Aalto University

Alen, Ilari; Öhman, Mikael; Kaipia, Riikka; Rajala, Risto

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Ilari Alén[1a], Mikael Öhman[1b], Riikka Kaipia[1c,2] and Risto Rajala[1d]

[1] Dept of Industrial Engineering and Management, Aalto University,
P.O. Box 11000, FI-00076 Aalto, Finland
[1a] ilari.alen@aalto.fi, [1b] mikael.ohman@aalto.fi, [1c] riikka.kaipia@aalto.fi, [1d] risto.rajala@aalto.fi
[2] Dept of Technology Management and Economics, Chalmers University of Technology,
Vera Sandberg's Allé 8 SE-412 96 Gothenburg, Sweden

Abstract

As technology evolves and the amount of available data increases across industries, companies race to develop their analytics capability. This research seeks to understand what constitutes the analytics capability, and how it should be developed in the context of a multinational corporation. For this end, we conduct an in-depth single-case study in a multinational manufacturing company, where we interview 30 informants working with, or dependent on analytics for decision making. Based on the data, we form our conception of the analytics capability by using the Gioia method. We then examine the dynamic nature of the analytics capability through deriving projections based on the data, which allows exploration of on how the capability should be developed and how it will eventually evolve.

We identify 13 dimensions comprising the analytics capability which we group into four categories: Culture, Governance, Methods, and Technology. The analytics capability is deeply rooted in the organizational fabric displaying complex interdependencies within and between categories. Further, the projections highlight the contingent nature of analytics as different analytic ends require different means. Based on the study we conclude that: 1) Evaluating the maturity of the analytics capability on a firm level is not meaningful, but should rather be done on a means-ends basis; 2) The Analytics capability creates a foundation of structural ambidexterity on which dynamic capabilities can be built; 3) Combining the Gioia method with projections in exploratory research is argued to result in more robust conceptualizations of novel phenomena.

Keywords: Data analytics, Analytics capability, Organisational decision making, Gioia method, Projection

1.   Introduction

As organizations seek to build a competitive advantage based on leveraging data, they are developing their analytics capability (Davenport et al., 2001). Part of this pursuit is about creating or leveraging the right technology for turning data into insights, which is reflected in buzzwords such as big data and machine learning. A more profound aspect of this pursuit has been characterized as a paradigm shift in the practice of management, where gut-feeling is replaced by logical reasoning and fact-based decision-making (Mortenson et al., 2015).

Considering the urgency, impact and importance of developing the analytics capability, research on how companies do it, is surprisingly scarce. Maturity models attempt to capture this, but they tend to be poorly documented (Rajterič, 2010), oversimplifying reality while lacking an empirical foundation (De Bruin et al., 2005; Mccormack et al., 2009). Further, they are mostly based on ex post empirical analysis, offering little guidance to companies pioneering the analytics capability in their industry (Mettler, 2011). Further, the unit of analysis of current maturity models is the entire organization, whereas we show that developing the analytics capability is more nuanced, advocating a means-ends approach, rather than an organizational transformation approach. Hence, in contrast to prior research, we seek to provide a multifaceted answer to the research question: *How to organize for the analytic capability?*

We answer this question through conducting an in-depth case study of a multinational manufacturing company, in the midst of developing its analytics capability. In order to grasp the analytics capability, we analyse the interview data using the Gioia method, arriving at a conceptual representation of the analytics capability. We also construct three projections based on interviews and workshops in the case company, which are essentially shared ideas of what the organization should be capable of achieving through analytics. We then reflect these projections against the conceptual representation of the analytics capability, leading us to

question the suitability of organization-level tools (such as the typical analytics maturity model) for development of the analytics capability. Our results indicate that, especially in terms of governance and methods, the analytics capability needs to be developed on a means-ends basis. We also argue that successful development of the analytics capability forms the basis for ambidextrous performance, as it is instrumental in determining the balance between exploration and exploitation. This emerged from the interviews as the analytics capability was on one hand seen as a set of supporting processes, striving to instil efficiency and conformance, and on the other, as a range of exploratory projects, driven by heterogeneous and changing customer needs. Both of these aspects are supported by complementary and partially shared organizational structures and practices, which make up the analytics capability. Based on these insights we conclude that the analytics capability is a complex and organisation-wide capability which develops rapidly and possibly somewhat unpredictably, ideally forming the basis for ambidextrous performance.

