International Journal of Business Intelligence Research
Volume 11 • Issue 1 • January-June 2020

13 Organizations' Attempts to Become Data-Driven

Mikael Berndtsson, University of Skövde, Skövde, Sweden
https://orcid.org/0000-0001-8362-3825

Christian Lennerholt, University of Skövde, Skövde, Sweden

Thomas Svahn, Advectas AB, Malmö, Sweden

Peter Larsson, Advectas AB, Malmö, Sweden

ABSTRACT

Becoming a data-driven organization is a vision for several organizations. It has been frequently mentioned in the literature that data-driven organizations are likely to be more successful than organizations that mostly make decisions on gut feeling. However, few organizations make a successful shift to become data-driven, due to a number of different types of barriers. This article investigates, the initial journey to become a data-driven organization for 13 organizations. Data has been collected via documents and interviews, and then analyzed with respect to: i) how they scaled up the usage of analytics to become data-driven; ii) strategies developed; iii) barriers encountered; and iv) usage of an overall change process. The findings are that most organizations start their journey via a pilot project, take shortcuts when developing strategies, encounter previously reported top barriers, and do not use an overall change management process.

KEYWORDS

Analytics, Business Intelligence, Change Management, Strategy

1. INTRODUCTION

Several organizations have a vision to become data-driven (Davenport & Bean, 2018; Halper & Stodder, 2017; Watson, 2016), since those type of organizations are likely to capitalize on business insights more frequently than organizations that are not data-driven (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Halper and Stodder (2017) classify an organization as data-driven "when it uses data and analysis to help drive action—even if that action is a deliberate inaction." In theory, data-driven organizations can apply data-driven decisions for all types of analytics (descriptive, predictive, prescriptive), and all types of decisions (operational, tactical, strategical). In practice, we assume that most organizations aim for a subset of combinations of analytics and decisions.

Managers have taken several steps to initiate transformations to a data-driven organization, by introducing mantras such as - business insights are based on data and not opinions - into strategy documents, held large kick-off events, educated employees in Self-Service Business Intelligence (SSBI) tools, and hired data scientists and AI-programmers. Despite these good intentions, most of the organizations still struggle and few of them seem to reach their vision. In two recent surveys (Bean & Davenport, 2019; Halper & Stodder, 2017) roughly 30% of the organizations had made a successful shift to be data driven. The other organizations struggled with their barriers or had not

DOI: 10.4018/IJBIR.2020010101

started to move towards a data-driven culture. According to Halper and Stodder (2017), the biggest barrier to being data-driven was "lack of business executive support/corporate strategy" (42% of 264 respondents), and the most frequently mentioned step managers took to develop a data-driven culture was "make the case to corporate leadership to invest in BI and analytics" (57% of 230 respondents). In response to the low share of organizations that make a successful shift to become data-driven, Davenport and Bean (2018) suggested that organizations "… need more concerted programs to achieve data-related cultural change".

Change management (Moran & Brightman, 2001; Todnem By, 2005) has previously been identified as a success factor for implementing business intelligence systems (Olszak & Ziemba, 2012; Pham, Mai, Misra, Crawford, & Soto, 2016; Yeoh & Koronios, 2010). As the area of business intelligence is closely related to data-driven organizations and analytics, change management has also been suggested in the literature (Berndtsson, Forsberg, Stein, & Svahn, 2018; Forbes-Insights & EY, 2015) as an enabler for establishing a data-driven organization. In a survey of 564 senior executives, conducted by Forbes Insight and EY, 59% of the respondents that considered themselves as top-performing, claimed that change management was "extremely important" to the organizations' overall analytics initiative (Forbes-Insights & EY, 2015). Hence, change management has an important role to play when organizations intend to scale up their usage of analytics. However, none of the sources provide any details on how such a road map or program, inspired by change management may look like.

The objective of this paper is to investigate how 13 organizations started their journeys towards becoming data-driven, given previously reported barriers and potential usage of change management as an enabler. This paper is also a response to the recommendation by Arnott and Pervan (2014), to increase the usage of case studies within the field of decision support systems, as an approach to improve the relevance of conducted research.

In the remainder of this paper, we present a brief introduction to data-driven organizations and related barriers. Thereafter, we present our research approach. In the succeeding sections, we present our findings. Finally, related work and conclusions are presented.

2. BACKGROUND

2.1 Data-Driven Organizations

The concept of collecting and analyzing data in the context of an organization is not new. According to Power (2007), the implementation of computerized Decision Support Systems (DSS) can be traced back to the mid-1960s. A genealogy for the DSS field for 1960–2010 is provided in (Arnott & Pervan, 2014), and as of the 2010s, there were two areas in the DSS field that received much attention: knowledge management-based DSS, and business analytics. The former field has its roots in knowledge management, organizational learning, and AI. The latter area is rooted in data warehousing, database theory, negotiation support systems, and group support systems. As decisions in data-driven organizations can span all types of analytics (descriptive, predictive, prescriptive), data-driven organizations have a DSS that overlaps both knowledge management-based DSS, and business analytics.

Sample definitions of data-driven organizations and data-driven cultures are provided in Table 1. What is common among these sample definitions, is that they all share an underpinning process of i) collect data, ii) use analytics to derive insights, and iii) make a decision based on derived insights.

McAfee and Brynjolfsson (2012) investigated 330 companies and discovered:

The more companies characterized themselves as data-driven, the better they performed on objective measures of financial and operational results. In particular, companies in the top third of their industry in the use of data-driven decision making were, on average, 5% more productive and 6% more profitable than their competitors.

Table 1. Sample definitions

Reference	Definition
(Anderson, 2015)	A true data-driven organization is a data democracy and has a large number of stakeholders who are vested in data, data quality, and the best use of data to make fact-based decisions and to leverage data for competitive advantage.
(Berndtsson et al., 2018)	A data-driven culture is characterized by a decision process that emphasise testing and experimentation, where data outweighs opinions, and where failure is accepted –as long as something is learnt from it.
(Buitelaar, 2018)	Data-driven organizations can be best characterized by their desire to turn data into action and their organizational approach.
(Halper & Stodder, 2017)	… an organization is data-driven when it uses data and analysis to help drive action—even if that action is a deliberate inaction

Citations to the previous quote have frequently been mentioned in the literature and in business presentations, as one of the reasons why organizations want to become data driven. Furthermore, data-driven decision-making has also been mentioned in the context of Big Data (McAfee & Brynjolfsson, 2012) and Business Intelligence and Analytics (Chen, Chiang, & Storey, 2012; Davenport & Harris, 2017; Wixom & Watson, 2010).

The work of Anderson (2015) provides examples of what a data-driven organization looks like in practice, and also provides a template for vision statements. The following vision categories for a data-driven organization are suggested (Anderson, 2015):

- **Strong leadership**, where leaders champion the idea that data is a strategic asset, that is very important to have in place when making informed decisions.
- **Open and trusting culture**, which implies broad access to a set of coherent data sources. In addition, analysts are assumed to proactively reach out to various departments and collaborate.
- **Self-service analytics culture**, where most of the time is spent on ad-hoc analysis and predictive analytics. Most of the standard reports are automated.
- **Broad data literacy**, implies that employees have strong analytical skills, know how to interpret graphs, and share their insights.
- **Objective, goals-first culture**, implies that the organization has written down a clear vision for its direction.
- **Inquisitive, questioning culture**, implies that colleagues should not be afraid to ask for data that backs up expressed opinions, and
- **Testing culture**, where the norm is to frequently run experiments to test ideas.

