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HOW TO CULTIVATE ANALYTICS CAPABILITIES WITHIN AN ORGANIZATION? – DESIGN AND TYPES OF ANALYTICS COMPETENCY CENTERS

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Research paper

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Abstract

Today, the ability to exploit big data using advanced analytics bears considerable potential to create competitive advantages. Therefore, business leaders need to make crucial design decisions on how to cultivate these capabilities within their organization. Analytics Competency Centers (ACCs) are an important organizational solution to spread analytics capabilities by providing leadership, expertise and infrastructure. In this paper, we analyze nine analytics competency centers of major global players across several industries - based on a series of interviews with executives, consultants and data scientists. We identify strategic and structural design options, common processes, best-practices, and potential future development paths. In particular, we distinguish between two generic types of centers that differ in their strategic orientation and their choice of design options. Our work contributes to organizational design theory addressing the question on how analytics capabilities can be nurtured for competitive advantage. It should provide concrete guidance to business leaders on how to design and apply ACCs as an organizational option.

Keywords: big data, advanced analytics, competency center, shared service center, center of excellence.

1 Introduction

Organizations today face the challenge to resort to advanced analytics to turn the continuously growing amount of (big) data into business value (Chen & Zhang 2014). In fact, those companies that substantially utilize data and apply analytics already create competitive advantages and outperform their competitors (Lavalle et al. 2011).

The range for applications of big data and analytics appear to be extremely broad: while some organizations benefit by optimizing processes and cutting costs (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh, Byers, et al. 2011; Kart et al. 2013), others try to start to measure "the immeasurable" (Dietrich et al. 2014) in order to support their strategies, e.g. by assessing customer intimacy (Habryn 2012) or by determining customer lifetime network value (Klier et al. 2014). On top of these advantages, Davenport (2013) suggests an "enrichment" of existing products and services using analytics, eventually leading to entirely new data-driven business models (Chen et al. 2011; Hartmann et al. 2016). Thus, big data and advanced analytics create a continuum of business transformation options (Schüritz & Satzger 2016).

In order for any organization to take advantage of those options, it needs to tackle various different challenges: Gaining access to relevant data might already constitute a significant impediment. However, a study among 3,000 executives reveals that the most frequent challenges are understanding how analytics should be used, a lack of management bandwidth, and a lack of skills within business units (Lavalle et al. 2011). Business leaders, therefore, need to systematically build skills and evaluate use cases for analytics: As data scientists are rare, organizations need to decide how to make analytics skills available to the organization (Davenport & Patil 2012). In general, enterprises may choose either to source skills from outside consultants on demand (Schulz & Brenner 2010) or, alternatively, to build up skills on their own where needed (Porter & Heppelmann 2015). For the latter, often special centralized units within the organizations are built as a special form of shared service centers, regularly denominated as competency centers or centers of excellence. For previous technology introductions, these centers have proven to be very effective (Granebring & Révay 2005; Marciniak 2012), so, e.g., for the introduction of business intelligence (Hostmann 2007), enterprise resource planning (Eriksen et al. 1999), or coupled systems (Zhao & Zhang 2008). These competency centers allow an organization to build up new skills and to leverage them across the organization. In the big data context, we, therefore, aim to understand *how organizations design Analytics Competency Centers in order to cultivate analytics capabilities across the organization?* Under the lens of contingency theory, we further investigate *what contingencies are relevant for Analytics Competency Center design and what attributes differentiate those designs.*

We set out to explore recently established Analytics Competency Centers (ACCs) of nine leading companies across different industries. In our interviews with executives, consultants and data scientists we focus not only on the status quo ACC set-up, but also on anticipated changes based on the individual experiences gathered so far. We have applied qualitative content analysis to synthesize the insights. In the following, we present the results of our analysis in terms of objectives, functions, structure, roles, as well as processes and governance, providing a menu of design options. In addition, we identify two generic types of ACCs with different strategic orientations and operational implications. Thus, based on the first empirical analysis of Analytics Competency Centers, we aim to contribute to contingency research for shared service centers for analytics. In addition, we provide concrete organizational design support for business leaders who consider or implement ACCs in order to secure analytics skills and to build competitive advantage.

The paper is structured as follows: In section 2, we first provide context as to the significance of advanced analytics for an organization, as to competency centers in general and ACCs in particular. Section 3 describes our research methodology detailing how we set up, conducted, and analyzed the interviews. Section 4 presents the synthesis of the cases with a repository of design options, followed by the identification and interpretation of ACC types in section 5. Section 6 briefly summarizes our results, acknowledges limitations and provides implications for business as well as for future research.

2 Related work

In this section, we clarify the meaning and importance of advanced analytics, as it is the underlying focus of Analytics Competency Center. We further introduce contingency theory as the underlying theory of our research and illustrate the concept of Shared Service Centers, a centralized organization unit that fits the concept of ACC. Finally, we position ACC as a special type of those centers.