2.   Previous Research

The academic discussion lacks consensus on how analytics should be defined (Holsapple et al., 2014; Mortenson et al., 2015). In their synthesis on business analytics research, Holsapple et al. (2014) identify six distinct classes of definitions, where analytics is defined either as a movement; a collection of practices and technologies; a transformation process; a capability set; specific activities; or a decisional paradigm. For the purpose of this research we defined analytics as *all the activities, which transform data into action*, which is arguably even more inclusive than the definition offered by Holsapple (2014, p. 134): "Evidence-based problem recognition and solving that happen within the context of business situations".

On a strategic level, analytics is seen as a distinct capability (Davenport et al., 2001), which firms need to build. With its foundations in the resource-based view (RBV) (Barney, 1991), a capability refers to a firm's ability to achieve its goals by deploying its resources (Amit and Schoemaker, 1993). As capabilities are manifested in the complex interactions of firm's resources (Eisenhardt and Martin, 2000; Teece et al., 1997), they are dependent on the firms resources, but cannot be acquired in the same way as resources (Teece et al., 1997). These principles also hold for the analytics capability, where having tools and technologies (resources) is a necessary, but insufficient precondition of building competitive advantage on analytics (Acito and Khatri, 2014).

Academia has produced an abundance of models for assessing the maturity of Information Systems (IS) and Business Intelligence (BI) (Mettler and Rohner, 2009), which arguably (from their perspective) describe the aspects of the analytics capability, as we have defined it. These maturity models however, lack a widely accepted way of assessing them (Mettler, 2011), and their incomparability (especially in BI) has led to a recommendation not to solely rely on a single model (Rajterič, 2010). The maturity models have also been criticised of being poorly documented (Rajterič, 2010) oversimplifications, typically lacking an empirical foundation (De Bruin et al., 2005; McCormack et al., 2009).

An explicit analytics maturity model is constructed by Cosic et al. (2012), based on a comprehensive review and consolidation of previous research. They build their model based on the theoretical foundations of resource-based view and dynamic capabilities. In doing so, they follow design guidelines defined by Hevner et al. (2004) and the design approach proposed by Becker et al. (2009), with the exception that the model lacks empirical refinement (iterative development) and validation (usage and evaluation) as prescribed by Becker et al. (Becker et al., 2009). Later, Cosic et al. (2015) seek to remedy the first of these deficiencies through conducting a Delphi study where practitioners are asked to evaluate the maturity model. And while this led to slight refinement of their maturity model, it is yet to be used and evaluated.

The extent to which maturity models are able to support the development of the analytics capability has also been questioned with other, empirically grounded maturity models, due to them being based on ex post analysis (Mettler, 2011). And despite recurring calls for empirical research for how to organize for the analytics capability, research on the subject is scarce. Davenport et al. (2001) offer some insights on the subject when discussion whether analytic resources should be centralized, decentralized or outsourced. They (Davenport et al., 2001, p. 126) note that (1) sophisticated modelling and analysis requires high skills and should thus be centralized or even outsourced, (2) when market- or product specific knowledge is required, analysis should be de-centralized and (3) changes in resource positioning are subject to firm cultural orientation.

The knowledge-based view (KBV) of the firm (Grant, 1996), which extends RBV, resonates with the insights above, arguing that positioning is not about where resources are located, but rather where decisions are made. This is based in the argument that organizations are essentially devices for integrating knowledge for value creation (Grant, 1996). Essential for integration is the transferability of knowledge, which determines the organizational structure. When decisions rely on tacit knowledge, decision-making tends to be decentralized (Grant, 2013), While easily codifiable knowledge enables centralized, or even outsourced decision-making (Fransson et al., 2011).