The concept of analytics is frequently used within the context of data-driven organizations and data-driven decisions. According to Watson (2013), analytics can be categorized into: i) descriptive analytics (what has occurred), ii) predictive analytics (what will occur), and iii) prescriptive analytics (what should occur). Traditional business intelligence, with a data warehouse solution, relies on descriptive analytics, whereas advanced analytics (predictive analytics, prescriptive analytics) relies on solutions from areas such as data mining, and artificial neural networks (Turban et al., 2015). A similar taxonomy of analytics is provided in (Delen & Ram, 2018).

According to Davenport (2018), analytics can be divided into four eras of analytical focus:

- **Analytics 1.0,** an era dominated by traditional business intelligence and descriptive analytics.
- **Analytics 2.0**, an era that focused on using analytics in the context of big data.

- **Analytics 3.0**, an era in which traditional organizations start to use big data and analytics, and develop products that are based on data and analytics.
- **Analytics 4.0**, an era where AI-technologies are adopted on a wider scale within organizations.

An organization can be considered to be data-driven, regardless of which era it might belong to. The key aspect is that an organization use analytics on collected data to make decisions, and the decision making culture adheres to, e.g., the vision categories suggested in (Anderson, 2015). Hence, an organization that has implemented the latest AI-tools, but not managed to change its culture for making decisions, is not a data-driven organization. The exception to this rule is an organization that heavily relies on automated decisions.

Related maturity models in the literature have primarily focused on maturity models for business intelligence and analytics, e.g. (Davenport & Harris, 2017; Eckerson, 2009; Halper & Stodder, 2014; Lahrmann, Marx, Winter, & Wortmann, 2011; Lismont, Vanthienen, Baesens, & Lemahieu, 2017). We have come across one maturity model that explicitly targets data-driven organizations (Buitelaar, 2018). The maturity model for data-driven organizations suggested by Buitelaar (2018) consists of five stages (reporting, analyzing, optimizing, empowering, and innovating), and ten dimensions (data, metrics, skills, technology, leadership, culture, strategy, agility, integration, and empowerment).

2.2 Barriers

Barriers to establishing a data-driven organization have previously been reported in three well-known surveys: MIT Sloan survey (LaValle et al., 2011), TDWI survey (Halper & Stodder, 2017), and Big Data Executive Surveys 2017-2019 (Bean & Davenport, 2019; Davenport & Bean, 2018; NewVantagePartners, 2017, 2018, 2019). Respondents from these surveys are mainly C-executive decision-makers such as managers, business/IT executives, chief data officers, and chief analytics officers.

The top three barriers and percentages of respondents that mentioned the barrier from each survey were:

MIT Sloan survey (LaValle et al., 2011)[1]:
- ◦ Lack of understanding of how to use analytics to improve the business ~38%
- ◦ Lack of management bandwidth due to competing priorities ~34%
- ◦ Lack of skills internally in the line of business ~28%

TDWI survey (Halper & Stodder, 2017):
- ◦ Lack of business executive support/corporate strategy 42%
- ◦ Difficulty accessing relevant data 37%
- ◦ Lack of skills 34%

The Big Data Executive Surveys have over the years slightly changed the wording and grouping of barriers in their surveys, towards more general abstract wordings. Hence, for the purpose of this work, we chose to use the results from the survey from 2017, as it is more fine-grained in terms of enumerated barriers. As a comparison, insufficient organizational alignment is the top barrier in 2017 as well in the survey for 2019. Barriers from the 2017 survey (NewVantagePartners, 2017):

- Insufficient organizational alignment 43%
- Lack of middle management adoption and understanding 41%
- Business resistance or lack of understanding 41%

The top three barriers from each survey share some similarities and can be grouped into three categories, as seen in Table 2.

Barriers related to the category a*nalytics vs business* are barriers that indicate that employees (of all types) lack the necessary knowledge and skills to use analytics to adopt a data-driven culture in their daily work. Barriers from all three surveys are represented in this category.

Barriers related to the category *management* can be further divided into lack of support from senior management and resistance from middle management. To some degree the management barriers can appear due to lack of knowledge, i.e. what are the benefits of a data-driven organization, which in turn can result in situations where senior management view a move towards a data-driven organization as yet another buzz-word field that is competing for resources. Barriers from all three surveys are represented in this category.

The *data* category has only one barrier and compared to the other barriers, it is the only barrier that is more on the technical side.

For the purpose of this paper, we will use the barriers described in succeeding subsections.

2.2.1 Lack of Understanding and Business Resistance

The barriers (1) Lack of understanding of how to use analytics to improve the business, and (5) Business resistance or lack of understanding, are grouped together under the heading of lack of understanding and business resistance. The barriers of (1) and (5) appear when employees see the change to be more data-driven either as an area that is hard to understand, or a change that will challenge their position.

2.2.2 Lack of Skills

The barriers (2) Lack of skills internally in the line of business, and (3) Lack of skills, are grouped together under the heading of lack of skills. The barriers of (2) and (3) appear when there is a mismatch between the current skills of the employees and the envisioned required skills, for working within a data-driven organization.

2.2.3 Insufficient Organizational Alignment

According to Sender (1997), organizational alignment "is the degree to which an organization's design, strategy, and culture are cooperating to achieve the same desired goals." Thus, insufficient organizational alignment is an indication that the senior management's vision and direction for moving towards a data-driven organization, is not in line with what happens in practice in the workforce. The reasons for the lack of alignment are several. One reason is that no supporting strategies have been developed for how analytics should be used in the line of business. Hence, employees do not know how to adjust their daily work. Another reason is that employees do not see the buy-in to adjust their work to a data-driven approach since their salary is based on other parameters.

Table 2. Main categories of barriers to adoption of a data-driven organization

Category	Barriers
Analytics vs business	(1) Lack of understanding of how to use analytics to improve the business (MIT Sloan) (2) Lack of skills internally in the line of business (MIT Sloan) (3) Lack of skills (TDWI) (4) Insufficient organizational alignment (Big Data Executive Survey) (5) Business resistance or lack of understanding (Big Data Executive Survey)
Management	(6) Lack of management bandwidth due to competing priorities (MIT Sloan) (7) Lack of business executive support/corporate strategy (TDWI) (8) Lack of middle management adoption and understanding (Big Data Executive Survey)
Data	(9) Difficulty accessing relevant data (TDWI)

2.2.4 Lack of Senior Management Support

The barriers (6) Lack of management bandwidth due to competing priorities, and (7) Lack of business executive support… are grouped together under the heading of lack of senior management support. The barriers of (6) and the first part of (7) appear when a data-driven initiative needs to attract funding and approval from senior management, regarding launching an organization-wide project.

The lack of interest from senior management is an indication, that moving towards a data-driven organization is not an urgent and convincing topic on the agenda for senior management. In other words, the supporting business case and potential profits are not convincing enough. From the senior management perspective, a move towards a data-driven organization is yet another topic that is competing for attention and resources.

2.2.5 Lack of Corporate Strategy

The barrier (7) Lack of corporate strategy, appears when no organization-wide supporting strategies are developed. A general vision, e.g., we should be data-driven, might be in place, but no supporting strategies for how to move towards a data-driven organization are developed. Lack of corporate strategy can also appear when partial supporting strategies have been developed, e.g., strategies have been developed for introducing a new technical platform, but strategies have not been developed for how employees should use the new technical platform.