2.1 Advanced Analytics

Analytics has its roots in the information centers (also known as end user support centers) of the 1980s that provided end user support and ensured the deployment of new technologies (Mirani & King 1994). They were advancing more sophisticated statistical and data mining techniques, mainly to analyze structured data predominantly stored in relational database systems (Clark et al. 1990). Today, underlying data is frequently denoted as “big data” - not just addressing the volume of information, but also referring to value, variability, variety, velocity, and veracity (Chen & Zhang 2014). Individual companies operate with diverse definitions of this term, depending upon their level of maturity (e.g. experience with distributed system, amount of data already used) in working with big data (Demirkan et al. 2015). In the literature, the terms data mining and analytics as well as business intelligence are often used interchangeably, but all imply the general process of exploration and analysis of data to discover and identify new and meaningful patterns in data to improve decision making (Berry & Linoff 2000; Davenport 2006; Fromm et al. 2012). For the purpose of this paper, we will simply refer to *data and analytics* and treat it as one concept without distinguishing between data vs. big data and basic analytics vs. advanced analytics. We understand it as the application of statistical and mathematical methods that can be descriptive, predictive, or prescriptive (Demirkan et al. 2015). Organizations find a wide range of possible scenarios to benefit from data and analytics. They optimize their business by raising process efficiency or creating additional insights into their customer base (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh & Byers 2011). Today, companies in many industries offer comparable products can distinguish themselves by their business processes, by "wring[ing] every last drop of value from those processes" (Davenport 2006, p.100). New cloud technologies enable scalable processing power, and user friendly applications allowing a wide range of departments to benefit from data and analytics (Satzger et al. 2015). On top of these internal optimizations, some organizations even extend the value propositions by applying data and analytics to offer completely new data-driven services (Schüritz & Satzger 2016). Regardless of the particular use case, organizations that utilize data and apply analytics seem to outperform their competitors and, thus, to have created a competitive advantage (Lavalle et al. 2011).

2.2 Organizational Design and Shared Service Centers (SSCs)

According to (structural) contingency theory, there is no one best organizational design. The organizational design is rather dependent on the current contingencies the organization is facing (Donaldson 2001). One of the dominant contingencies in literature is the organizational strategy (Blarr 2012; Venkatraman 2016); others may refer to the size of an organization, the products and services it offers, or the technologies it wants to utilize. Depending on the contingency the organization should be designed along certain attributes. These attributes describe the organization (Huber 2009), and are also referred to as characteristics (e.g., Jackson & Ni 2013)), features (e.g., Romanelli 1991)) or factors (e.g., Mintzberg 1980)). Contingency theory states that the organization achieves a higher performance if the composition of attributes *fits* its contingencies (Van de Ven & Drazin 1985).

Shared service centers (SSC) have gained importance in the last decade and can be found in many organizations as a means to centralize and to best leverage internal skills (Singh & Craike 2008). While there is no broadly accepted definition of an SSC (Singh & Craike 2008; Schulz & Brenner 2010), it can be seen as an organization where similar business functions are consolidated into one accountable semi-autonomous unit to offer defined services to internal clients (Bergeron 2003).

Establishing an SSC is an organizational design task in itself that must be performed in response to relevant contingencies.

However, extant research hardly sheds any light on either the contingencies or the attributes of SSC organizations. One notable exception, although not relying on contingency theory, is the work of Goold et al. (2001) who analyze SSC organizational design and distinguish SSCs delivering services for *transaction-oriented processes* opposed to SSCs supporting *complex, knowledge-based processes*. SSCs that offer services for transaction-oriented processes aim for economies of scale by consolidating skills and resources, often in low cost locations. Via this consolidation, they drive down costs and improve efficiency, while at the same time improving quality and professionalism (Cooke 2006; Davis 2005). In addition, by centralizing core processes, the organization may exploit additional potential for optimization, e.g. via standardization (Ulbrich 2006). The kinds of transaction processes bundled in SSCs are manifold, e.g. processes for accounts receivables, procurement, or expense administration. Employees focus on historic or current transactions and apply explicit knowledge (Bryan & Herbert 2012). An SSC offering services for *complex, knowledge based-processes* describes a cross-organizational group that is offering means to reduce time-to-value (McCoy et al. 2002). Processes typically found in this area are financial analysis and software development (Quinn et al.

2000). While not often termed as such in academia, in industry this SSC type is often referred to as a center of competency (CoC) / competency center (CC) (Marciniak 2012) or as a center of excellence (CoE) (Bryan & Herbert 2012).

2.3 Analytics Competency Centers (ACC)

The use of analytics is progressively disseminating from specialists toward business users to improve their strategic and operational decisions. While the business user may be an expert in his domain, he is, however, very unlikely to also be an expert in data science. As the business user is not a data scientist, he must either rely on the explicit advice of a data analyst, or "employ analytic applications that blend data analysis technologies with task-specific knowledge" (Kohavi et al. 2002, p.212). In the past, the centralization of such functions has substantially contributed to implement enterprise resource planning (ERP) and business intelligence (BI) systems. These centers placed emphasis on reporting, historical analysis and dashboards. Together with other data-related teams, they created enterprise-wide data marts and warehouses to establish a foundation for trusted information (Lavalle et al. 2011) – according to our provided terminology above, these SSCs were focusing on *transaction-oriented processes*. The organizational entities have often been named business intelligence competency centers (BICC) or business intelligence centers of excellence (BI CoE) (Dresner et al. 2002) – a now slightly confusing terminology as the terms CC and CoE in industry predominantly refers to a unit that fits the definition of knowledge-oriented SCCs.

