warehouse. For advanced analytics, the goal is to prepare the data set so that a data scientist can work on it. These differences make the work of someone (a data engineer in this case) working in a traditional BI CC very different than someone in an advanced analytics CC. This is displayed in the difference in tooling. Traditional BI CCs employ SQL experts. Advanced analytics CCs employ Python experts (Participant B & I).

All participants underline the importance of a business analyst or storyteller. Someone needs to make the translation between IT and business. As advanced analytics people are often 'einzelgängers' (Participant E), their model does not leave their laptop. Someone who engages and inspires the business is needed.

> *"But we do need people to understand the tool as well, right. And so I need somebody who knows what the hammer is, and I need somebody who can hammer very well." (Participant A, Pos. 101)*

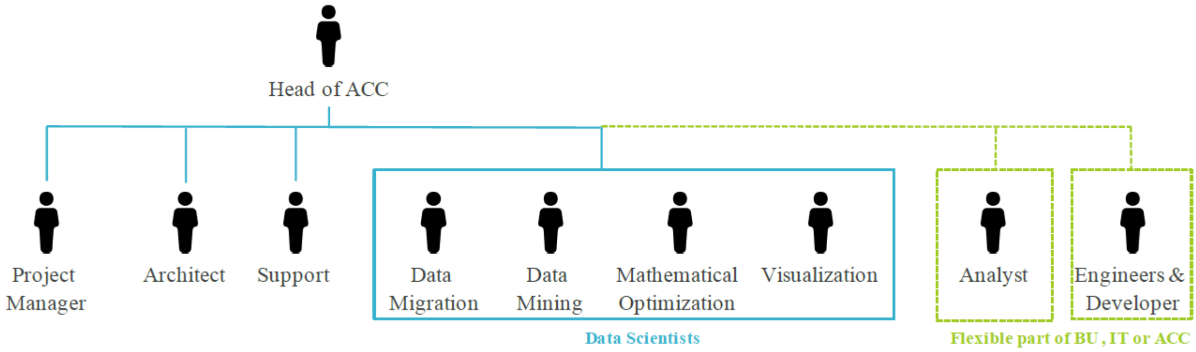


Figure 14: Roles in BI&A competency centers – from (Schüritz et al. 2017)

Decision making

In traditional BI CCs, a clear structure and hierarchy on who takes decisions in projects is in place. Often, this is the responsibility of the product owner or IT architect. In the advanced analytics CCs, the decision process is more by spread out over the members of the multidisciplinary team. Of course, someone decides, but as the people are more broadly and deeply oriented (the 'T-shaped professional'), the decision is a collective one (Participant G).

	Traditional BI CC	**Advanced Analytics CC**
Structure & roles		
Size	Relatively large, ± 2% of company	Relatively small, ± 0,4% of company
Teams		
- Multidisciplinary teams	✓	✓
- Teams within center	✓	
Leadership & reporting		
- Head of center	✓	✓
- Sponsorship of higher management	✓	✓
- Head reports to	CFO or CIO	CDO or CEO
Roles		
- Project manager	✓	✓
- Development role	BI developer	Data scientist
- Business analyst	✓	✓
- Data engineer	✓	✓
Decision making process	Structured	Organic

Table 8: Traditional BI CC vs Advanced Analytics CC – Structure and roles

5.6 PROCESS

The project process for traditional BI CCs and Advanced Analytic CCs is the same on high level. Each participant indicated these higher-level processes. An intake takes place, after which the project ends up on the project backlog. When the project is picked from the backlog, it goes into the development phase where the actual product is being made. Then, the product is scaled up to production in a live environment. When the product is fully working, it goes into the maintenance phase where it is being monitored and slight changes are made if needed. An overview of these phases is displayed on the first row of Figure 15. When zooming in on the phases, differences between the two centers emerge.

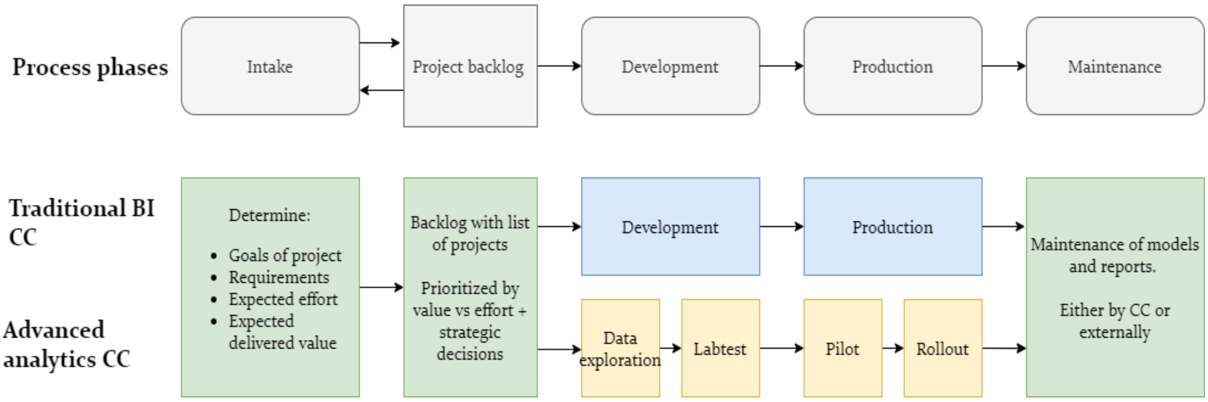


Figure 15: Traditional BI CC vs Advanced Analytics CC - Project process

Intake

For every interviewed organization, the intake process was roughly the same over the two centers. How projects are initialized for an intake differs per organization. Sometimes the business comes with data related questions themselves, sometimes the advanced analytics CC holds an ideation session to show business their added value or needs to promote their services in a different way.

A question or request comes in from the business at one of the centers. The goal of the intake is to determine the goal of the project, the business requirements, the expected effort and expected gained value from the project outcome. Furthermore, questions are asked about the user of the product, the way it is going to being is going to used and other user expectations.