2.2.6 Lack of Middle Management Adoption and Understanding

Resistance from middle management, have previously been reported in (McShea, Oakley, & Mazzei, 2016). A data-driven organization will challenge any middle manager that often makes decisions based on gut feeling. Furthermore, as highlighted by (Di Fiore, 2018), introducing AI-based tools into decision making, is likely to shift the decision power closer to the front line. Hence, a move towards a data-driven approach to decision making is likely to stir up emotions in middle management, since it threatens their skills and positions. Resistance from middle management, is an indication that there is no buy-in for the middle management to become data-driven.

2.2.7 Difficulty Accessing Relevant Data

The barrier *(9) Difficulty accessing relevant data* can appear in at least three situations. First, it can appear when new types of analytics (e.g. data mining) are introduced that require access to previously not used data, or when old data is analyzed in another way than it was originally intended for. Finally, it can appear if the surrounding decision-making processes change. For example, a shift from frequently submitting requests the IT-unit to deliver data that can be further analyzed, to a culture that is more self-service, requires easy and timely access to relevant data for decision-makers. In our experience, few interfaces to internal databases in an organization are designed with a self-service approach in mind to access data.

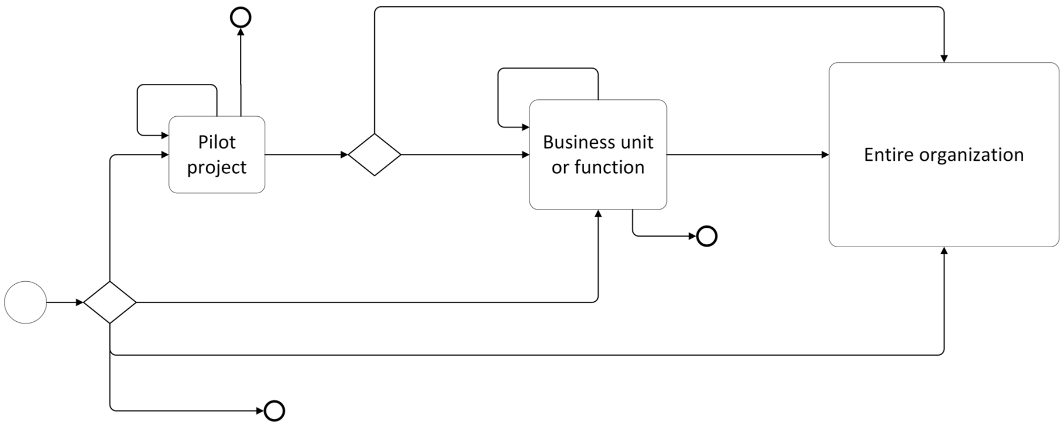
3. RESEARCH APPROACH

In this article, we will use two frameworks for analyzing our collected data. The frameworks are shown in Figure 1 and in Figure 2.

Organizations that intend to scale up their usage of analytics and become data-driven have several paths in front of them. In general, there are four main paths to take:

- **Path 1**. Do pilot projects on analytics, then scale up the analytics initiative to a business unit or business function, before making a final push to scale up the usage of analytics to the entire organization.

Figure 1. Different paths to take when scaling up the usage of analytics

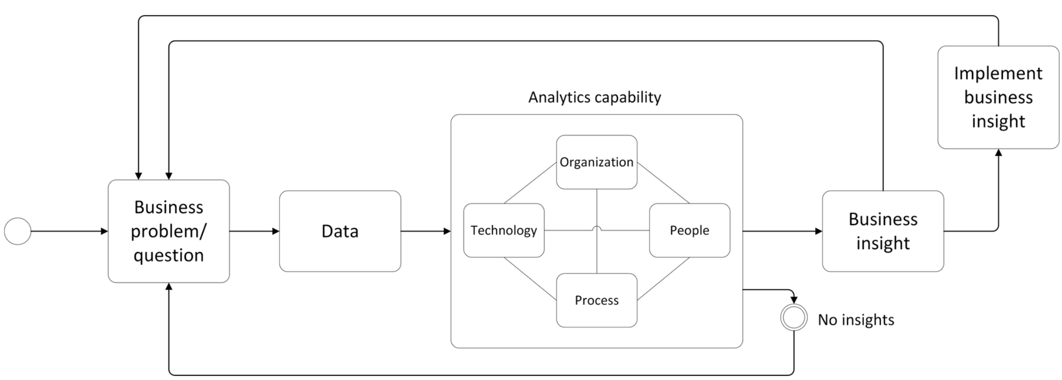


- **Path 2**. Do pilot projects on analytics, and then scale up the analytics initiative to the entire organization.
- **Path 3**. Scale up the usage of analytics to a business unit or a business function, and then scale up to the initiative to the entire organization.
- **Path 4**. Scale up to the usage of analytics to the entire organization, without doing prior pilot projects or tests on business unit/function.

In addition to the four main paths, there are variations of the paths that include loops of pilot projects, termination of initiatives, etc.

The sample analytical framework in Figure 2 describes, on a conceptual level, how organizations use analytics to derive insights. First, a business problem or business question must be present, before relevant data is collected, and prepared for analysis. In order to analyze the data, organizations use their analytical capabilities, which can be divided into: i) technology (and tools), ii) organization of analytical competence, e.g. AI-unit, BICC, iii) decision process, and iv) people, that are involved when analyzing the data. The outcome of applying analytics to the collected data is: i) no insights can be drawn from the collected data, ii) business insights can be drawn, but no action is taken, or iii) business insights can be drawn, and actions are taken to implement the insights. In comparison

Figure 2. A sample analytical framework (adapted and extended from (Vidgen, Shaw, & Grant, 2017)



to the framework of (Vidgen et al., 2017), we add a component for "Business problem / question", and the three potential outcomes of performing analytics.

In this paper, we investigate four research questions:

- **What path do organizations take when they start to scale up their usage of analytics, in order to become more data-driven?** A typical recommendation in the literature (Franks, 2012) is to start small – with a pilot project (paths 1-2) if an organization wants to evaluate the potential benefits of applying more advanced forms of analytics. Furthermore, Davenport, Harris, and Morison (2010) suggested that organizations that already have CEO sponsorship can do the "full steam ahead" path, and bypass pilot projects (paths 3-4).
- **What type of supporting strategies for becoming more data-driven are developed?** According to Kotter (2012), a clear vision with supporting strategies are mandatory for any successful change transformation. Similar statements can also be found in the literature on data-driven organizations (Anderson, 2015; Watson, 2016). At the same time, lack of an overall corporate strategy, and insufficient organizational alignment are frequently mentioned as top barriers in the literature.
- **What type of top barriers have the organizations encountered?** Several barriers to become data-driven have been reported in the literature (Halper & Stodder, 2017; LaValle et al., 2011). The aim of this question is to investigate if the top barriers enumerated in Section 2.2 also appear in our investigation.
- **To what degree has an overall change management method been used?** Change management has been suggested as an important enabler for establishing a data-driven organization (Forbes-Insights & EY, 2015). The aim of this question is to investigate if the involved organizations have used change management methods in their transformation.