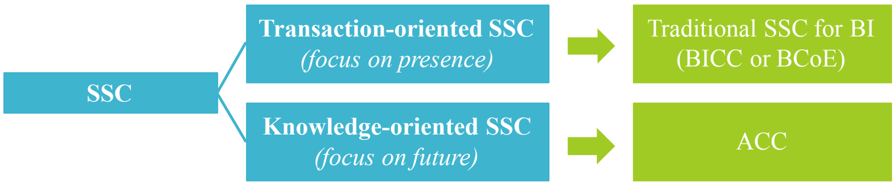

Figure 1. Overview of types of Shared Service Centers (SSC)and their realizations for analytics

In recent years, also for analytics, *knowledge-oriented* SCCs emerged, with primary focus on offering analytics and data mining as an internal service across the organization (Watson 2015). Gartner predicts that by the end of 2017 already a quarter of all large firms will have a dedicated unit for data and analytics (Cearley et al. 2016). Adding to terminological confusion, different companies have called these centers Big Data CoC, Big Data Lab, Analytics Competency Center, Analytics Center of Excellence or Analytics Service Center. While there is no common term for this type of center, we will call them Analytics Competency Centers (ACC) - as this term was most broadly used among the organizations in our sample.

So far, the ACC phenomenon is still rarely covered in research. It is still unclear how these new centers are formed, how they operate, how they are designed and what their functions are. Therefore, existing literature does not inform us well on our specific research inquiry of the design of ACCs and its contingency.

3 Research Methodology

In line with our research question, we want to understand how organizations design Analytics Competency Centers; we, therefore, sought the expertise of ACC practitioners. Expert interviews are well suited as they generate specific knowledge about the situation that is investigated (Pfadenhauer 2007; Gläser & Laudel 2010). This section explains how the interview questions were chosen and how the sample was composed (section 3.1), as well as how the data was analyzed and interpreted (section 3.2.).

3.1 Design of interviews and sample selection

First, in order to explore the research area and to identify the topic areas for the main study, two pre-study interviews were conducted. This ensured that all relevant aspects of the research area were covered, and they helped us to discover the best way to execute the main interviews. Two interviewees were selected based upon their experience and knowledge in being part of establishing an ACC or in consulting during different analytics engagements. The first interviewee was the sales leader for a major global IT provider of analytics solutions, and was instrumental in establishing an ACC within that provider. The second interviewee was an analytics consultant of another major IT-provider who had been involved in several analytics projects either as a data scientist or as a project manager. Thus, the two experts contributed different perspectives on ACCs. In open unstructured interviews both experts discussed what organizational design issues have been made in their past projects. This created a better understanding of the issues and topics around the ACC therefore revealed relevant and interesting exploration areas for us: objectives, functions, structure, processes, governance, best practices and IT. Based on the literature review, the results of the two pre-study interviews and a brief literature review on the areas, the scope and the design of the main study was determined.

The main study consists of semi-structured expert interviews with open-ended questions as described by Gläser et al. (2010). The interviews were divided into the six topics identified in the pre-study. In each topic, the interviewee was asked how their respective ACC is designed (eg. “What employee roles are part of the center?”, “How are the projects funded?”). Each question was followed up until a complete understanding of the topic area could be established. The topic *objective and functions* is comprised of questions about motivation, objective targets, and value propositions, while the topics *structure, governance* and *processes* covered roles and culture in the ACC, organizational hierarchy, cost distribution and core processes. In addition, the interviewees were asked about their lessons learnt, success factors and most commonly used technologies (*best practices*). Finally, the topic *challenges* included questions about their project and people management issues and we asked the interviewees for concrete improvement suggestions. A guided schedule ensured that all these important aspects were covered during the interviews (Mayer 2012).

Number of cases	Industry	Employees	Revenue
2	IT-Services	>80,000	>€20B
2	Energy & Chemicals	>50,000	>€55B
5	Manufacturing	>80,000	>€60B

Table 1. Overview of sample

In order to select a set of cases to explore, we were guided by the selection questions of Gorden (1975, p.587): “Who has relevant information? Who is able to give precise information? Who is willing to provide information? Who is available?” By reviewing the major companies operating in Germany that currently have vacancies in the area of data scientists, a long list of 22 companies was created. After a first contact, only 15 companies turned out to run a shared service center approach, while the rest is looking for data scientists in a specific area only, and, therefore, is not relevant for our study. Based on availability and willingness for an interview, our final selection comprised nine globally leading companies from manufacturing, chemicals and IT services (cf. Table 1).

All have established an ACC in Germany in recent years, either as a new unit or as an evolutional step of a former BICC, and have already completed at least a number of projects. Within this sample, we conducted 12 interviews, each lasting between one and two hour, performed between May and August 2016. The interviewees have had different roles within the ACCs, such as executives, consultants, data scientists or have been an internal client of the ACC. A majority has already held at least two of those positions during their career. With three exceptions, the expert interviews happened face-to-face with the advantage of getting more information because of the private atmosphere (Mayring 2002). Interviews were conducted either in German or English, recorded and transcribed.