Another relevant extension of RBV is offered by Teece et al. (1997) who note that a fast pace of change in the business environment calls for dynamic capabilities, where resources and capabilities are continually adapted, integrated, and/or reconfigured (Eisenhardt and Martin, 2000; Teece et al., 1997). Dynamic capabilities can be related to organizational structure through organizational learning (Sirmon et al., 2007), highlighting the pursuit of balance between exploration and exploitation (March, 1991). When successful, this pursuit results in what is termed an ambidextrous organisation (Birkinshaw and Gibson, 2004; O'Reilly and Tushman, 2004; Tushman and O'Reilly, 1996), which in terms of structural ambidexterity has been characterized as "project teams that are structurally independent units, each having its own processes, structures, and cultures, but are integrated into the existing management hierarchy." (O'Reilly and Tushman, 2004, p. 79). Ambidexterity is also discussed in terms of contextual ambidexterity, where individual employees divide their time between exploitative and explorative activities (Birkinshaw and Gibson, 2004).

3.   Research Method

The lack of consensus on the definition of analytics not only reflects the novelty of the topic, but also implies a lack of clear boundaries for the phenomenon. Together, these aspects warrant an explorative single-case study (Yin, 2009), with the necessary flexibility, richness and holism for generating understanding of the phenomenon (Miles et al., 2013). Our research question calls for understanding how to organize for the analytics capability, hence choosing a single company, or organization is justified. However, our definition of analytics – activities which transform data into action – is arguably more granular, calling for an embedded unit of analysis (Yin, 2009).

In order to add an embedded dimension of analysis of a conceptually ambiguous phenomena, we use what we term *projections*. In terms of means to ends, projections are desired ends as expressed by the interviewees, to which the scope of means are not yet entirely clear. Inspired by use-cases in software engineering (Jacobson, 1992), we use projections to understand the process of developing the analytics capability in a case where it is still developing. In doing so, we test for within case variance with respect to the research question, highlighting the robustness of our conceptualization of the analytics capability.

In absence of a sufficient a priori theoretical or conceptual foundation, we take a grounded theory approach (Glaser and Strauss, 1999), allowing inductive theory development. This

approach requires a rich understanding of the focal phenomena, which is arguably provided by qualitative data (Eisenhardt, 1989; Gioia et al., 2013; Miles et al., 2013; Yin, 2009), such as semi-structured interviews and field observations. In the analysis of the interview data, we relied on the Gioia-method (Gioia et al., 2013), through which the conceptualization of the analytics capability was derived from the data. The projections were also derived from the interviews, based on explicitly and implicitly expressed "ends" shared by several interviewees, and subsequently validated by the company.

3.1   Data Collection

As per our definition of analytics, translating data into action is arguably something that happens throughout the organization on different levels in the organizational hierarchy, leading to a challenge of "sampling" in choosing whom to interview. In order to find the right interviewees we employed a top-down approach where we identified teams in process of developing the analytics capability, through interviewing the key people of business units, who then gave the name of the lead of teams, who subsequently shared their view on who we should interview next. This iterative process of data collection can be described as snowballing, which is typical for inductive, theory-building analysis (Miles et al., 2013). Aside of providing a comprehensive view of the focal phenomena, this approach also allowed triangulation of data (Meyer, 2001).

The semi-structured interviews were designed to bring out the interviewees own perspective, using open-ended thematic questions (King, 2004). Follow-up questions were used to get more detailed answers on topics which were emerging as important. These semi-structured interviews comprise the primary data for this study, and are summarized in Table 1. While the analysis was done on the primary data, other sources of data were used to enrich context and background of findings. These other sources included notes on meetings, attending on workshops on the topic, case company intranet records, and field notes from informal discussions.