We use a case study approach (Yin, 2014), since the investigation is exploratory, and investigates, what path organizations take, and what type of strategies that are developed, etc. Furthermore, we will explore multiple cases, and then draw conclusions from them. Choosing multiple cases may affect the resulting outcome in terms of generalizability since it supports the validity of the result while avoiding potential biases (Leonard-Barton, 1990; Pan & Tan, 2011).

Data collection. Data has been collected from 13 organizations during 2016-2019, which had initiated projects with respect to improving their usage of analytics on an organization-wide scale. The organizations (named A-M) are anonymous in this investigation, and they operate in a range of different businesses such as retail, transportation, bank, insurance, and manufacturing (see Appendix A). The number of employees ranges from 100 up to 14 000. Vision and strategy documents (Word files, PowerPoints) were collected from these organizations.

Interviews were done in three organizations (A, J, K). Organization A is within transportation with around 4500 employees. We interviewed a digital transformation officer, who was driving the change to be more data-driven, and a manager for global marketing, that represented the end-user perspective. We asked questions about the current status of their project, and the barriers they had encountered. Each interview lasted approximately one hour. We did these interviews at organization A, since they had, at the time of data collection, the most ambitious change project out of the investigated organizations. Organization A had an explicit focus on scaling up the usage of advanced analytics and AI in the organization.

Both organizations J and K are within bank and finance with around 2000-6500 employees, and they were interviewed since they had an explicit focus on scaling up their usage of self-service business intelligence. We interviewed in total of 15 respondents who have participated in the project of implementing and using SSBI in the organizations J and K. Their roles ranged from vice president, consultants, analysts, architects, SSBI evangelists, BI developers, business improvement manager, strategists, business controllers, IT specialists, managers, to end-users. Each interview lasted approximately one hour, and we asked the respondents questions about their experiences with implementing and using SSBI.

Finally, we had access to data science consultants that had been involved in pilot projects in organizations A-C, and H-I. These interviews lasted approximately 30 minutes each, and they provided valuable insights into any barriers the organizations had encountered when conducting pilot projects.

4. FINDINGS

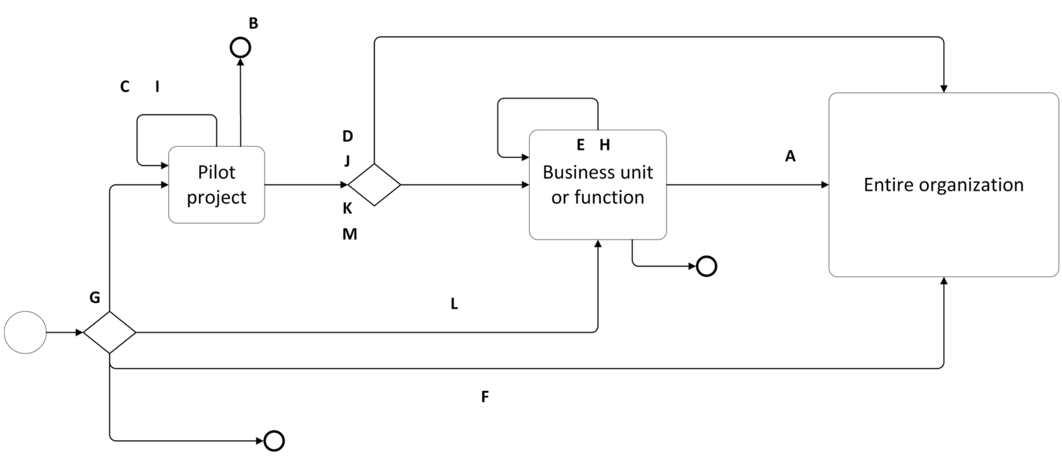
4.1 What Paths do Organizations Take?

The positions of the organizations in Figure 3, reflect their current estimated position as of 2019. In this research, we are not interested in how quickly the organizations have scaled up their usage of analytics. Instead, our focus is on the various paths organizations have taken. The most common path that organizations took was to start with a pilot project. Only two organizations (L and F), bypassed the pilot projects with a "full steam ahead" approach.

Comments (left to right in Figure 3):

- **Organization G** has a roadmap in place but has not taken any steps further to scale up the usage of analytics. Reasons for the lack of progress are not available to us.
- **Organizations C and I** have launched several pilot projects, but have not been able to scale up analytics beyond the pilot. Change of staff and lack of champion of analytics are some reasons why these two organizations have not been able to scale up beyond pilot projects.
- **Organization B** did a pilot project on advanced analytics, but due to lack of support from senior management the analytics scale-up was closed down.
- **Organizations D, J, K, and M** have all done pilot projects and are now in the process of preparing data and technical platform for a scale-up to either the entire organization or to a business unit/function.
- **Organization L** has chosen a "full steam ahead" approach, and are directly trying to scale up analytics to a business unit/function. Similar to organizations D, J, K, and M, organization L is also in the process of preparing data and the technical platform.
- **Organization F** has also chosen a "full steam ahead" approach and is directly targeting a scale up to the entire organization. As of now, a suitable technical platform is in place.

Figure 3. Paths organizations took to scale up



- **Organizations E and H** are in the process of scaling up usage of analytics to a business unit/function. These two organizations have a suitable technical platform in place.
- **Organization A** has done a couple of projects on advanced analytics before a scale-up was done to a business function. Attempts are now being made to scale up the usage of analytics to the entire organization.

What separates the leading organization (A) from the organizations (C, I, B) that are struggling? Organization A has had support from senior management, an analytics champion, highlighted early success, and are now educating employees on a bigger scale. This is in contrast to the struggling organizations that encountered barriers such as lack of support from senior management and lack of an analytics champion (that can drive and lead the scale-up).

As organizations move from left to right in Figure 3, aspects that go beyond having data and a technical platform in place become more important. Organizations that conduct a pilot project can have a technical focus, and there is usually no need to focus on how the pilot fits into future decision processes or how employees should work with the findings from the pilot. Organizations that are in the middle of Figure 3, are trying to scale up analytics to a wider group of people. Hence, business users start to raise questions such as, will we receive training in the new tools, what is the buy-in for making a change to more analytics, or how is analytics integrated into the decision processes? On the right side of Figure 3, organizations frequently use analytics to drive and implement new business insights. This implies that mechanisms need to be in place for fostering a data-driven culture, see for example the 12 vision statements suggested by Anderson (2015).

4.2 What Type of Supporting Strategies are Developed?

The investigated 13 organizations, all had the intention to scale up their usage of analytics. Data regarding supporting strategies were collected when the organizations were in the early stages of preparing a wider usage of analytics. That is, the intention was to scale up analytics beyond conducting pilot projects. Hence, we assumed that these organizations should have developed supporting strategies.