3.2 Analysis of interviews

The interviews are analyzed based on inductive category building, a qualitative content analysis method, according to Mayring (2002).This method aims to build generalizable categories without referring to other theoretical concepts by using a systematic, rule-and-theory-based procedure. The

major process steps are defining abstraction levels and formulating macro operators for reduction like skipping, generalizing, constructing, integrating, selecting, and bundling paraphrases.
First, in order to structure the analysis, themes are determined. The *themes* correspond to the research questions and are partly determined in the pre-study (objective and functions, structure and roles, processes and governance). Second, *categories* and *subcategories* are then constructed within these themes. For that purpose, the text is coded by paraphrasing it in a simple statements compromised of shortened common language. Parts without relevant content are dropped. The first paraphrase of the considered material builds the first category. Matching categories are combined and paraphrases that belong to the same topic are subsumed under a new category (e.g., roles) and become subcategories (e.g., data scientist) in the theme (e.g., structure). Best-practices and challenges are assigned to corresponding themes. Having evaluated 25 percent of the material, the categories were reviewed by a second researcher. Finally, all collected data was coded using the described processes. The process is iterative, resulting in changes to the category hierarchy. The coding process is supported using the software MaxQDA 12.
After one researcher had performed the coding of all the material, a second researcher reviews the paraphrasing and the category system in order to minimize misinterpretation and bias by the coder. Disagreements are discussed and resolved (Fastoso & Whitelock 2010). Additional questions and uncertainties that arises during the analysis are posed to the interviewee by email. The results of the coding are interpreted in small groups of fellow researchers and are presented in the following sections.

4 ACC Design Options

Based on the analysis of nine ACCs, we synthesize the data and present the results in the following section. The results are grouped in the topic areas: (1) *objectives and functions,* (2) *structure and roles* and (3) *processes and governance*. Each topic area consists of a synthesis of the details that were identified during the interviews and are presented as potential options for the organizational design of an ACC. The descriptions of the design options are enriched with additional insights that were discovered during the interviews and are based on the experiences of the ACCs.

4.1 Objectives and functions of ACCs

During the study we identified four main drivers for establishing an ACC in an organization. In some cases, management made a *strategic decision* to invest in analytic capabilities by establishing an ACC, while others were formed as a reaction to internal *demand for analytical capabilities* by the organization. Some organizations already had a (transaction-oriented) BICC in place which *organically grew* to become an (knowledge-oriented) ACC. In some cases, external *competitive pressure* also led to the founding of ACCs.
All ACCs focus on supporting some or all of the objectives and adopt a series of corresponding functions to fulfill them (Table 2): The ACC should advocate analytics and identify potential for data-driven business models to lead the *transformation towards a data-driven company*. A data driven company is described as an organization that heavily relies on data to make decisions and take actions. To provide *analytics expertise* and act as a central contact, ACCs achieve economies of scale by centralizing the analytics skills across the organization and connecting ACC experts, business units and external service providers. The ACC identifies and creates *uses cases* that are supposed to optimize business process, products and services. It further evaluates the feasibility and value contribution of such use cases. Developing a *data strategy* and governance that lays out how to gain data access in terms of integration and migration is also one of the major responsibilities of an ACC. Some companies, therefore, decided to develop and maintain a data lake - a single data repository that tackles the challenges of data silos and monolithic systems (Woods 2011; Stein & Morrison 2014). The data governance is accompanied by the function of *platform management* with the main purpose of enterprise architecture integration. The ACC is further responsible for *knowledge management* and the definition of standards with the intention to benefit from best practices. Because the ACC has deep

knowledge and capabilities in advanced analytics, it does not just support the end-user deployment; it also provides cross-organizational trainings to drive *broad adoption of analytics within the organization.* These trainings aim to increase awareness of the services available from the ACC, to teach employees of BUs how to identify issues that data analytics can be useful in addressing, and to judge the amount of effort and resources required in different scenarios. The *IT governance for analytics* objective focuses on the appropriate management of licenses, vendors and external service providers as well as risk and change management that are required for analytics solutions.

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 2. Overview of objectives and associated functions of an ACC

4.2 Structure and roles of ACCs

As organizations form a dedicated unit to build up the necessary skills, the question arises how to set-up such a unit in terms of the required roles and skills. Typically, a team of key stakeholders from across the organization is tasked with defining the ACC and staffing models. The potential roles are illustrated in Figure 2:

Top leadership of each ACC usually comprises a *head* and a *deputy*; depending on the size and physical dispersion of the center, there may also be local directors. Their major responsibility is to create leverage in the organization to ensure sufficient resource availability.

Once created, three common roles within the ACC are *project managers* (PMs), *architects* and *support functions*. The *project manager* oversees the different analytics projects. While this can be a dedicated position, project managers mostly occupy a dual role, also acting as data scientists or architects themselves. The *architect* has the responsibility to develop the central platform that analytic solutions are operating on, whereas this role only occurs if the organization actually follows a platform strategy. The work of architects includes the design of the data and information architecture for the analytics solutions that are part of the platform. His responsibilities further cover the data warehouses and decision support systems as well as information strategy development, logical and physical data modeling, metadata management, and data staging techniques. The *support functions* take over responsibilities like reporting and communication activities (e.g., internal marketing, event management, etc.). Especially at the initial setup of each ACC, the need for effective internal marketing often seemed to have been underestimated.