Projects at the traditional BI CCT are often more one-time, straightforward reports. Projects at advanced analytics CCs are often of a more explorative nature (Participant B, C, D, F, I). Therefore, requirements are less known beforehand at the advanced analytics CC. This is accepted and anticipated by the center. The intake is comparable to phase IA from Schüritz et al. (2017) in Figure 10.

When coming in for an intake, the business often has little idea if their question is suitable for the traditional BI CC or the advanced analytics CC. The business has a problem that benefits from data processing and turn to one of the centers they seem fit. It regularly happens that the business is redirected to the other center (Participant I).

The business might need to bring budget. Dependent on the funding model an organization chooses, the budget for projects is brought on by the business (per project). Without budget, no project.

Project backlog

Projects for which an intake has been done are collected on the backlog. Here, a project is picked to transfer to the development phase. Projects are picked considering, cost & effort, results in terms of delivered value and strategic motivations.

Development

For the traditional BI CC, the development phase is straightforward. The data sources used for the development of the product are known from the intake (Participant A, B, D, I). In this phase, development and testing of the dashboard or report takes place.

Due to the question being less clear and hence the data sources still unknown, the development phase at the advanced analytics CC is less straightforward. This is why, after the intake, a data exploration phase takes place. This phase is comparable to phase IB from Schüritz et al. (2017) in Figure 10. Here, potential data sources are explored. In this phase, the potential value of the model is explored, and challenges and issues are initialized. A large part of the advanced analytics projects is discarded in this phase, as the potential value is not deemed high enough.

After the exploration phase, the labtest phase is entered. Here, the model is tested in a small and controlled environment (like a lab) and evaluated on value. This phase is comparable to the first half of phase II from Schüritz et al. (2017) in Figure 10.

Production

In the production phase, projects from the traditional BI or advanced analytics CC are released into the 'real word'. Projects are tested regarding their performance in the production environment.

For the traditional BI CC, again, this phase is straightforward. For the advanced analytics CC, this phase is split up into two smaller phases: pilot and rollout.

In the pilot phase, the model is tested and monitored outside of the lab, but still in a very small environment. The pilot phase is comparable to the second half of phase II from Schüritz et al. (2017) in Figure 10. In the rollout phase, this environment is scaled up and the model is in full production. The rollout is comparable to phase III C, D, E from Schüritz et al. (2017) in Figure 10.

Maintenance

When the product is finally working, it is of essence to keep it that way. Maintenance must be done to keep the product 'fit to purpose' and working. For most of the interviewed traditional BI CCs, the maintenance is performed by the center itself. For the advanced analytics CCs, this is a sensitive subject. The expertise of a (junior) data scientist is needed to keep the models running. However, the data scientist's potential lies in developing models, not maintaining them (Participant E, I). However, the same concept may apply to traditional BI CCs. Up and until now, there is no consensus on who should maintain the products produced by the two centers (Participant A, G, H)

Go, no-go moments

Go, no-go moments are built in to ensure no budget is wasted on projects that will not deliver (enough) value. There is at least one go, no-go moment at the transfer from each phase to the new phase. It is recommended to build in multiple go, no-go moments (Participant E, I), preferably at the beginning of the process (Participant I). Here, the invested effort is still low. The go or no-go is decided by the head of the CC, the product owner (often someone from the business), or a BI&A Board. A BI&A Board consists of the CDO/CAP and managers from decentral departments. The role of the board is to give direction to the CCs and help with prioritization.

Way of working

More and more businesses embrace the agile way of working. Especially in IT focused areas, working agile has become the standard (VersionOne 2020). Not surprisingly, many participants use and recommend agile (as opposed to a waterfall way of working) for the development of traditional BI or advanced analytics products (Participant A, B, C, F, H). The iterative and incremental delivery of value combined with the short cycles make it a no-brainer according to the participants. Especially when exact requirements are not known beforehand, like in advanced analytics CCs projects, agile methods shine. The agile way of working also forces you to regularly adjust to customer requirements. For both type of centers, this is crucial (Participant F).

For traditional BI CCs, the path for delivering the final product follows the same trajectory as an average IT department: The project passes several (Scrum) sprints where small pieces of functionality are realized. The functionalities are tested and implemented. Ultimately, the product is finished and brought into maintenance.

As mentioned above, the advanced analytics CC has an explorative mindset. Therefore, functionality cannot be delivered in sprints in the way the traditional BI CC does. The value first has to be explored. Hence, in combination with agile, many advanced analytics CCs (Participant C, D, I) use a method that is more suitable for an R&D-like environment: CRISP-DM. The methodology defines a flexible sequence of six phases, which allow the building and implementation of advanced analytics models to be used in a real environment, supporting business decisions (Moro, Laureano, and Cortez 2011).

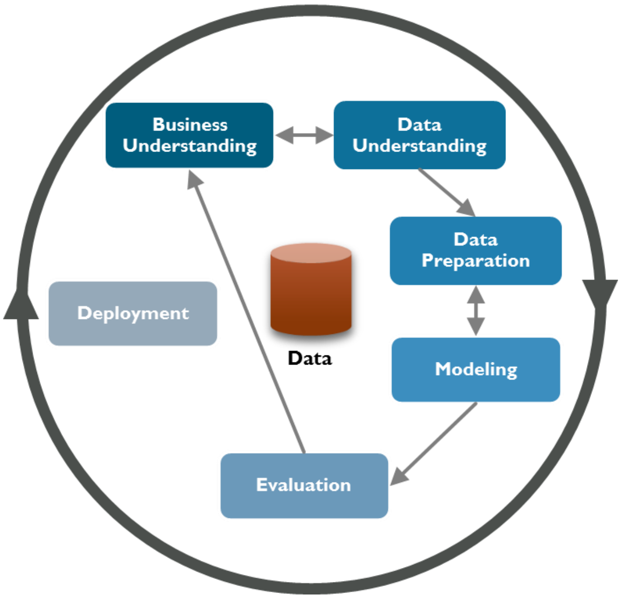


Figure 16: The CRISP-DM methodology, edited from Chapman et al. (2000)

Development culture

The projects of the advanced analytics CC are of an explorative, innovative nature, as opposed to the projects of the traditional BI CC, which are aimed to deliver direct results. This difference in nature of tasks translates into culture aspects. The advanced analytics CC is often seen as a 'playground' where they fiddle around with data toys (Participant A, E, F, H).