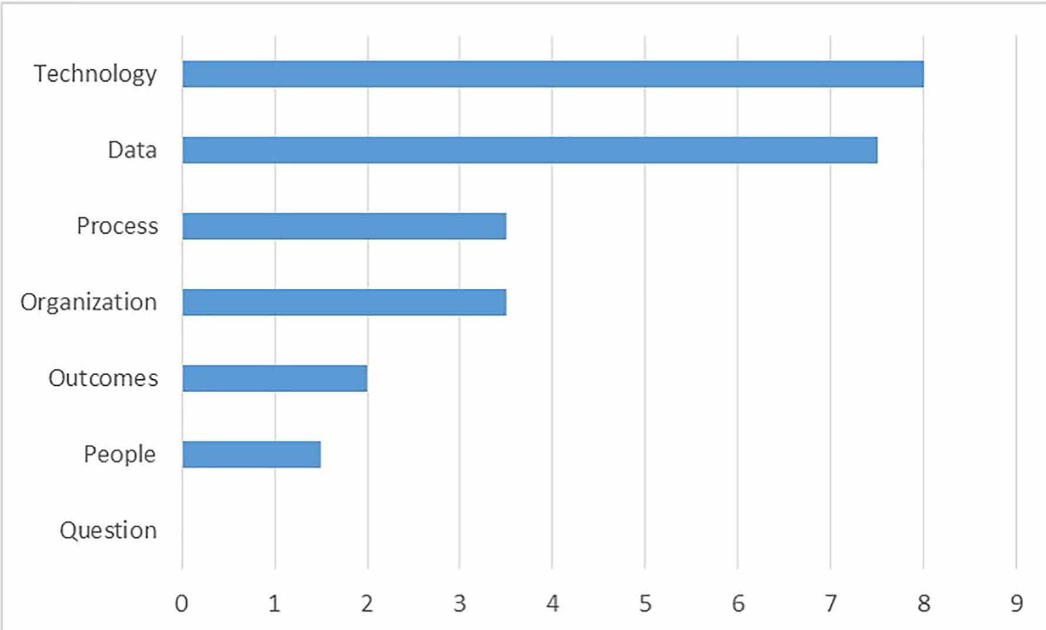
The framework in Figure 2 was used as a template for investigating what type of strategies that could have been developed:

- Question, what type of strategies are needed to foster a culture where business questions (or business problems) are frequently raised and analyzed further?
- Data, what type of supporting data is needed, and how will it affect data governance and data quality?
- Technology, what type of supporting technologies are needed for supporting the data and type of analytics that the organization intends to use?
- Organization, what type of organization of analytics competence is needed for supporting the type of analytics the organization intends to use?
- Process, how should analytics be used in decision processes?
- People, what type of analytical skills do people need, and how can the skills be raised?
- Outcomes, how are business insights taken care of?

The findings from our investigation are shown in Figure 4 and Figure 5. If an organization had developed a strategy for a given aspect, it received one credit. Organizations that had partially developed a strategy received half a credit. As anticipated, not all organizations had developed supporting strategies. Eight organizations had developed overall strategies, and five organizations had no documented strategies at all.

The most common strategies developed were strategies for technology (and tools), and data, Figure 4. Supporting strategies for how people should work with analytics, raise their skills, or how

Figure 4. Supporting strategies developed, points allocated per type of strategy



outcomes of the analytics should be taken care of were rare. No strategies were found for fostering a culture where business questions were raised, collected, and analyzed further.

Furthermore, the investigation revealed the following, Figure 5:

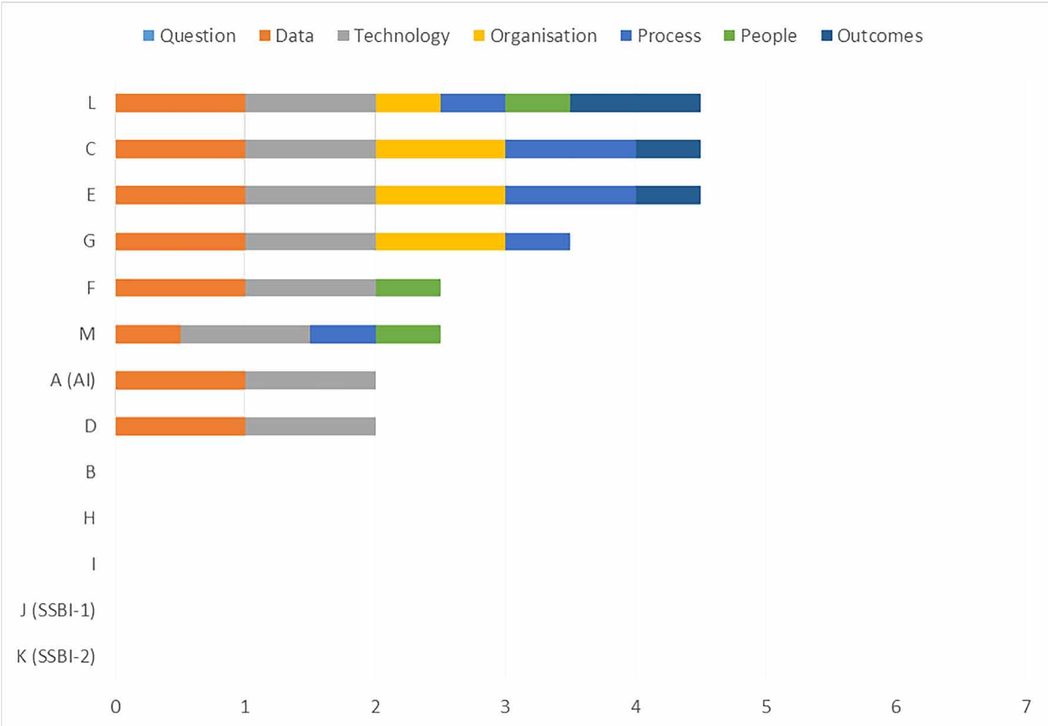
- Three organizations (C, E, G) had developed strategies for how to organize analytical competence. Organization L had partially mentioned this aspect, hence the half credit. It was surprising to discover that organization A, which already had an established BI-unit within the organization, had no developed strategies for how the new AI-influenced competence should be integrated into the existing organization.
- Two organizations (C, E) had developed strategies for how analytics should be used within decision processes. Organization L, G, and M mentioned this aspect only partially, hence the half credit.
- Three organizations (L, F, M) had partially developed strategies for how people should work with analytics and raise their skills. The other organizations had no strategies for this aspect.
- Organization L had developed strategies for how outcomes of the analytics should be collected and also implemented. This aspect was partially developed by organizations C and E.

None of the investigated organizations, had - moving towards a data-driven organization (or similar) - as their primary reason for the change. Instead, the organizations used derived versions of the categories in (Anand & Barsoux, 2017): global presence, customer focus, nimbleness, innovation, or sustainability. For example, if the primary vision was to increase the knowledge about customers, analytics was used as the main mechanism for supporting such a vision.

4.3 Barriers Revisited

Three of the investigated organizations had a clear focus on important enablers for being data-driven:

Figure 5. Supporting strategies developed with respect to the framework in Figure 2 and per organization



- Organization A had a clear focus on scaling up the usage of advanced analytics and AI, within the organization.
- Organizations J and K had a clear focus on scaling up the usage of self-service business intelligence.

Given the clear focus on advanced analytics, AI, and self-service business intelligence, we chose to interview Organizations A, J, and K, in order to investigate if they had encountered the previously reported top barriers for organizations that intend to become data-driven.

4.3.1 Lack of Understanding and Business Resistance

This barrier appeared in Organization A.

A data science consultant, who had participated in a pilot study at Organization A, made the following comment: "they saw it as a threat instead, that is my interpretation and our interpretation based on their actions, so to say, withholding documentation… cannot deliver licenses." This quote is an example of business resistance. In this particular example, attempts were made to slow down the change process during the pilot study.

4.3.2 Lack of Skills

This barrier appeared in all three organizations (A, J, K).