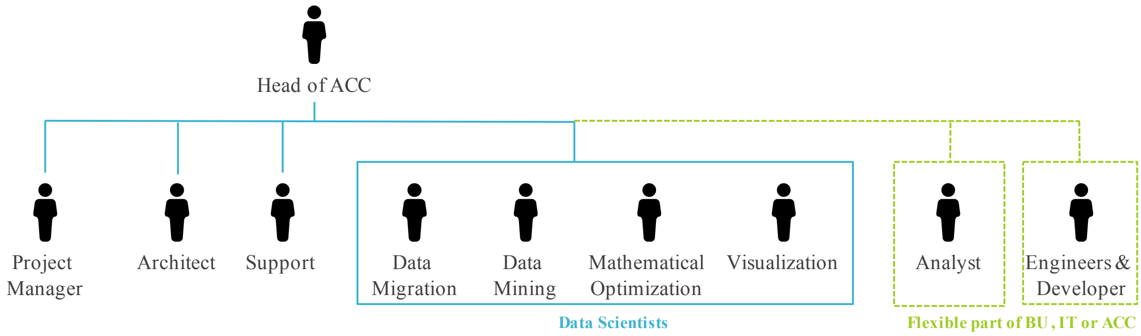

Figure 2. Roles needed in an ACC to perform analytics projects

The core role within the ACC is that of a *data scientist* – a profession recently called out as "the Sexiest Job of the 21st Century" in Harvard Business Review (Davenport & Patil 2012): They are "the explorers who investigate the data, looking for insights that have business value" (Watson 2015, p.6). The ACC may comprise different data scientist sub-roles: specialists for *data migration*, *data mining*, and *mathematical optimization*. As it is important in some areas to visualize the data in order to take action, some ACCs choose to create the role of specialist for *visualization*.

Regardless of the data scientists' specialization, ACCs usually encourage them to be part of every data mining step at least once to give them a better understanding of the effort involved in each phase. Nearly all ACCs studied are searching for additional data scientists for their teams; they want to become independent of external service providers that so far are usually still employed in each project phase. Organizations seek data scientists that have a broad business and process experience, deep data modelling and mathematical skills, advanced communication competency, as well as engineering and database expertise. In the long-run, as organizations establish a data lake strategy, ACC executives plan to create additional roles for *optimizing data quality* and *maintaining the data lake*.

Every analytics project also requires deep business understanding to interpret the data and to translate the results into actual business value and concrete actions. This role is usually denoted as *analyst*. Analysts have special business expertise that helps to interpret the results of the data mining process. This role is particularly necessary as data scientists often lack the necessary business understanding. Analysts can either be part of the business unit as a dedicated contact point for the ACC, or a rotating function depending on the context of the project. In some cases, analysts are permanently associated with the ACC itself. In order to tackle this need for better business understanding, one of the larger ACCs in our sample has established "content clusters" where project managers and data scientists are specialized in certain departments like sales, marketing finance, etc. as well a "cross-organizational cluster". While nearly all ACCs mention the lack of business understanding in their ACC teams, the clustered one did not exhibit this weakness. Depending on the degree to which the ACC is involved in the implementation phase of a project, it may also be staffed with *engineers and developers* to implement the solutions. These roles, however, can also be part of corporate IT.

All of these roles form a unit that in most cases reports to the CIO. Interestingly enough, ACCs are typically culturally very different from the rest of the IT organization: The sampled ACCs work in a type of start-up atmosphere with a high tolerance of failure and a high degree of openness and knowledge sharing. Generally, two different philosophies to organize the typically young and diversified teams can be found: They are either set up as centralized on-site collaboration teams or as virtually dispersed teams mainly interacting on a virtual basis.

4.3 Processes and Governance of ACCs

One of the main objectives of an ACC is to enable data-driven decision making. In order to do so, use cases with business units such as sales, finance, operations, production, and marketing need to be created, tested, and implemented. All ACCs in our sample run on a project basis and are very similar in the way they operate and create value - thus a general process can be synthesized. Each process step is assigned with common terminology and alterations in the process are indicated by adding options (eg, A or B). As illustrated in Figure 3, the synthesized process is divided into three major stages: *use case creation, proof of concept, and implementation*.