> *"I see very few organizations that are successfully running an advanced analytics CC. Often it is limited to a club where people are messing around with data for fun, like a playground." (Participant C, Pos 14).*

A different dynamic between the two is present, as advanced analytics CCs rarely bring a model to the production phase, while BI have products in production and under maintenance. The advanced analytics CC has a smaller responsibility to deliver, resulting in a more free and open culture (Participant H). On the other hand, having less responsibility to deliver is exactly where the power of the advanced analytics CC lies and what enables them in being innovative (Participant D, I).

Because projects at the traditional BI CCs undergo a more demand driven process (business wants a report, traditional BI CC delivers it), it fits established structures, benefitting from a more hierarchical and bureaucratic culture (Participant B, G & I).

Process	**Traditional BI CC**	**Advanced Analytics CC**
Intake		
- Identifying needs	✓	✓
- Requirements	Clear	Not clear
Backlog		
- Prioritizing through value vs effort vs strategic considerations	✓	✓
Development		
- Data sources	Already clear	Explored in exploration phase
- Testing	✓	✓ In labtest phase
Production		
- Testing and monitoring performance	✓	In two different phases: pilot and rollout
Maintenance		
- Not fixed by whom	✓	✓
- Relatively new question		✓

Table 9: Traditional BI CC vs Advanced Analytics CC - Process

5.7 Governance

5.7.1 Organizational model

Hybrid or central

Both types of CC can exist in a hybrid and central organizational model (3.2). In the definition, an organization with BI&A activities organized in one place has a central organizational model. In a hybrid model, BI&A activities are organized centrally as well as scattered over the different departments. Dependent of where you draw the line of what an organization is, the interviewed organizations all have a central organizational model. BI&A activities are centralized in one place and not scattered throughout the organization. The traditional BI CC and advanced analytics CC found at Bank A are part of a sub department of the Bank. Other sub departments have CC too. However, as this sub department is relatively large (1000 people), this department are considered as organizational unit on its own and the CCs can be classified as part of a central organizational model. It stands out that although our small subset is less representative, it does not follow the same distribution as Lismont et al. (2017), who find that 47% of organizations use a central model, and 23% use a hybrid model.

Centralization

The motivation to centralize BI&A activities is mentioned in 5.4.1. Besides this motivation, there are some remarks on centralization prerequisites from a governance point of view:

- There needs to be a strong IT infrastructure (Participant A, C & E). As the CCs make use of the companywide IT infrastructure, data can only be stored and processed centrally when the IT infrastructure allows it.
- There needs to be a balance between push and pull from the business (Participant A & I). Centralization might cause losing BI&A out of sight, especially in the case of advanced analytics, where projects are of explorative nature. Dependent on the business, the center might need to promote their services and/or balance the projects they take on.
- There needs to be a decision from higher up to invest in and formalize BI&A activities. Support from the 'C-suite' is needed.
- There needs to be a way decentral knowledge is ensured into the central hub (Participant B & C). The business knowledge is in the decentral departments. This is why there is regularly worked with multidisciplinary teams or business analysts from outside of the center. Saxena and Srinivasan (2012) affirms this by stating that if a true data driven culture is the goal, entirely centralizing is impossible. The decentral expertise is always needed to make the decisions.
- There needs to be monitoring from the center (Participant B, C, H). With cloud technology maturing, it takes little effort for a data scientist to start up e.g. Amazon WebServices and start quickly modelling themselves (Quadrant III of Damhof model). This is not forbidden but must be handled with care.

Virtual or fully staffed

As discussed in 4.3.3, organizations can choose for a virtual or physical CC. Every CC at the interviewed organizations is a physical CC, except from the advanced analytics CC at Public Sector D. This virtual CC is described as a precursor to a fully staffed CC and 'round table' where information management people and product owners come together to prioritize business cases (Participant E). Because of the scarcity of advanced analytics capacity, there is a need to regulate and divide this capacity so that it can have the most impact on the business. Furthermore, Participant E and G described that sporadically people in the virtual advanced analytics CC also handle projects together.

BI&A CCs on the organizational chart

In every interviewed organization, the advanced analytics CC was separately organized from IT. Only one of the interviewed organizations had their traditional BI CCs as a part of IT, but Participant C indicates this happens more often. Many participants emphasized that both type of centers must not fall under IT. BI&A is not IT driven; it is business driven. Therefore, it must have that focus too on the organisation chart (Participant B, C, H). In most cases, the advanced analytics CC was organized as a separate service department somewhere in the business. In two cases, organizations had a dedicated data & analytics department where the advanced analytics CCs resided. It is noteworthy that in these organizations, the traditional BI CCs were not part of that department (Participant A & H). This is not a conscious decision, but a combination of circumstances. E.g. a car manufacturer placed the traditional BI CC under the engineering department because most value could be delivered there. Bank A placed the traditional BI CC under the finance department because this department has a long history of reporting to the bank regulator.

5.7.2 FUNDING MODEL

Participants named a few different funding models for the two types of CCs, corresponding with those found in literature described in 4.3.3 and 4.4.3. As traditional BI CCs and advanced analytics CCs are both types of shared service centers, participants indicate all models can be used for both types of centers.

Overhead costs / CC covers the costs model

This model is used by almost all the traditional BI CCs. Furthermore, it is used by the advanced analytics CC of Public Sector B. In this model, a budget is allocated to the CC. For traditional BI CCs, this model is the standard as they have been around for a long time and the organization have become dependent of them.