In Organization A, the manager for global marketing made the following comments regarding the urgency for the business people to immediately start to raise their skills in data-driven decision making: "In these projects, you look at all the technology, and everything that can be done, but what does that matter if we do not understand it on the business side, or even have processes to cope with it, and these are [the reasons] we cannot wait until everything is finished [on the technical side], we have to start now." This comment was made when company A had started to formulate and communicate their vision to be data-driven to the employees for the first time. As a reaction, several employees started to discuss whether they had the necessary skills to adjust their work according to the formulated vision.

In Organizations J and K, many users were self-taught and used any SSBI-tool they liked, the skills of individual SSBI-users and the quality of produced reports varied a lot: "We work with different software to make our analyses. They are pretty easy tools to use, but far from obvious to use. Many of our users lack general IT skills. Users need an SSBI intro, some kind of minor education, to learn for a few days and hours."

4.3.3 Insufficient Organizational Alignment

This barrier appeared in Organization A.

The manager for global marketing at Organization A, made the following comments regarding how the vision to be more data-driven was perceived by some people in the business side: "The business people have not boarded the [data-driven] train …. there are several visions, but we need to relate it to the business side, how should we use these tools, if we cannot agree upon how we should work [in the future] ... then we have a challenge…I now see that we are going in parallel tracks".

4.3.4 Lack of Senior Management Support

This barrier did not appear in any of the three organizations (A, J, K).

In organization A, senior management gave their approval early (pilot studies).

The usage of SSBI in organizations J and K, started by individuals or groups that conducted pilot projects, and then spread to other individuals and groups, via an analytical underground. Once the adoption of SSBI became widespread and it showed positive benefits, senior management approved it in hindsight.

4.3.5 Lack of Corporate Strategy

This barrier appeared in all three organizations (A, J, K).

Organization A had only developed strategies for data and technology. Strategies were not developed for other aspects such as how to organize analytical competence, or how employees should work with advanced analytics.

Organizations J and K had not developed any strategies at all.

4.3.6 Lack of Middle Management Adoption and Understanding

This barrier appeared in Organization A.

The data science consultant we interviewed, had encountered clear business resistance from middle managers already in the pilot study. Furthermore, the digital transformation officer at Organization A, made the following comment: "It's middle managers, that's where it stops. Much prestige, ... [you hear comments like] 'I have an ambition in my career, and here you come and destroy everything'… as a person and middle manager you can either act like… this is fun, I can learn more about it, and how can we do this better, and it is only good that we remove 80% of my work, because then I can sit and think about how we can make more money, or there are those who say, I have been working with Excel for 40 years, 7 hours a day, this is how the work is done, and no one can do it better than me, … then you develop an algorithm that does the [same] work in 3 milliseconds."

4.3.7 Difficulty Accessing Relevant Data

This barrier appeared in all three organizations (A, J, K).

Organization A experienced problems with respect to data quality, once they started to use advanced analytics. The problems were mostly due to using old data in new ways.

Both Organizations J and K experienced data-related challenges, where users did not know who to contact, or how to access the data they needed. One user made the following comment: "It is difficult to access the available data that is out there. It is possible to access and use it fully, but very few know how to."

4.3.8 Summary

A summary of the encountered barriers is provided in Figure. 6

All three organizations had difficulties in accessing relevant data. Organization A encountered this barrier, despite that they already had a data warehouse and strategies for data in place. Thus, providing access to data for more advanced types of analytics is challenging.

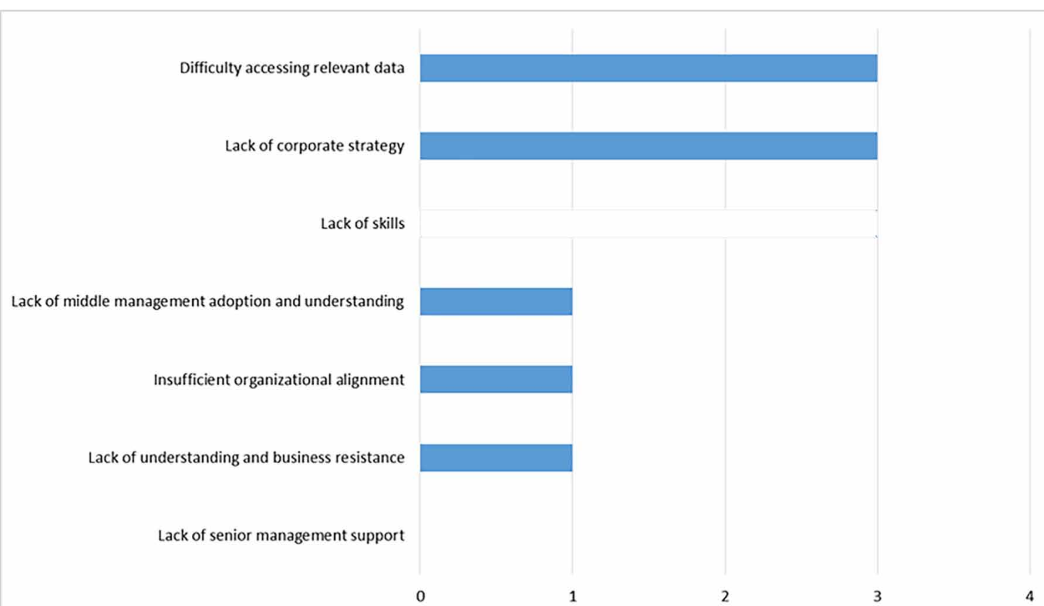
None of the three organizations had an overall corporate strategy for analytics, which some employees were keen on to point out. Without an overall strategy in place, the scale-up of analytics runs the risk of being stalled and siloed. This is tightly related to the barrier lack of skills that was pointed out in all three organizations. An organization that does not foresee the need to raise the skills in analytics among its employees, are likely to end up with frustrated employees that do not use analytics to its full potential.

All of the organizations in our investigation had received approval from senior management to scale up the analytics. Hence, this barrier should – as expected – not occur.

4.4 Usage of Change Management

Change management has recently been mentioned as an important enabler for becoming a data-driven organization (Forbes-Insights & EY, 2015). However, in our investigation, none of the 13 organizations used an overall change management process, e.g., the Kotter change model (Kotter, 2012). Instead, we saw the usage of fragmented elements of change management. Most of the organizations used pilot projects, as a way to create urgency around the topic and show the benefits of being data-driven to senior management. Senior management then gave their approval to continue. These initial steps

Figure 6. Summary of encountered barriers



are in line with the first step/accelerator of the Kotter change model, create urgency and get approval from management.

The fragmented (or no) usage of change management starts to appear once approval has been received from senior management, for example:

- A team with mostly technically skilled people is asked to lead the change, e.g., organization A.
- No vision and supporting strategies are developed, e.g., organizations B, H, I, J, and K.
- Strategies are only developed for technical aspects, e.g., organizations A and D.
- Buy-in for people to change their behavior is not developed, e.g., organizations C, E, F, G, A, and D.

Our conclusion is that the investigated organizations have been successful in creating urgency around analytics and received approval from senior management. However, they have not been successful in applying change management to their roadmap.