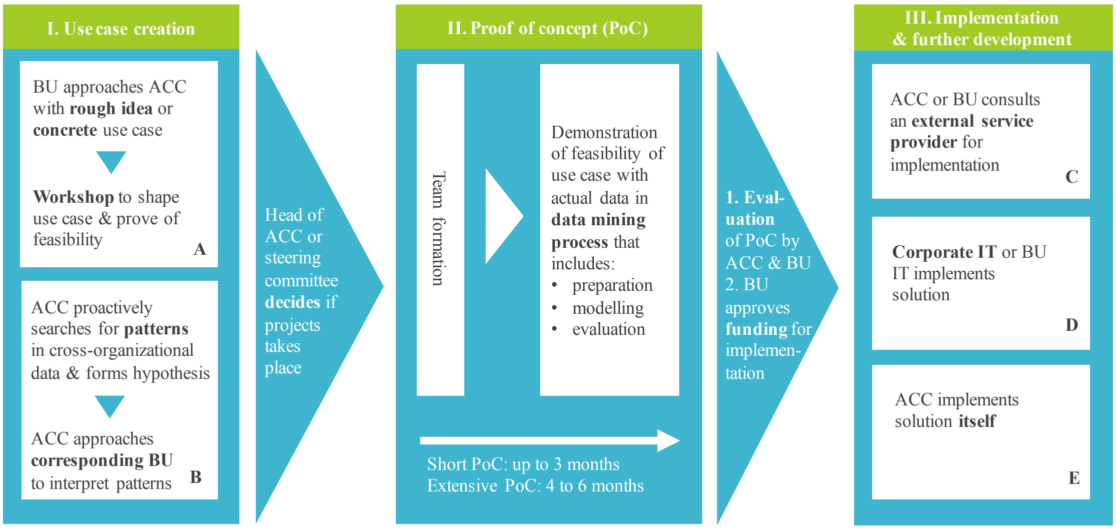

Figure 3. General process of ACC

In the *use case creation* phase, ideas to apply analytics are first conceptualized and elaborated. We observe two different ways in which they are initiated. Either (A) the business unit (BU) approaches the ACC with a use case, or (B) the ACC proactively explores the available cross-organizational data for patterns and creates hypotheses based on their findings. If the BU approaches the ACC, the level of involvement of ACC differs: While some ACCs focus on concrete ready-to-execute use cases, others support the investigation and definition of a use case by hosting design thinking workshops or data discovery sessions, in which data scientists and business users search for patterns in a pre-selected sample of data. Usually, one to three ACC team members are involved in a use case creation. At any point in time, each ACC team member is involved in three projects on average and five projects at the maximum.

After the team has identified a solid field of application, discovered potential data sources and defined a business case, the use case enters a stage gate. At this point, in most of the sampled ACCs, the ACC management team decides whether a project enters the next phase. The decision is based either on gut feeling, or, in an increasing number of cases, on a priority ranking based on KPIs that reflect possible BU savings, costs, estimated time frame, and impact on the whole organization. However, some organizations have come to realize that some form of steering committee with a wider involvement of the BU can increase acceptance of the decisions made.

Once a project gets approved, it enters the *proof of concept* (PoC) phase. Now the team actually works with the available data to prove the feasibility of the use case. The team is usually comprised of a project manager, data scientists and analysts from the ACC and sometimes includes a member of the business unit (for testing and feedback). The depth of BU involvement differs, ranging from high commitment and daily interaction to an irregular involvement for inquiries and feedback. Part-time BU team members include top decision-makers as well as users who will later rely on the analytically retrieved insight. The creation of the PoC follows typical data mining process models including data preparation, modeling and evaluation, e.g. CRISP-DM (Wirth & Hipp 2000). Within the sample, two types of PoCs are apparent: *short PoCs* with a duration of up to three months, including the data mining process on a small sample of data, and *extensive PoCs* taking four to six months, including the acquisition and migration of a larger amount of data. Unlike the short PoCs, the longer PoCs usually result in ready-to-implement solutions.

Once the joint PoC evaluation by ACC and BU confirms the feasibility and the BU is able to allocate the necessary funds, the *implementation & further development* phase is entered. Often the further development, testing, as well as the actual implementation of the solution is an iterative process. The implementation is handled either (cf. Figure 3) by corporate IT (C), by an external service provider (D), or by the ACCs themselves (E). ACCs that also take responsibility for the implementation usually restructure the project team when entering the implementation phase: While the PM often times remains in place and engineers and developers join the team, data scientists are transferred to new projects.

To better understand the process governance, the difference in financing models needs to be taken into account. When establishing an ACC, the organization needs to decide if either the BU bears the cost for the use case and proof of concept phase (phases I and II in Figure 3) or if the ACC has a dedicated budget on its own that it can freely use to engage in projects. Deciding for either one of these models has manifold implications:

While it is very common for *business units to pay for services* received by shared service centers (Schmidt 1997), it does have certain shortcomings in the specific case of analytics competency centers. Allocating the cost of ACC services solely to the BU means that the number of use cases presented to the ACC is limited by the BU's budget. Further, the BU considers the ACC a service provider rather than another unit of the organization on eye level. This leads to less collaboration and may hamper creativity in the creation of new use cases, particularly in cross-organizational projects. Lastly, from the perspective of the BU, paying for the service might be cheaper than developing its own analytics competencies by hiring data scientists, but it is still difficult to afford the service for smaller BUs with less resources.

In comparison, pro-active cross-organizational projects are more likely to happen if the *ACC is covering the cost*. In this model, the ACC is acting independently and is willing to acquire and aggregate more data in an effort to get a bigger picture, benefitting the company as a whole instead of focusing solely on the issue of a single BU. Furthermore, there are no delays due to budget approval processes on the BU side, and the ACC can act with higher speed and agility. Acting on its own budget, the ACC experiences more freedom in selecting projects and making decisions. However, covering the whole project costs may lead to a massive amount of use cases presented by the BUs. In this situation, selecting the projects often does not follow a rigorous decision process, but instead selection is tainted by political power. These circumstances potentially lead to less pressure to deliver great results and a more lenient work attitude.

To mitigate the pros and cons, organizations in which the ACC is solely responsible for the project costs have switched to a hybrid cost distribution model or plan to do so in the long run, effectively splitting the costs between BU and ACC. In a *hybrid financing model*, the ACC has a dedicated budget to finance certain defined parts of the project (e.g. use case creation), it has its own innovation budget for proactive, cross-organizational projects, and has a budget to cover short-term cash flow issues of the BU to start the PoC or implementation phase (e.g. start process of data integration while BU is still waiting for budget approval).

5 ACC Types

As part of the interviews for the nine ACCs, a self-assessment of easily distinguishable attributes alongside the themes is carried out. These attributes are identified in the pre-study and can be mostly placed on a binary dimension.