Subscription-based model

This model is used by the traditional BI CC of Bank A and the advanced analytics CC of Public sector C. The model emphasizes buy-in of the business. Up front, they pay a certain amount to make unlimited use of the resources of the business. This ensures a few things:

- The business prioritizes business questions themselves. As it is their 'own' capacity, they think twice about the effort/value of every business case they confront the CC with.
- Budgetary discussions are cut out of the intake process at the CC. As the business already payed for the services of the CC, the intake process is now about prioritizing business.

  Participant C and H both recommend this model for both types of CC.

"The subscription-based model worked very well. It ensured that the conversation at the intake was about delivering value, instead of budgetary matters. Because earlier, it was a classical 'chicken or the egg' story. The business said: I don't have money yet; I need to clear some budget. To clear some budget, I need to know how much your product is going to cost me. And we said: To know what the product is going to cost you I need money to estimate it." (Participant H, Pos. 85)

Pay per use model / business unit pays for services model

This model is not used by any of the interviewed CCs. This model is discouraged for advanced analytics CC, as it requires an estimation of value. This value is often unknown beforehand for advanced analytics CCs (Participant B).

Hybrid funding model

This model is a combination between the overhead costs and pay per use funding model. The CC has an allocated budget for themselves but also asks additional budget from the relevant department per business case. This model is used by the advanced analytics CC of retail A and Bank A. For Bank A, from the moment an advanced analytics model is live, business units are charged per usage (pay per use model). After the model passes the production phase, it begins to deliver value for the business.

	Traditional BI CC	**Advanced Analytics CC**
Governance		
Organizational model		
- Hybrid	Not found but can be	Not found but can be
- Central	Found	Found
Virtual	Not found but can be	Found
Organisational chart		
- Part of IT	Found should not be	Not found should not be
- Part of BI&A department	Not found but should be	Found
Funding model		
- Overhead costs	Found	Found
- Subscription-based	Found	Found
- Pay per use	Not found	Not found should not be
- Hybrid	Found	Found

Figure 17: Traditional BI CC vs Advanced Analytics CC – Governance

5.8 Success & Future of BI&A CCs

5.8.1 Success definition & Factors

Success definition

The success definitions of the CCs are connected to their objectives. They succeed if they can reach those objectives. For both the CCs, that is to help the organization becoming data driven by delivering business value from data. Furthermore, traditional BI CCs succeed if they help to run the business by providing essential insight in the business' processes and data. For both types of centers, they succeed if they can help the business manage external drives and ensure the future of the business (innovation). Respectively by providing accountability or to improve services or products.

Success factors

To ensure the success of both type of centers, participants named many success factors. Some of those are mentioned above, others are new:

- *Knowing data sources*
  For both types of CC, the content and quality of the data must be known. For the advanced analytics CC, the quality itself is less important, as long as it is known (Participants B, C, G).
- *No silo thinking*
  Both types of CC need to make use of the fact that they are shared service centers, overarching politics in business and silo thinking of decentral departments. They can connect these departments (Participant A, B & H)
- *Time to market*
  A frequent cause of complaints for traditional BI CCs is time to market. The business has to wait for answers for too long after they asked their question. CCs must ensure a reasonable time to market, or better manage expectations (Participant C & D).
- *Organizational readiness*
  As mentioned in 0, organizational readiness is important for the starting point of CCs. It is also an important factor in keeping the CCs up and running. The business needs to be ready to keep supporting the CCs (financially). CCs can work to earn this support by showcasing their work and listening to critiques (Participant A, H & I).
- *Making sure it will be used*
  This success factor has ties to organizational readiness. The CCs need to make sure their products will be used. For advanced analytics CCs, to make a model is one thing, but to bring it to the end-user is another (Participant I). The model must be explainable (why is there a '7' here while I am expecting a '9'?) (Participant E), it must not be forced on people but focus on their needs (Participant G) and technically it needs to be feasible to embed in processes of decentral departments (Participant H & I).
- *Focus on value*

Focussing on value, rather than on the technique (advanced analytics CCs) or the budget (both types of CCs) is a challenge. Keeping 'the eye on the price' and let the peripheral matters be is important. The subscription-based funding model is recommended the most for more experienced CCs. This emphasizes the conversation on how to get the most value out of the budget, rather than the budget itself (Participant C & H).

- *Good governance*
  Participant D compares good governance to an orchestra; brilliant musicians still cannot play a beautiful peace without good orchestration. The task of those in the governance seat is to actively connect people and talk to people to get to know their wants and needs. They need to form the organisation so that BI&A people can do their work properly.
- *BI&A-business integration*
  This success factor has ties to good governance. Making sure that what is built by the BI&A CCs is actually what the business wanted is a challenge. This is why business analysts, who make this translation are essential (Participant A, D, E & F). Business expertise is always located decentral. This expertise needs to reach the CC. This can be done either via a hybrid organizational model or having decentral business analysts in the multidisciplinary team (Participant A & C). Also, mapping the business requirements is not a one-time matter. This should be a continuous process. Working agile ensures this (Participant F& H). Furthermore, it is of importance that business expectations are managed well (Participant C, D & I)
- *Agility*
  Agility is our ability to response to change. The agile way of working is a set mindset and a set of tools and techniques to achieve this agility. As explained above, the agile way of working helps in continuously mapping business requirements. Agility in itself is important so that organizations can adapt quickly and stay innovative (Participant A, B & C).
- *Strong IT foundation*
  As described in 5.7.1 there needs to be a strong IT infrastructure for the CCs to work on.
- *Push and pull balance*
  As described in 5.7.1 there needs to be a balance between push and pull regarding business cases.
- *How traditional BI CCs & advanced analytics CCs are perceived*
  Often, an advanced analytics CC is announced with a big bang. 'Analytics is the future, in a few years, the traditional BI CC does not exist anymore', is often said. Naturally, the traditional BI CC may feel threatened by this. It is important to keep recognizing the added value of the traditional BI CC, if there is still value.
  On the other hand, advanced analytics CCs have a challenge to prove that they are more than a playground where experiments take place. They need to showcase their worth.
- *Traditional BI CC & advanced analytics CC collaboration*
  Both centers can learn a lot from each other about data and being a shared service center. It would be stupid not to make use of that knowledge (Participant D and E). Furthermore, working together on data can benefit the efficiency.