5. DISCUSSION

Having vision and supporting strategies in place are highly recommended in the literature (Anderson, 2015; Bisson, Hall, McCarthy, & Rifai, 2018; Kotter, 2012; Watson, 2016). Our findings were that roughly 60% (8 out 13) had developed supporting strategies for scaling up the analytics. However, most of the developed strategies were for technical aspects such as cloud platforms, tools, data governance, and data quality. Only three organizations had partially developed strategies for how people within the organization should work with analytics. Given the absence of strategies in general, and in particular the lack of strategies for how people should work with analytics. It is no surprise that the barriers lack of corporate strategy, insufficient organizational alignment, and lack of understanding and business resistance appears in surveys e.g. (Halper & Stodder, 2017). A few of the organizations that were part of our study are now – a couple of years after the vision and technical strategies were launched - trying to catch up on the people strategies. They are now educating their employees in analytics and data literacy, on a bigger scale. However, organizations should not adopt a one-size-fits-all approach to educate its employees. Instead, create different education paths depending upon technical background and end with a joint internal project (Berndtsson, Lennerholt, Larsson, & Svahn, 2019).

In a previous project (Rose, Berndtsson, Mathiason, & Larsson, 2017), we investigated best practices for running pilot projects in advanced analytics. Although the pilot projects used a systematic process, a derived version of CRISP-DM (Wirth & Hipp, 2000), none of the pilot projects had explicit steps for advancing beyond the pilot project.

We agree with Sandkuhl (2019) that organizations too often put a technical focus on adopting AI into an organization. In order to put more focus on the organizational context, Sandkuhl (2019) proposes a new method component for enterprise architecture management: i) model organizational AI context, ii) elicit AI requirements, iii) analyze AI context, and iv) decide on feasibility.

Existing literature that describes a systematic process for moving towards a data-driven organization is limited and fragmented. Typically, the suggested processes in the literature consist of *n* arbitrary steps that are relevant, but the steps do not cover the entire spectrum of what it implies to move a data-driven organization. For example, Watson (2016) provides a high-level framework of a fact-based decision culture, and six approaches for moving towards a fact-based decision-making culture: i) use dashboards/scorecards as a starting point, ii) focus on early wins, iii) ask what analytics were used, iv) empower operational decision making, v) provide incentives to change, and vi) some employees may need to be replaced. These six approaches are mostly targeting the micro change management perspective (Kang, 2015), e.g., use dashboards or replace some employees. Barton and Court (2012) suggest three steps: i) choose the right data, ii) build models that predict and optimize business outcomes, and iii) transform your company's capabilities. These steps mix basic recommendations for collecting data and using predictive analytics, with a more high-level suggestion to transform the company's capabilities. Davenport et al. (2010) present a generic road map on the macro change management perspective, consisting of five stages of maturities: i) analytically impaired, ii) localized analytics, iii) analytical aspirations, and v) analytical competitors. In addition, five elements (success factors) are presented: access to high-quality data, enterprise orientation, analytical leadership, strategic targets, and analysts. Organizations identify their current level within each of these elements and then apply the provided generic guidelines for moving from one stage of maturity to another stage of maturity for each element.

Although generic road maps and advice exist for how to become a data-driven organization (Barton & Court, 2012; Davenport et al., 2010; Watson, 2016), large responsibilities are put on the transforming organizations to add both context and structure to the generic transformation advice. None of the above road maps seem to reuse similar work within change management. We envision that a tighter merge of research from the two research communities is needed in order to develop a more systematic approach for becoming a data-driven organization.

For example, using a slightly modified version of the well-known Kotter change model on the macro-level (Kotter, 2012), that has explicit steps for forming a balanced team, developing a vision and supporting strategies, etc., would have been a better approach for our investigated organizations to follow. In such a situation, all of the organizations would have developed supporting strategies for all aspects of the sample analytical framework in Figure 1. This is in contrast to the current initial technical focus, where strategies and buy-in for "people + analytics" at best, arrives as a patch to the analytics initiative a couple of years later.

6. CONCLUSION

In this article, we investigated the initial journey that 13 organizations took, to scale up their usage of analytics to become a data-driven organization.

The significance of our research is a first view on what steps organizations take in practice to scale up their usage of analytics. Our findings are that most organizations start their journey via a pilot project, take shortcuts when developing strategies, encounter previously reported top barriers, and do not use an overall change management process.

The implications of our findings for practice are to develop strategies for both technical and non-technical issues at the same time. Several of the barriers that we encountered, could easily have been avoided or reduced if proper supporting strategies had been in place. Furthermore, organizations that intend to scale up their usage of analytics, should use methods from change management as a guide. Instead of running the scale-up transformation in an ad hoc manner.

We encourage researchers to do additional investigations on what steps organizations take in practice to scale up the usage of analytics. Further investigations need to be done to describe in which situations the different paths are suitable to take. In the end, a better roadmap for scaling up the usage of analytics on both the macro and micro level can then be developed.

ACKNOWLEDGMENT

The work is partially supported by the Knowledge Foundations of Sweden.

REFERENCES

Anand, N., & Barsoux, J.-L. (2017). What everyone gets wrong about change management. *Harvard Business Review*, (November-December): 80–85.

Anderson, C. (2015). *Creating a Data-Driven Organization*. O'Reilly Media.

Arnott, D., & Pervan, G. (2014). A Critical Analysis of Decision Support Systems Research Revisited: The Rise of Design Science. *Journal of Information Technology*, *29*(4), 269–293. doi:10.1057/jit.2014.16

Barton, D., & Court, D. (2012). Making Advanced Analytics Work For You. *Harvard Business Review*, *90*(10), 78–83. PMID:23074867

Bean, R., & Davenport, T. H. (2019). *Companies Are Failing in Their Efforts to Become Data-Driven*. Harvard Business Review Digital Article.

Berndtsson, M., Forsberg, D., Stein, D., & Svahn, T. (2018). Becoming a data-driven organisation. *Paper presented at the European Conference on Information System (ECIS)*. Academic Press.

Berndtsson, M., Lennerholt, C., Larsson, P., & Svahn, T. (2019). A Blueprint for Training Future Users of Self-Service Business Intelligence. *Business Intelligence Journal*, *24*(1), 30–38.

Bisson, P., Hall, B., McCarthy, B., & Rifai, K. (2018). *Breaking away: The secrets to scaling analytics*. McKinsey.

Buitelaar, R. (2018). *Building the Data-Driven Organization: a Maturity Model and Assessment. (Master)*. Leiden University.

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *Management Information Systems Quarterly*, *36*(4), 1165–1188. doi:10.2307/41703503

Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73–80. doi:10.1080/2573234X.2018.1543535

Davenport, T. H., & Bean, R. (2018). *Big Companies Are Embracing Analytics, But Most Still Don't Have a Data-Driven Culture*. Harvard Business Review.

Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: Updated, with a New Introduction: The New Science of Winning*. Harvard Business Review.

Davenport, T. H., Harris, J. G., & Morison, R. (2010). *Analytics at work: smarter decisions, better results*. Boston, MA: Harvard Business Press.

Delen, D., & Ram, S. (2018). Research challenges and opportunities in business analytics. *Journal of Business Analytics*, *1*(1), 2–12. doi:10.1080/2573234X.2018.1507324

Di Fiore, A. (2018). *Why AI Will Shift Decision Making from the C-Suite to the Front Line*. Harvard Business Review.

Eckerson, W. W. (2009). *TDWI's business intelligence maturity model*. The Data Warehousing Institute.

Forbes-Insights, & EY. (2015). *Analytics: Don't forget the human element*. Forbes Insights.

Franks, B. (2012). *To Succeed with Big Data, Start Small*. Harvard Business Review.

Halper, F., & Stodder, D. (2014). *TDWI analytics maturity model guide*. The Data Warehousing Institute.