Role	BUS	R&D	IT	Total
Manager	4	3	2	9
Development Manager	3			3
Project Manager	5	1	1	7
Data Scientist	2	2		4
Analyst	4		2	6
Expert			1	1
Total	18	6	6	30

Table 1. The role of and unit of the interviewees.

3.2   Analysis

The inductive qualitative analysis was done according to the Gioia method (Gioia et al., 2013). The Gioia method enables structured analysis of complex phenomena, which is initiated through informant-centric coding of the interview. This phase generates 1st-order concepts using the vocabulary of the interviewees, which gives novel concepts the opportunity to emerge. In second phase of the analysis, 2nd order themes are created by the researcher, as she uses her own words to group and label the concepts emerging in the first phase (Gioia et al., 2013). As the 2nd order themes are based on the researches world-of-view the reasoning logic is not purely inductive, but has also abductive elements (Mantere and Ketokivi, 2012).

The analysis was initiated by open coding the interviews for different statements seemingly related to analytics. The codes were then printed out and clustered on a large sheet of paper, forming the 1st order concepts. During this process, some overlapping codes were merged and in some cases renamed to better describe their content. In the next phase, the 1st order concepts

were further grouped under 13 2nd order themes, in a way which "described and explained the phenomena" (Gioia et al., 2013). Finally, the 2nd order themes were grouped into four 3rd order overarching themes, in an attempt to create a more structured view of the analytics capability. In the findings of this study the thematic codes are referred to as capability dimensions, whereas the overarching themes are referred to as capability dimension groups.

So far the analysis resulted in a static snapshot of the analytics capability, as perceived by the interviewees. In order to answer our research question however, we needed to make projections on whether and how the derived capability was to be adapted, in terms of organizational design, to what was expected from it (Figure 1). The projections were drawn from the interviews data, in which interviewees shared anecdotes about their current work, and how it could be improved. The interview protocol also had a section dedicated to possible projections and future development where the informants could explicitly state their needs and hopes regarding on data analytics. The projections were established by grouping the comments from the interviewees according to the main actors in the projections, and writing a narrative which combined all the characteristics into a comprehensive whole.
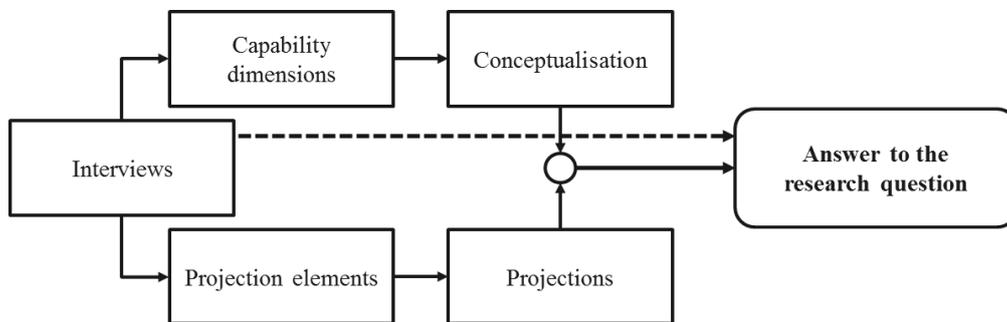

Figure 1. The analysis of interviews.

The relevance of the resulting projections was then validated by a senior company representative in a meeting, based on which three projections were deemed most promising in terms of technical and business feasibility. As these projections arguably represent a likely path of development in terms of what the organization will be capable of, we argue that any deviation in how these projections unfold in terms of the derived analytics capability outlines whether or not the capability is manifested in uniform structures and processes throughout the organization.

3.3   Case Description

The case company is a global equipment manufacturer, with a substantial part of its revenue coming from business to business services such as maintenance and modernizations. With its headquarters in Finland, the company has operations in over 60 countries and presence in around 100 countries, with global, regional and local organizations. The company has a long history of geographic expansion through acquisition of local companies and local "country organizations" retain strong control over their operations. Aside of corporate functions, the global organization seeks to support local organizations in improving quality and efficiency.