5.8.2 FUTURE OF BI&A CCS

Up and until now, this research has given a descriptive and historically view on BI&A CCs. Below, the future of the centers is addressed shortly.

Shift to self-service (BI)

The above-mentioned statement about traditional BI CCs not existing anymore in a few years has everything to do with the rise of self-service BI. As traditional BI CCs mature, so do the tools they make use of. Self-service BI tools have been developed in the search of "democratizing" BI (Henschen 2014; HBR Analytics Services 2012). Self-service BI seeks to give business users access to selection, analysis, and reporting tools without requiring intervention from a technical department (Corral et al. 2015). The rise of self-service BI is recognized by Participant B, C, D, G & H. Self-service BI helps the business becoming data driven because they can base their decisions even faster on data.

Participant B's prediction is, that in 10 years, advanced analytics is where traditional BI is now. Tools are automated to such an extent that business users can drag and drop advanced analytics models. Because Advanced analytics covers the predictive and prescriptive analytics, this goes a step further than traditional BI. When prescriptive analytics is automated, humans are not needed anymore to translate the insight into action (Participant B & D). All the actions can be automated too. The question is if this is the direction you want to go in with advanced analytics CCs. The alternative is to become like the traditional BI CCs, something that delivers insight but is not automated (Participant D).

Shifting to hybrid

The increased usage of self-service BI means that more business cases are solved decentral by the business department themselves, rather than going to the CC. This means there is a shift to a decentral organizational model. However, the expectation is that traditional BI CC is not disappearing. Centralization is still needed to monitor initiatives and initialize projects that have a companywide goal rather than a decentral one. Hence, the organization model will shift to a hybrid one, where BI&A activities are performed decentral as well as centrally.

The centers working together

On the question if the participants think the centers could be combined to being one, they answered differently. All participant who have experience with two type of centers answered that the centers could work more together than they do now.

> *"Within COMPANY G3, there are centers that do innovate stuff with new technologies. To exaggerate, those are the cowboys. On the other side is the traditional BI CC, who are above*

all very reliable. Data quality is very high. They are supported with structured processes and their services are running smoothly. Those two worlds could help each other a lot.

Participant G adds on this that the centers are often working on the same theme. They use the same or different data, can treat it in a different way, but are both type of centers can profit from collaboration.

To merge both centers into being one is not a very popular thought. The two worlds are too far apart from each other to be merged (Participant C, G & H)

"It is dependent on many factors. But looking at the profiles of the employees of the center, I think that they are too far apart from each other. That is my opinion. I do not expect that a report-developer will work on data scientist-projects, or vice versa. They just are different fields of expertise." (Participant H, Pos. 109)

Participant F & I do think the CC can be merged into one or be at least on the same place in the organizational structure. This ensures that all types of BI&A (descriptive, diagnostic, predictive, prescriptive) are in the same place (Participant I). Furthermore, as the intake process is generally the same over the two centers, it might be useful to merge this part of the process (Participant G & I).

	Traditional BI CC	Advanced Analytics CC
Success & Future of CCs		
Success definition	See objectives	See objectives
Success factors		
- Knowing data sources	✓	✓
- High quality of data	✓	
- No silo thinking	✓	✓
- Reasonable time to market	✓	Important but not yet a focus point
- Organizational readiness	✓	✓
- Making sure it will be used	✓	✓
- Focus on value	✓	✓
- Good governance	✓	✓
- BI&A – business integration	✓	✓
- Agility	✓	✓
- Strong IT foundation	✓	✓
- Push and pull balance	✓	✓
- How the CCs are perceived	✓	✓
- Collaboration between the CCs	✓	✓
Future of centers		
- Shift to self service	Now	On longer term
- Shift to hybrid	Now	On longer term
- Centers working together	Merge intake. Collaborate on themes	Merge intake. Collaborate on themes

Figure 18:Traditional BI CC vs Advanced Analytics CC - Success & Future of CCs

6 CONCLUSIONS

This research performed a qualitative study on the comparison of two types of business intelligence & analytics shared service centers: traditional BI competency centers and advanced analytics competency centers. This research was carried out by performing desk research and 9 semi-structured in-depth interviews.

In the previous chapters, a research method was drafted to answer the research question (2), methods for organizing BI&A were explored (3), one method was chosen for further analysis (4) and the two types of CCs from this method were compared by analysing 9 interviews (5). In this chapter, the research question will be answered and limitations and recommendations for future work are described.

6.1 RESEARCH QUESTION

The research question is: *How do traditional business intelligence competency centers differ from advanced analytics competency centers and how is that reflected in its objectives, structure, roles, processes, and governance?*

To answer the research question and reach the research objective, two different guiding questions have been defined. These questions describe the context to answer the main research question.

1. Which ways are there to organize business intelligence & analytics?
2. What are traditional BI CCs and what are advanced analytics CCs?

6.1.1 QUESTION 1

Firstly, to create the context, the field in which we are operating must be identified. Thus, a term and definition for the collective term of both traditional BI and advanced analytics is identified (3.1.2): Business Intelligence & Analytics (BI&A): "the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand its business and market and make timely business decision" (H. Chen et al., 2012).

Secondly, organizations must make a choice out of three different models implement BI&A activities in an organization: Decentralized, centralized or hybrid.

Decentralized (3.2.1)

The decentralized model is most common in practice. It places a group of data scientists in each business unit or business function. The data scientists report to the individual business unit leaders. Hereby, decentral knowledge expertise is ensured. However, companywide (strategic) overview and prioritization misses and companywide projects are complicated to execute.