Plotting these attributes in a simple visual representation allows for further visual analysis. Figure 4 captures all nine sampled ACCs along five attributes out of thirteen1 that are relevant for the strategic direction of the ACC: Focus refers to the primary "customer" of the ACC. In two cases the ACC exclusively serves internal business units, in one further case the ACC also interacts directly with customers of the organization, thus offering analytics-as-a-service. In all other cases, the ACC serves internal stakeholders, but also focuses on product and service improvements that potentially impact the customer. Cost distribution defines the unit financing the biggest share of analytics projects as described in section 4.2. In hybrid-cost models, the lion's share of funding still comes from either the ACC or the particular BU involved. Agility refers to the flexibility in a project; low agility means the project has a preset of inflexible restrictions in terms of cost, time and scope whereas a high agility means more flexible restrictions. Responsibility describes which unit is taking the lead in executing the projects: Either the business unit acts as the owner of the project or the responsibility is shared in a joint project. The last characteristic refers to culture: While some ACCs have a very hierarchical approach in structuring and managing their ACCs, others choose a very flat organization with high peer-to-peer communication.

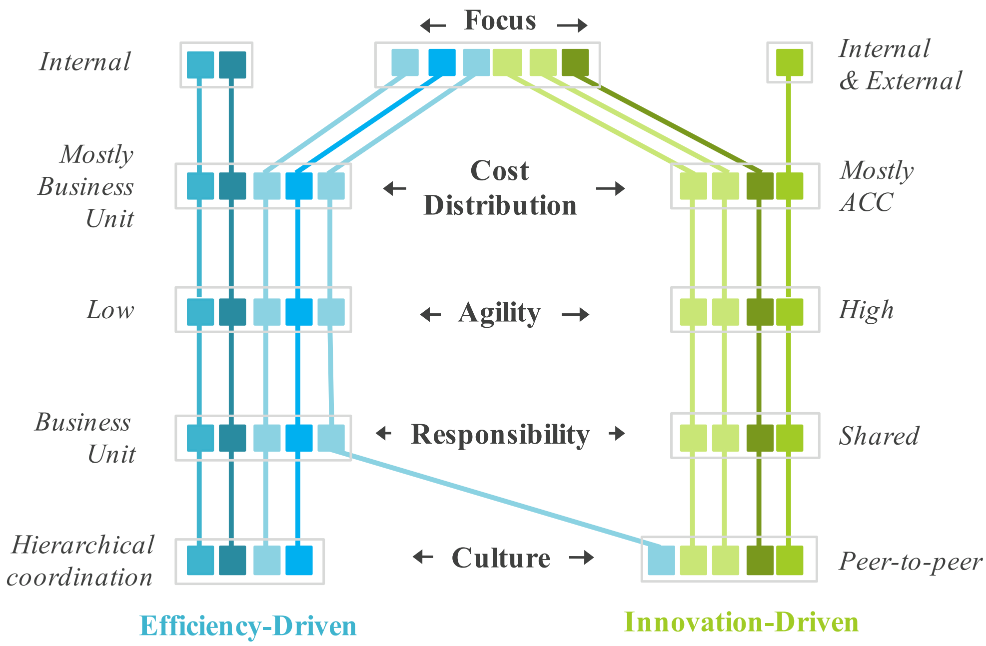

Figure 4. Types of ACC

Analyzing the plot of the key attributes (), two distinct types of ACCs can easily be identified: A number of ACCs screened, exhibit attributes on the left side of the visualization bar - they represent one type of ACC that we call *efficiency-driven ACCs*. Another type of ACC, in which the attributes tend towards the right side of the visualization bar, we call *innovation-driven ACCs*. Based on these two types of ACCs, additional insights can be generated as the type of an ACC correlates with other information gathered. This section describes the two types of ACCs, and the additional correlations and their implications in more detail.

[1] Additionally, we collected: Establishment of data lake vs. not, use of standard database vs Hadoop cluster, platform strategy vs not, data mining methodology CRSIP vs SEMMA vs own, short projects vs. long projects, center expansion necessary vs. not and support by external service provider vs not.

5.1 Type 1: Efficiency-driven

Efficiency driven ACCs have a mostly internal focus or an internal and external focus in terms of product and service improvements. They do not dispose a dedicated budget, they act as service provider for business units and, except one, they are organized in a hierarchical manner.

When analyzing the ACCs that are efficiency driven, it becomes apparent that all of them are organically grown; they had been formed out of former BICCs, other analytics-related teams or individual "industry 4.0" projects. They had been founded under the strategic imperative to centralize all analytical skills into one unit and to achieve economies of scale, thus the name efficiency driven.

These ACCs see themselves as internal service providers that support business units in analytics projects. Therefore, they *do not have dedicated budgets* and they are usually approached by BUs with concrete use cases. The ACCs are then reimbursed by the requesting BUs for all the process steps where they render service.

Although those ACCs do not consider themselves agile, some of them *aim to become more agile* and seek relief from strict IT governance as well as a higher position in the organizational hierarchy to gain more leverage.

During the study, we found the tendency that all efficiency-driven ACCs want to *change their cost distribution*. In the long run, they want to establish a hybrid cost model to become more agile and change from a mere service unit to a more innovation-driven ACC with higher cross-organizational focus.