Halper, F., & Stodder, D. (2017). What It Takes to Be Data-Driven (Vol. Q4). TDWI.

Kang, S. (2015). Change Management: Term Confusion and New Classifications. *Performance Improvement*, *54*(3), 26–32. doi:10.1002/pfi.21466

Kotter, J. P. (2012). Accelerate! *Harvard Business Review*, *90*(11), 44–58. PMID:23155997

Lahrmann, G., Marx, F., Winter, R., & Wortmann, F. (2011). Business intelligence maturity: Development and evaluation of a theoretical model. *Paper presented at the Proceedings of the 44th Hawaii International Conference on System Sciences*. Academic Press. doi:10.1109/HICSS.2011.90

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big Data, Analytics and the Path From Insights to Value. *MIT Sloan Management Review*, *52*(2), 21–32.

Leonard-Barton, D. (1990). A Dual Methodology for Case Studies: Synergistic Use of a Longitudinal Single Site with Replicated Multiple Sites. *Organization Science*, *1*(3), 248–266. doi:10.1287/orsc.1.3.248

Lismont, J., Vanthienen, J., Baesens, B., & Lemahieu, W. (2017). Defining analytics maturity indicators: A survey approach. *International Journal of Information Management*, *37*(3), 114–124. doi:10.1016/j.ijinfomgt.2016.12.003

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, *90*(10), 60–68. PMID:23074865

McShea, C., Oakley, D., & Mazzei, C. (2016). *How CEOs Can Keep Their Analytics Programs from Being a Waste of Time*. Harvard Business Review Web Article.

Moran, J. W., & Brightman, B. K. (2001). Leading organizational change. *Career Development International*, *6*(2), 111–118.

NewVantagePartners. (2017). *Big Data Executive Survey 2017*. NVP report.

NewVantagePartners. (2018). *Big Data Executive Survey 2018*.

NewVantagePartners. (2019). *Big Data and AI Executive Survey 2019*.

Olszak, C. M., & Ziemba, E. (2012). Critical Success Factors for Implementing Business Intelligence Systems in Small and Medium Enterprises on the Example of Upper Silesia, Poland. *Interdisciplinary Journal of Information, Knowledge, and Management*, *7*, 129–150. doi:10.28945/1584

Pan, S. L., & Tan, B. (2011). Demystifying case research: A structured–pragmatic–situational (SPS) approach to conducting case studies. *Information and Organization*, *21*(3), 161–176. doi:10.1016/j.infoandorg.2011.07.001

Pham, Q. T., Mai, T. K., Misra, S., Crawford, B., & Soto, R. (2016, July). Critical success factors for implementing business intelligence system: Empirical study in Vietnam. In *Proceedings of the International Conference on Computational Science and Its Applications* (pp. 567-584). Springer.

Power, D. J. (2007). A Brief History of Decision Support Systems. version 4.0. Retrieved from http://dssresources.com/

Rose, J., Berndtsson, M., Mathiason, G., & Larsson, P. (2017). The advanced analytics Jumpstart: Definition, process model, best practices. *Journal of Information Systems and Technology Management*, *14*(3), 339–360. doi:10.4301/S1807-17752017000300003

Sandkuhl, K. (2019). Putting AI into Context - Method Support for the Introduction of Artificial Intelligence into Organizations. *Paper presented at the 2019 IEEE 21st Conference on Business Informatics (CBI)*. IEEE Press. doi:10.1109/CBI.2019.00025

Sender, S. W. (1997). Systematic agreement: A theory of organizational alignment. *Human Resource Development Quarterly*, *8*(1), 23–40. doi:10.1002/hrdq.3920080105

By, T. (2005). Organisational change management: A critical review. *Journal of Change Management*, *5*(4), 369–380. doi:10.1080/14697010500359250

Turban, E., Sharda, R., Delen, D., Aronson, J. E., Lian, T.-P., & King, D. (2015). *Business intelligence and analytics: systems for decision support*. Harlow, Essex: Pearson Education.

Watson, H. J. (2013). All About Analytics. *International Journal of Business Intelligence Research*, *1*(4), 13–28. doi:10.4018/jbir.2013010102

Watson, H. J. (2016). Creating a Fact-Based Decision-Making Culture. *Business Intelligence Journal*, *21*(2), 5–9.

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. doi:10.1016/j.ejor.2017.02.023

Wirth, R., & Hipp, J. (2000). CRISP-DM: Towards a standard process model for data mining. *Paper presented at the 4th International Conference on the Practical Applications of Knowledge Discovery and Data Mining*. Academic Press.

Wixom, B., & Watson, H. (2010). The BI-Based Organization. *International Journal of Business Intelligence Research*, *1*(1), 13–28. doi:10.4018/jbir.2010071702

Yeoh, W., & Koronios, A. (2010). Critical Success Factors for Business Intelligence Systems. *Journal of Computer Information Systems*, *50*(3), 23–32.

Yin, R. K. (2014). Case Study Research (5th ed.). Sage.

ENDNOTES

[1] Exact figures are not available in the survey.

APPENDIX A

Table 3. Operations of anonymous organizations

Organization	#Employees	Business	Path	Strategies developed
A	4500	Transportation	Several pilots were done, and scaled up to business function level. Attempts are now done to scale up to the entire organization.	Data and technology
B	1000	Retail	One pilot was done. Analytics initiate was closed down due to lack of senior management support.	No strategies
C	100	Manufacturing	Several pilots were done. No further progress due to change of staff and lack of champion.	Data, technology, organization, and process
D	3000	Retail	Several pilots were done. Focused then on preparing a wider technical platform, for scale up to the next level.	Data and technology
E	3000	Manufacturing	Several pilots were done. A technical platform is in place, and are currently applying analytics to the level of business function.	Data, technology, organization, and process
F	1500	Service	BI platform in place. Trying to scale up the usage of analytics directly to the organization level.	Data, technology, and (partial) people
G	400	Technology	The organization has a roadmap to scale-up, but has not taken any steps.	Data, technology, organization, and (partially) process
H	1500	Retail	Several pilots were done. Currently applying analytics to the level of business function.	No strategies
I	400	Transportation	Several pilots were done. No further progress due to change of staff and lack of champion.	No strategies
J	6500	Bank and finance	Several unofficial pilots were done, scale-up approved by management	No strategies
K	2000	Bank and finance	Several unofficial pilots were done, scale-up approved by management	No strategies
L	1000	Recreation and amusement	Initiated an approach to directly scale-up analytics to the level of business function.	Data, technology and outcomes. Partial strategies developed for organization, process, and people.
M	14000	Construction	Pilot projects have been done and a roadmap has been created. Technical platform scaled up for next step.	Technology. Partial strategies developed for data, process, and people.

Mikael Berndtsson is an assistant professor in computer science at University of Skövde, Sweden. He has a Ph.D. in computer science from University of Exeter, UK. His research interest includes business intelligence and analytics: in particular, how organizations can establish themselves as data-driven organizations.

Christian Lennerholt is a Ph.D. student in informatics focusing on self-service business intelligence at University of Skövde, Sweden.

Thomas Svahn is a management consultant focusing on analytics strategy, and the COO of Advectas AB. He has a Master of Business Administration from University of Gothenburg, Sweden.

Peter Larsson have worked with machine learning and AI since 2004 and acts as a trusted advisor to companies and organizations with the ambition to become data driven and move towards proactive decision making.