Centralized (3.2.2)

The centralized model places all data scientists in a single unit. This unit is often called a competency center and functions as a shared service center. Other business units can make use of the centralized hub's services. By centralizing, standardization of tools, skills and processes is ensured. Furthermore, companywide (strategic) overview is secured, and companywide projects can be carried out by the central BI&A team. Decentral expertise is missing so a challenge is to create a good connection with the decentral functions that acquire the center's services

Hybrid (3.2.3)

The hybrid model aims to overcome the shortcomings of both the decentralized as the centralized model. It places data scientists in both a central unit as well as decentral throughout the organization. The hybrid model combines the advantages from both models mentioned above but is hard to implement right.

As there is no best organizational design, there is no best model. The organizational model best suited depends on the organization's current contingencies.

6.1.2 Question 2

To answer the question what traditional BI CCs and advanced analytics CCs are, desk research has been performed.

In literature, a substantiated distinction between the two type of CCs is made only once, in the article of Schüritz et al. (2017). However, in practice, this distinction is often made. All interviewed organizations have both type of BI&A CC established. Furthermore, the participants indicate this is the case in most organizations.

Both CCs are types of shared service centers, meaning they serve a companywide goal and other departments can make use of their services (4.1).

Traditional BI CCs are centers that place emphasis on descriptive and diagnostic analysis (reporting, historical analysis, and dashboards). They focus on the past.

Advanced analytics CCs are centers that focus on predictive and prescriptive analysis and are thus focusing on the future.

6.1.3 Research question

In literature, characteristics of both type of centers are described. These characteristics are compared in section 5.1.2. The literature provided us with some insight, but this was deemed not extensive enough. No direct comparison was made between the two types of centers. In section 5.3 through 5.8, this comparison is made.

Traditional BI CCs and advanced analytics CCs both recognize the need to centralize their services, resulting in companywide overview and sharing of knowledge and other resources. Both types of CC have the same higher objective: Gain business value from data and transform organizations in becoming more data driven on the way. However, the way they aim to realize this objective differs, as also explained in the answer to guiding question 2 (6.1.2). Traditional BI CCs focus on descriptive and diagnostic analysis and make use of historical, internal data to build reports and dashboards. Advanced analytics CC focus on predictive and prescriptive analysis, are explorative of nature and make use of internal and external data to build models that help the business improve their products or services. Traditional BI CCs help to govern the organization while advanced analytics CCs help to shape the future of the organization.

The described difference is expressed by the way both centers view data. While for the traditional BI CC good data quality is of the highest importance, advanced analytics CCs mainly need volume. The Damhof quadrant model distinguishes different views on data. The traditional BI CC falls in the upper two quadrants, using a systematic development style. The advanced analytics in the lower two quadrants, using an opportunistic development style (5.4.2).

Although they differ in size (traditional BI CCs are often 5 times as large as advanced analytics CCs), both type of centers are structured in a similar way. Naturally, they both need leadership, they are both organized in multidisciplinary teams and roles match in basic role description. The day-to-day work in the centers differs because of the underlying technology, tools, and view of data. This makes the people not directly interchangeably (5.5).

The project process is different for the CCs. This is caused by the underlying difference of descriptive vs. explorative analysis of the centers. The process of the traditional BI CC follows a structured, long matured development process while the advanced analytics CCs needs a freer process where they can explore initiatives. Not all is different as both type of CCs needs to hold an intake with the business to map their needs. Furthermore, both make use of the agile way of working (5.6).

Both types of centers can be organized virtually or fully staffed. Participants indicate both CCs should not be part of IT but should be separately organized. They can choose from a variety of funding models, of which the subscription-based models seems to fit both type of centers best (5.7).

Certain matters require extra attention for both traditional BI CCs as advanced analytics CCs. Organizations need to make sure they give the CCs the support they need, financially and in the organizational structure. The CCs in return need to make sure their products are used. They must be user-friendly and explainable. Furthermore, both CCs need to focus on value at all times. Sometimes, too much attention is given to subordinate matters (5.8.1).

As the shift to self-service BI is happening, the future of the traditional BI CC looks differently. Many tasks may be organized more decentral in the future, shifting the organizational model to a hybrid one. Traditional BI CCs remain relevant for overview, prioritization, and companywide business cases. For advanced analytics CCs, a similar shift is not expected in the near future.

6.2 Other conclusions & recommendations

Completeness of characteristics

Inspired by Schüritz et al. (2017), the characteristics objectives, structure, roles, processes, and governance are used to describe and compare the competency centers. Regarding validity and completeness, it is of interest to explore if any other characteristics were missing in this research.

At the end of each interviews, the participants were asked if they missed something or had anything to add to the interview. Only one participant (D) indicated that he was missing a characteristic; innovation. As the innovation component has proven to be significantly present in the characteristics, objectives and process , the initial characteristics were deemed complete enough to give describe of traditional BI CCs and advanced analytics CCs.

One BI&A competency center?

An underlying question to our main research question is if the centers could be merged into one or are too different. All the described characteristics are of influence on the answer to this question. The crucial overarching point here is that the main objective is the same, but the way they aim to reach this objective is very different. The centers use different types of BI&A (descriptive & diagnostic vs predictive & prescriptive), have a different view on data, use different technologies and need different people to master the technologies.

Furthermore, the process to develop the product, the development culture, and the product itself are very different.

Overall, it can be concluded that the two centers differ too much to be merged into one. However, the intake process is generally the same over the two centers. Moreover, the business often has little idea if their business case is one for the traditional BI CC or for the advanced analytics CC. Hereby, it is recommended to merge the intake process into one, and divide business cases over the CCs after the intake.

Also, it is recommended to place the two centers under one organizational unit. For example, under a department named 'Business Intelligence and Analytics'. One Chief Data/Analytics Officer can head the department and the center's lead report to the same person. The centers work on the same themes and share the philosophy on how to solve the problem: with data. Participants indicated the CCs need to collaborate more and can learn from each other. As the centers are in line with each other, placing them under the same organizational unit will benefit this collaboration and knowledge sharing.