Organizations that have an efficiency-driven ACCs in place point out that functions and activities as well as their governance are very service-driven. In this way, they are similar to the described SSC that delivers services for transaction-based processes. They are facing the issue that the ACC needs to convert their tactical attitude into a more strategic mindset in order to take a leading role in the transformation of the company, as is often demanded and required of them.

5.2 Type 2: Innovation-driven

Innovation-driven ACCs have an internal and external customer focus in terms of product and service improvements - one of the ACCs even offers its expertise to customers. Innovation-driven ACCs control their own budget and do not need to seek reimbursements from business units to engage in projects. The innovation driven ACCs' culture is marked by a peer-to-peer coordination. They operate with high agility fairly independently of corporate IT processes and governance.

The ACCs that are associated with this cluster are mostly formed because of a *strategic, top-down decision*. They are formed under the strategic imperative to cultivate analytical decision-making across the organization, explore data-driven business models and eventually create a competitive advantage.

These ACCs describe the value they provide as an environment for innovation, where new technologies should be explored and tested, and failures are expected; thus, they were labelled as innovation driven.

Due to the *financial independence* of the innovation-driven ACCs, they are able to pro-actively identify cross-organizational use cases and to engage in them. Only the last development and implementation phase is typically funded by the beneficiary or a supporting higher-level funding source.

While innovation-driven ACCs seem like the desired role model, they are not without downsides. Business units in organizations that implemented an innovation driven ACC complain that the ACCs availability and speed is low, and that there is a high co-determination by the ACC. Rather than addressing BU challenges with targeted solutions, innovation-driven ACCs often seek solutions that can be integrated across the organization, which can add complexity and cost. This mostly results from the autonomous funding of the ACC. The ACC is therefore not limited by the scope or budget imposed by a BU to deliver a fast solution that serves the needs of that BU alone.

It is noteworthy that both ACC types revealed a desire to converge. Eventually, innovation-driven ACCs will have to create justification of their services to secure funding. Efficiency-driven ACCs, on the other hand, already recognized that being an exclusive service provider limits their ability to proactively tackle use cases and exploit interdepartmental synergies.

6 Conclusion

Our analysis of nine Analytics Competency Centers provides the first empirically derived picture of this emerging organizational construct that is supposed to foster analytics in the organization via a centralized unit. It has revealed several insights for the topic areas *objectives and functions*, *structure and roles* as well as *processes and governance*. Each is described with a comprehensive set of synthetized design options that help to develop an ACC and further research such an organizational construct.

In addition, we have identified two different center strategies in our sample: The efficiency-driven ACC that acts as a service provider as well as the innovation-driven ACC that leads the transformation of the organization. We, therefore, contribute to research on shared service centers by providing concrete attributes for the organizational design of analytics-focused SSCs (ACCs). We further add to contingency research by identifying the center strategy as one contingency of ACC design. Each strategy shows a different composition of dependent attributes: focus, cost distribution, agility, responsibility, and culture. Both contributions build an important foundation for future research.

6.1 Managerial Implications

Looking at how globally leading enterprises create competitive advantage by establishing an ACC can be helpful to companies that already founded an ACC or are planning to do so:

First, for organizations that want to cultivate analytics via a competency center, this work presents a 'menu' of design options. This menu provides a starting point for developing the unit based on the experience of nine globally leading companies. By applying best-practices, new ACCs should be built in a more effective manner, and the types and current trends of the established ACCs should assist managers to better understand the effect of certain design decisions.

Second, existing ACCs have the option to benchmark themselves against other established units. The results in section 4 and 5 illustrate the scope of responsibility of comparable units and provide some guidance on shaping an own ACC.

Third, by uncovering the unique challenges of each type, and comparing them to the development history of the ACC, organizations that have established an ACC or are in the process of developing an ACC may proactively address these issues.

6.2 Limitations and future research

The selection of the sample and the ways of gathering data exposes the study to certain limitations. Overall, three different types of limitation apply and shall be addressed in future research.

First, for restrictions of interviewee availability, only one interview was conducted for most of the ACCs. A more diverse perspective from users of the ACC and from different roles within the ACC may reveal a more differentiated picture. Future research should consider a case study approach and analyze the ACC from different stakeholder perspectives.

Second, this study focuses on organizations that are early adopters of the ACC model, i.e. major organizations that have already established an ACC and are addressing the issues of cultivating analytic skills. However, we cannot say with certainty that these options are the only viable or most effective ones at this point. A broader study of organizations that want to cultivate analytics within the organization using different approaches may reveal a better understanding of the suitability of a center approach as such.

Third, due to the composition of our sample, all ACCs have already completed some of their projects, but all of them are still somewhat immature. As the capabilities and organizational practice with analytics mature, the ACC might change as well. Further, all analyzed ACCs are based in Germany; therefore, the sample contains a geographical bias.

Forth, this qualitative analysis of ACCs has revealed a series of attributes and identified a contingency. In future research, a large sample and cluster analysis should be used to verify the results. This may also reveal new contingencies and other interdependencies.

We can expect the ACC to gain more widespread importance in industry as approaches to systematically develop and nurture analytics capabilities within the organization. Gartner claimed at their Business Intelligence & Analytics Summit 2016 in London that the "BICC is dead" (Duncan 2016) . However, this needs to be refined in that transaction-oriented BICCs may lose importance, while many of them may develop into knowledge-oriented shared service centers – the ACCs.

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