The case company is formally described as a matrix organisation, but due to the high level of expertise of its employees, and a strong process- and project-centric nature, its employees tend to describe it as a network-centric organisation. The case company is well-known for its strong R&D capabilities, and has been several times been referred to as the most innovative company in its field. In 2016, the company merged its R&D and IT functions to one technology division led by the CTO, answering to the CEO of the company.

At the time of the research, there was no centralised analytics function in the company, and every (global) business line had their own analytics initiatives and projects. The development

of the analytics capability was mainly driven by the global organization by providing tools, consultation, and training to regional and local organizations. Approximately a year before the research was conducted, the case company formed a strategic partnership with a multinational technology company with objective of speeding up development of capabilities related to digitalisation. The technology company is substantially larger than the case company and has several simultaneous development projects in the fields of business intelligence, cognitive analytics, and Internet of Things.

4. Findings

We begin this section by presenting the analytics capability, such as it was derived through analysing the interviews through the Gioia method. We then present the three projections synthesized from the data, followed by the main section of the analysis, where we contrast the projections against the conceptualization of the analytics capability, shedding light on *How to organize for the analytics capability*.

4.1 The Analytics Capability

Based on our analysis we identified 13 themes which comprise the analytics capability, here labelled capability dimensions (Table 2). These dimensions form a broad and intertwined whole, through which any given analytical activity can be understood. The capability dimensions were further categorized into four groups spanning from culture to technology, forming what could be considered a continuum ranging from fairly "vague" organizational characteristics to "hard" data and tools, affecting analytics. The dimensions in the *Culture* group are fundamental, and present in all analytics activities, while *Governance* holds dimensions essential to firm-wide coordination of the analytics capability. The *Methods* group holds dimensions related to making analytics part of the daily way of working, while the *Technology* group holds more concrete dimensions such as tools and data.

Group	Dimension	Description
Culture	Data-driven decision making	The mind-set of people is changed by management demanding logical reasoning in decision making. People have healthy trust on data, but understand the uncertainty behind analytical results, and they look a big picture in the process, not only one KPI.
	Actionable results	The outcome of analytics should cause either a positive action or prevent a negative action to happen. Results need to be accurate, but more important is to ensure a decision maker understands what can be done with a results, and can trust on the outcome.
	Agile development	Development of analytical solutions is done incrementally in close collaboration with the users. Targets are defined together so that the purpose of a solution is clear. All parties should understand they are working with new topics and therefore some uncertainties are present.
Governance	Strategic coordination	Analytics needs to be coordinated and aligned across a corporation. Strategy is seen as a guidance giving a direction and certainty, but not limiting the work. Strategic aspects also take into account the time span of the development, business tend to work in quartiles and R&D in years.
	Responsibilities & rights	In collaborative work responsibilities between people should be clear: a data creator should be responsible for data created, a data scientist for her model, and analyst for results, and the decision-maker for actions taken. Division of work between functions should be clear. User rights ensures safety in sensible data.

	Partnership management	There should be understanding how to operate with strategic partners, technical partners, and partners creating insight. Experiences should be shared and learnings gathered.
Method	Unified communication	A common vocabulary is essential for effective collaboration. Everyone should know the roles of individuals, teams, and systems. A common way to share results between analysts and decision-makers ensures the proper use of insight.
	Knowledge & competence management	Data and projects are explicitly defined. Knowledge is shared also in informal communication. Formal trainings are used to increase the competencies of individuals and for creating new capabilities. There should be a register of people working in analytics.
	Project management	Projects are a tool for knowledge creation. Requirements engineering, expectation management, and staffing for a project should be analytical. There should be learnings from past projects to decrease the amount of repetitive work done.
	Process management	The benefits of new knowledge is gained with processes. Processes increase efficiency by easing the work done. With processes analytics could become a part of everyday business, i.e. built-in to the way of working.
Technology	Tool management	The variety of analytical tools need to be orchestrated so that projects and processes find the proper tools for their usage. Tools should have similar user interfaces for easy usage. Balancing is needed also to find the right fit for purpose and modifying the process/project for the tool.
	Data creation	The creation phase is vital for the usage of data. Two aspects are critical: data should be recorded without distortions with easy interfaces and there should be no room for subjective perceptions. Data should be seen as a valuable asset and a part of employees everyday work.
	Data management	Data integration needs to be seamless. Data needs to be accessible fast and extraction of data should not distort the operational systems. Sufficient documentation of the data is needed for the process use of data.