Advanced analytics CC as evolution from traditional BI CC

The idea may arise that the advanced analytics CC is an evolution from traditional CCs because they have the same objective but one originated later than the other. It seems a logical step in technology evolution and organizational acceptance. As Figure 11 indicates, traditional BI and advanced analytics are in line with each other. They are in line with each other because they share the overarching objective of gaining value from data. They do this in different ways, as the computational sophistication (x-axis) and value proposition (y-axis) differ. Furthermore, Figure 12 indicates BI&A maturity, where advanced analytics is displayed in a higher maturity phase than traditional BI.

Evolution is defined as a gradual process of change in a certain direction. As the Figures 11 and 12 indicate, traditional BI definitely paved the way for advanced analytics. However, the question is if the one is an evolution from the other. A part of evolution, especially technical evolution, is that the evolved being is superior to its predecessor (a human, a faster computer chip, a better camera). For traditional BI and advanced analytics, this is not the case. Although advanced analytics has developed itself on the basis layed down by traditional BI, they both gain value from to data in their own way. As described, both have a fundamentally different view on data (descriptive vs explorative way of analysing), but both ways are valuable.

Furthermore, it is to be expected that both ways will stay valuable in the future. New technologies might enable automation of traditional BI to such an extent that humans are not or barely needed anymore. However, the descriptive way of reporting on current business processes must always be done. Hence, advanced analytics will not replace traditional BI.

6.3 Validity & Limitations

Research method

The thematic analysis approach to qualitative data analysis is heavily directed by the researcher. As the method focuses on identifying and describing both implicit and explicit ideas within the data, it can easily introduce bias into the analysis. As this research project is a solo project, the researcher had no third party to point out bias. To mitigate the risk of bias, the codebook was revisited several times.

Grounded-theory minded methods like the thematic analysis approach are useful when the area of study is new. Our subject is a new subject, but certain context was already filled in, limiting the thematic analysis method in reaching its full potential. This is most reflected in the choice of characteristics the two centers were compared on. These characteristics were selected from Schüritz et al. (2017). Hence many 'themes' which normally result from the thematic analysis were already clear beforehand. As mentioned in 6.2, we feel confident about the completeness of these characteristics. However, other characteristics may have risen when these were not identified from the start.

Something that also has an influence on the selection of characteristics is the absence of literature on advanced analytics CCs. With Schüritz et al. (2017) being the first one to describe advanced analytics CCs on these characteristics, the choice was an one without competition. If more literature was present, other questions might have been asked.

Interviews & participant validity

This research stands or falls with the quality of interviews and participants. We feel confident about the background of the participants. Participants must have relevant experience with at least one of the types of BI&A CC. They must have worked in or with the CCs or have helped set them up. Preferably, they have experience with designing organizational structures for BI&A.

All participants work in the intersection between Business and IT and have experience with BI&A competency centers. Seven out of nine participants have experience with both types of CC. Seven out of nine participants have experience in designing organizational structure in a BI&A context. Furthermore, they are represented over many sectors, making this research relevant over sectors.

However, four out of nine participants described the same organization. For these participants, particular attention was given to find out the situation at their organization as well as their own view on what works best. Still, a skewed few of reality may be found.

Furthermore, nine is a relatively low number of participants. Although generalization is not a goal on itself in this kind of context-based research (2.1.2), more certainty in claims could have been created if more participants were interviewed. This number was discussed with and approved by the research supervisor. Especially on claims not broadly supported by literature, like the development process at traditional BI CCs or advanced analytics CCs, having more participants would have been valuable.

This research is about differences and similarities between the two competency centers. When confronted with this question, people tend to focus on the differences, rather than the similarities. Stating the obvious similarities, e.g. both types of CCs are centralized, organizational entities can be useful for the research. Especially in a methodology that is based on transcript coding like ours, obvious statements are lost when not expressed explicitly by participants.

Comparative literature

Similar research does not exist (yet), making it difficult to compare this research with other literature.

6.4 Future research

As indicated, it is expected that self-service BI has an impactful future. For advanced analytics, this future seems further away. We suggest that the impact of 'democratizing' traditional BI and advanced analytics is researched in the context of central BI&A entities.

With this research we hope to have contributed to the knowledge of traditional and advanced analytics CCs. However, on advanced analytics CCs, very little research has been performed. More research on how to set up and maintain advanced analytics CCs can provide new insights and professionalize the sector.

No research was found on the process in traditional BI CCs. We suggest performing generalizable research on the development processes used in traditional BI CCs. The research on development processes in advanced analytics CCs is also scarce.

Furthermore, we suggest performing research on the impact of a funding models to the value and process of central BI&A units, or shared service centers. No research on the impact of different funding models was found.

This research has been performed on a post hoc basis. The existence of two types of BI&A CCs was observed and questions about which needs they satisfy in which way were drafted. These questions can be turned around. Research can be performed on the needs of an organization and what type of organizational unit would answer those needs best.

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APPENDIX A – INTERVIEW QUESTIONS

A. Introduction of the research subject

- Introduction to the topic
- Introduction to the definitions of traditional and advanced BI&A

Traditional BI focusses on telling *what happened* by creating the ability to comprehend presented information and then use it to guide business actions to achieve planned strategic goals successfully.

Advanced analytics helps to tell what is going to happen by using data, statistical and quantitative analysis, explanatory and predictive models.

- How do traditional business intelligence competency centers differ from advanced analytics competency centers and how is that reflected in its objectives, structure, roles, processes, and governance?

B. Introduction

#	*QUESTION*	*WHAT IS MEASURED?*
B1	What is your educational and professional background?	Interviewee's background. The interviewee's experience with BI&A related topics
B2	Can you describe your organization? a. If you worked in a traditional and advanced BI&A centers at different companies, can you describe both?	The market the organization operates in and its overall objectives
B3	Have you worked in or with BI&A centers? a. For how long? b. What was your (functional) role?	The interviewee's experience with BI&A related topics

In section C-H, respondents are asked to answer each question with the differences and similarities between characteristics of traditional BI CCs and advanced analytics CCs. If respondents have no experience with both types of BI&A CCs, they are asked to describe the characteristics of the BI&A type they do have experience with.