Table 2. Capability dimensions identified from interviews.

4.2   Projections

The projections of this study were constructed by combining comments about the possible use of analytics. Even though the sample of informants was broad, there were some recurring themes regarding the projections. First, the informants wanted to use more customer insight in their operations, which is aligned with the customer-centric corporate strategy. Second, many interviewees thought that sales data should be used more in R&D, thus the decisions would be made using more data than just personal perceptions from sales people. Third, many informants had a relatively simple wish for easier use of data from multiple sources. This resulted in the construction of three projections, representing different aspects of business:

1. R&D Project prioritization – R&D project prioritization could be made more market driven, and project staffing and budgeting could be improved. This could be done through combing market research data with analysis of product sales data and feedback from field technicians, deriving insight into current and future development needs.

2. Field Optimisation – Service quality and efficiency could be improved through a system monitoring and predicting the condition of equipment. This would enable sending proactive service needs to field technicians, while optimizing technician routes based on their current location, taking into account technician skills, and the spare parts they have with them or they can pick up on the way. The customer would also be notified about the situation and given an estimated time of repair. The system could also support field technicians in troubleshooting.
3. Sales Optimization – Improving focus of sales efforts and enabling advanced value propositions. (a) In the basic case, analytics would be leveraged in recognizing whether a customer is just using the tender to lower the price of an existing contract. The tool would help the sales person by giving an optimal customer specific configuration, calculating the costs of manufacturing, delivery and installation costs and proposing a customer individualized price with appropriate discounts. (b) In a more advanced case, analytics would be leveraged in estimating maintenance costs, giving a total cost of ownership, enabling advanced value propositions, such as offering a leasing contract (machine-as-a-service). Such a tool would also enable a sales person to discuss customer and configuration specific expected performance of the equipment and typical pain points. This could be done based historical data of similar setups combined with simulated usage of the proposed configuration.

4.3 The Analytics Capability in Light of the Projections

Based on the projections we discuss the required organizational structure in terms of the analytics dimensions presented above. We discuss organizational structure in terms of centralization / de-centralization of decision-making and responsibility, with three possible structures; centralised function, decentralised functions, and local functions. Here, the centralised function is to be understood as a team who has the responsibility of a dimension, the decentralised function is to be understood as product lines or separate global functions being responsible for a dimension, while the local function is to be understood as the responsibility laying with country units. Figure 2 illustrates the result of the analysis, showing that for the majority of dimensions the responsible entity is the same for all projections. However, most importantly there are also differences. Both are discussed in more detail below.
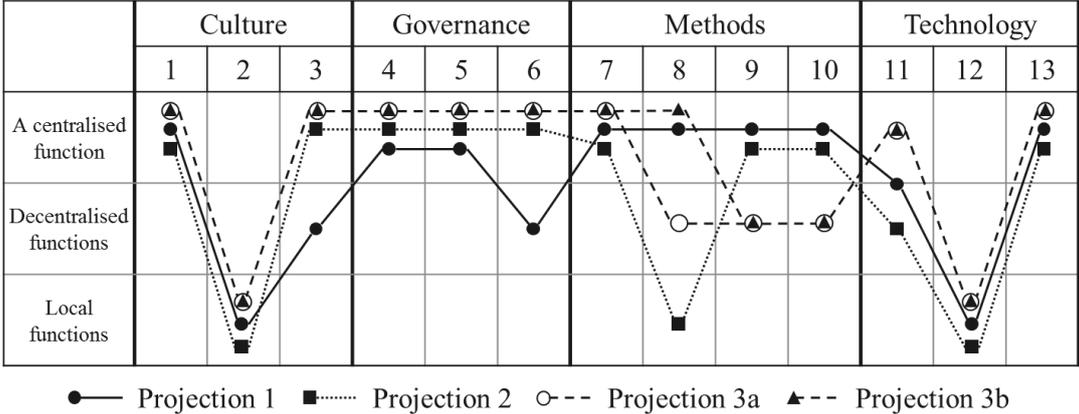

Figure 2. The analytics capability dimensions in projections.

Data-driven decision making – The understanding of the data-driven decision making and how it creates actions should be coordinated centrally to achieve common understanding and mind-set, and realistic expectations of results analytical models can deliver. A centralised function is in better position to define and shape the mind-set of people through communicating the basic

principles. In decentralized and local functions people should not be stressed with analytics initiatives, but they should acknowledge the need to back up their decisions with data. They should also understand what is expected of them when communicating with centralized and global functions, and they have to be committed to the change if analytics is to become an integrated part of everyday working near customers.

Actionable results – The responsibility for creating actionable results from analytics can only be where analytics is applied. On the other hand, results translated to concrete actions mainly on local level, implying that a centralised function cannot be responsible of monitoring that everyone creates impact with the analytics. The informants pointed out that the organisation has a long tradition being pragmatic and action-oriented, a mind-set which needs to be instilled in analytics activities.

Agile development – Due to agile development being understood in many different ways in the case company, the best solution would be to make it the responsibility of a centralised function, which is tasked to ensure that there is a shared view of the meaning of agile development in the organisation. R&D however was argued to operate in a different pace requiring more long-term thinking. Therefore the first projection highlighted the need for R&D to be able to define its own agile development without centralised coordination.

Strategic coordination – As the name implies this dimension should be the responsibility of a centralized function. Notable is that this function should support two-way communication; helping top-management gain a bottom-up understanding of the current state of analytics, while communicating and implementing a top-down analytics strategy. The centralised function can and should rely on existing structures for communicating strategic initiatives.

Responsibilities & rights – organizational responsibilities related to analytics should be defined by a central function, as well as the roles related to analytics. This work needs to be done together with business lines so that a common agreement is reached by the basis of current situation.

Partnership management – Partnerships in analytics are seen as complex projects without clear goals putting the focus on content. Here non-central functions are coordinated by a centralised team with insight gathered from the entire organisation. However, projection 1 offers a deviation where partnership management should be decentralised due to the experimental nature of R&D. Development cycles are longer and the required partners might be different compared to the operative field work or sales, and therefore the responsibility should be decentralised in the R&D function. There should however be active communication with the centralised function, and R&D learnings from working with partners should be spread across the organisation.

Unified communication – The language used when communicating through and about analytics should be unified through the communication of centralized functions. This can be expected to be a bi-product of centralized strategic coordination and introduction of a mind-set of data-driven decision-making.

Knowledge & competence management – In the case company analytics has so far mostly been developed by pioneering individuals, who develop their competencies by their own. The informants thought, that a centralised competence management would help to finding competent people and developing them further. The projections again offer some deviations in this dimension as projection 2 highlighted that local knowledge needs may differ central ones, creating a need for local knowledge and competence management. Projection 3b on the other hand required knowledge from many different parts of the organization, implying knowledge management should be centralised.

Project management and *Process management* – The case company drives development with global projects and has a strong process culture, leading to the view that these dimensions should be the responsibility of a centralized function. This view was further emphasized by

interviewees working doing analytics, where they share several cases where they had found out that someone was working on a similar project, or a similar project had already been done. However, in projection 3 (a&b) decentralized global responsibility was preferred, as the sales function is working close to customers and needs to have the flexibility to respond to the changes in markets.