C. BI&A Competency centers

#	*QUESTION*	*WHAT IS MEASURED?*
C1	What does BI&A mean to your company?	The value of BI&A to the organization
C2	How would you define the type of BI&A center that you worked in (1 sentence)?	The organization's definition of the BI&A center

C3	Can you briefly describe the kind of central organizational unit in which you work?	Explanation to definition given in C2
C4	How many years has the unit been established?	Measuring (part of) the BI&A center maturity
C5	What kind of business problems does the BI&A center work on?	The kind of output the BI&A center produces

D. Objectives

#	*QUESTION*	*WHAT IS MEASURED?*
D1	What was the motivation to establish the BI&A center? Is that still the motivation of its existence today?	The raison d'être of the BI&A center
D2	What are the BI&A center objectives? a. What does the BI&A center try to contribute to the business? b. How do they aim to do this?	What the BI&A center tries to achieve
D3	What kind of business problems does the BI&A center work on? a. How diverse are the types of business problems?	What the BI&A center tries to solve
D4	How would you define a successful BI&A center?	The organization's desired effect of the BI&A center

E. Structure & Roles

#	*QUESTION*	*WHAT IS MEASURED?*
E1	Can you describe how the BI&A center is organized? a. What is the size of the BI&A center in terms of people and budget? b. Does it have sub-teams? c. What does the leadership of the BI&A center look like?	Organizational structure of the BI&A center
E2	What roles does the BI&A center consist of? a. What are their responsibilities?	The different roles and responsibilities of the BI&A center
E3	What are the backgrounds (i.e. competencies and work experiences) of the BI&A center team members?	Background and expertise level of the BI&A center members

E4	Can you describe the culture in the BI&A center (openness, knowledge sharing, hierarchy, etc.)?	Organizational culture of the BI&A center

F. Processes

#	*QUESTION*	*WHAT IS MEASURED?*
F1	Can you describe the general process on how projects are handled?	The process flow of BI&A problems
F2	Are there possible multiple interpretations and solutions for the problems? a. If so, how does your team deal with these ambiguities? b. Is there a standard prescribed set of actions?	How the team handles disagreements and ambiguities in problem solving
F3	What are the most commonly used tools and technologies in the BI&A center?	Type of tooling and technologies the BI&A center uses

G. Governance

#	*QUESTION*	*WHAT IS MEASURED?*
G1	Where is the BI&A center placed in the overall organizational structure? a. What is the seniority level of the person leading the BICC? (C-level, senior management)	The organization's attitude to the BI&A center and impact it can have
G2	Who finances the BI&A center projects?	Financial structure of the BI&A center
G3	To what extent do the BI&A center results impact the core business? a. How much autonomy does the BI&A center have regarding taking decisions impacting other parts of the business?	The importance of the BI&A center to the organization and impact it can have

H. Other questions

#	*QUESTION*	*WHAT IS MEASURED?*
H1	Are there any large lessons learnt for the BI&A center?	Changes over time at the BI&A center and their reasons

H2	What issues are most holding back the BI&A center to reaching its objectives?	Elements limiting the BI&A center doing its work
H3	What aspect are most enabling BI&A centers to reach its objectives?	Elements enabling the BI&A center doing its work
H4	What do you believe to be the most prominent difference between traditional and advanced BI&A centers?	Difference between traditional and advanced BI&A centers
H5	Is there anything I forgot to ask? Anything you want to add?	Aspects the interviewee finds relevant that were not addressed in this interview
H6	Are you available for follow-up questions?	Interviewee's availability after the interview

APPENDIX B – CODEBOOK

Codes appearing more than once are added to the codebook.

1 center doing everything	Centralisation requirement	Go, no-go moments
AA by new generation	Centralization enhances cooperation	Good governance
AA maturity	Challenge	Governance - BI vs AA difference
AA people are scarce	Conservative culture	Hierarchy
Acceptance by end user	Cost benefits	Impact on business
Accountability	Crucial for business operation	Inconsistent definition data
Agility	Culture - BI vs AA difference	Increase value proposition
Analytics definition	Culture change	Innovation
Analytics playground	Damhof model split	Innovation
Available data science capability	Data driven	Innovation budget
Backlog with projects	Data quality importance	Innovative culture
BI & AA are different	Data science culture	Innovative issues
BI & AA collaboration	Data scientist	Internal process insight
BI & AA complementary	Decentral expertise	IT-Business integration
BI is waterfall	Department central funding	Jealousy
BI maturity	Determining data sources	Job automation
BI&A board	Determining scope	Knowing quality of data
BI&A CC definition	Different mindset	Knowledge sharing
BI&A maturity	Do not force people	Leadership
BI&A starting point	Employee background	Looking back vs looking ahead
Bringing insight to business	Ethical considerations	Maintenance
Business demands	Experimenting	Making sure it will be used
Business determines budget	Explainable model	Name for BI&A CC
Business model diversity	External consultants	Need for business understanding
Business problems	External influence	Need for central CC
Business problems - difference BI vs AA	Financial service market	Need for direction
Case histories	Financial structure	Not objectives
CC at multiple companies	Focus on value	Objectives - BI vs AA difference
Central doesn't work so shift to decentral	Future of AA	Organizational model

Participant educational background	Reliable information	Subscription based funding
Participant professional background	Reporting on business operation	Subscription financial model
Participant's role in project	Reporting structure	Success definition
Personal targeting	Requirement interview	Support from everyone in business
Phase after intake	Roles	Taking ethics into account
Pilot phase	Self sustainable CC	Teams
Predication accuracy	Shift to decentral	Time to market
Predictive analysis	Shift to self service BI	Time to market
Prioritize backlog	Shifting to hybrid	Tooling
Process - BI vs AA difference	Silo thinking	Traditional BI environment
Product owner / Storyteller	Size	Types of BI and AA
Project based funding	Split up per domain	Unknowledgeable data science
Project process	Stay innovative	use prediction as decision variable
Project requirements	strong IT foundation	Virtual BI&A CC
Public vs private sector	Strong technical knowledge	
Push and pull	Structure - BI vs AA difference	