Tool management – The centralised function should be responsible of analytics software and keep track of solutions made by these software. The decentralised units are responsible of defining the requirements for the tools together with the country units to ensure a proper tool used for a right purpose. Projection 1 highlighted that R&D uses more specialised software compared to other functions, and therefore need to retain some of the responsibility own decentralised global function. On the other hand, common software is better to be controlled by a centralised team as management and sourcing of user licenses is cheaper in one place.

Data creation – In all projections the majority of required data is created in local functions, which means that responsibility for creating data should remain there.

Data management – All projections indicate that data management should be centralized in order to standardize data, ensuring the data is comparable across the organisation. A centralised function should ensures data is collected following uniform principles in every place and phase, so that it can be used globally.

5. Discussion

Prior research on analytics has been multifaceted, lacking a uniform definition of the term itself (Holsapple et al., 2014). In contrast to prior research, which has tended to focus on technical aspects of the analytics capability (Acito and Khatri, 2014; Wamba et al., 2017), this research takes a wider, organizational perspective, laying the groundwork for understanding analytics as an organizational capability. In doing this, this study provides empirical grounding to a perspective which has previously, to the best knowledge of the authors, only been conceptually explored (cf. Cosic et al., 2015, 2012), or based on anecdotes (cf. Davenport et al., 2001). Consequently, aside of the empirically grounded conceptualization itself, we claim the present study makes two distinct contributions in understanding the analytics capability.

First, we find that deviations arising from contrasting the projections against the conceptualization of the analytics capability indicates that building the analytics capability is not a straight forward process, which is to be centrally controlled, but rather one with evolutionary and exploratory aspects, to be developed by different internal and potentially also external stakeholders. This questions the utility of evaluating the maturity of analytics on a firm level, offering an explanation to prior research which concludes that maturity models tend to be oversimplified (De Bruin et al., 2005; Mccormack et al., 2009).

Second, we find that in projections where analytics is to support exploratory activities, or reacting to changing markets, de-centralized capability-development was seen as necessary. This finding not only highlights the dynamic and evolving nature (Teece et al., 1997) of the analytics capability itself, but also that the analytics capability serves as a foundation, on which new dynamic capabilities are built. This is reflected in how informants saw the analytics capability supporting organizational learning, implying that the analytics capability is instrumental in creating structural ambidexterity, serving as an enabler of ambidextrous performance.

Further, we argue that a third contribution lies in the novel methodological approach employed by the study, where explorative research combining a Gioia analysis with projections derived from data, is able to create a dynamic understanding of an emerging phenomena. In terms of exploratory research and new theory development we argue that this approach enables more robust conceptualizations of new phenomena.

5.1 Practical Implications

This research shows that although technology plays and important role in building the analytics capability, organizational factors in terms of culture, governance and methods are equally important and highly complementary. While there seems to be one best way for building some of the aspects of the analytics capability, such as centralized data management and championing of a data-driven decision-making mind-set, some aspects are more ambiguous in this respect. Especially more explorative functions are argued to benefit from retaining partial control of developing the analytics capability for their purposes.

This implies that firm-level maturity models may serve as poor guidance when developing the analytics capability, as much of the analytics capability should be developed on a means to ends basis. Further, the analytics capability is instrumental in facilitating and thereby balancing exploration and exploitation. This implies that the analytics capability serves as a foundation for competitive advantage through enabling fast adaptation in changing business environments.

5.2 Limitations and Further Research

The conducted study is of explorative nature, and its single-case design does not produce readily generalizable results. While we argue that the embedded projections improve the robustness of the derived conceptualization, further research is needed to verify, challenge, refine and extend the present findings. Minding that the analytics capability is a fairly novel and continuously evolving concept, understanding of it could be furthered through 1) exploring capability development through a within industry multiple case-study, or 2) exploring differences in capability structure through or a cross-industry multiple case-study with industries subject to different levels of exploration.

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