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# Business analytics capabilities in Norwegian organizations

## Current state, challenges and a roadmap towards future excellence

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# Preface

This thesis is part, and marks the end of, our Master of Science in Business and Administration at the Norwegian University of Life Sciences.

2020 has been a challenging year in many respects, and we have been fortunate to have remarkable support from family and friends throughout working with our thesis. In the face of sudden change halfway through the semester, their contribution has been crucial in helping us cross the goal line.

We would like to express our sincere gratitude for the guidance and feedback we have received from our supervisor, Joachim Scholderer, along the way. This goes not only for this thesis but all of our time at the university, where Joachim has been an inspirator and crucial figure in our academic interests and development.

All master theses rely on external contributions, and our data foundation would not be possible without the aid of Digital Norway, our interviewees, and our survey respondents - thank you all for the time, knowledge and resources you have shared with us throughout this study.

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# Executive Summary

With the influx of big data, business analytics (BA) have become an increasingly influential part of all aspects of business. Through three studies, this thesis explores the state of BA in Norwegian companies using maturity and market orientation models as theoretical frameworks. The first study is an analysis of a large data set on digitalization, which finds that leadership capabilities are higher than digital capabilities. The second study consists of five interviews with industry experts, and looks in-depth on the current state and challenges related to BA. Lastly, study three provides a detailed overview of BA specific capabilities through a survey. From these studies, we find that senior management plays a key role in ensuring BA success, a factor that is generally well understood in Norwegian companies. The biggest challenges relate to data silos and BA-related skills with employees, which reduces the gains and impact from BA. Based on these findings, a framework is presented on how companies can ensure positive gains and impact from BA.

# Sammendrag

Stordata blir stadig mer aktuelt, og har allerede bidratt til dramatiske endringer for selskaper verden over. Gjennom tre studier utforsker denne masteroppgaven tilstanden for *business analytics* (BA) i Norge ved hjelp av modeller innenfor modenhet og markedsorientering som teoretisk rammeverk. Den første studien analyserer et større datasett om digitalisering, og finner at kapabiliteter innen lederskap er høyere enn digitale kapabiliteter. Studie to bygger på intervjuer med fem bransjeeksperter, og går i dybden på nåværende modenhet og utfordringer som møter norske selskaper i arbeidet med BA. Til sist kommer studie tre, som gir detaljert innsikt i bruk og tilstand for BA i rett under 50 norske selskaper, basert på vår egen spørreundersøkelse. Basert på disse studiene fremkommer det at toppledelsen spiller en nøkkelrolle for å sikre suksess med BA, et faktum som generelt er anerkjent og forstått hos norske selskaper. De største utfordringene knyttet til BA er datasiloer og manglende kompetanse hos medarbeidere, som reduserer gevinster og innvirkning fra BA. Basert på masteroppgavens funn, presenteres et helhetlig rammeverk for hvordan selskaper bør tilnærme seg BA for å høste gevinster.

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# 1. Introduction

## 1.1. Background and Objectives

With the digital revolution in full swing, organizations are rapidly changing their work practices to keep pace with industry 4.0. Digitalization refers to enabling, improving, and transforming operations, functions, models, processes, or activities by leveraging digital technologies (Gürdür, El-khoury, & Törngren, 2019).

For Norwegian organizations, digitalization has been on top of the agenda for some time. In 2017, 23 out of 29 of some of the country's largest organizations reported digitalization to be of a top strategic priority (Marschall, Korstvedt, & Krabbe, 2017). Norwegian beneficiaries have participated in EU-funded innovation and network programs such as CEF Telecom and ISA2 (both concluding in 2020), and Norway has for achieved top placements in the EU's Digital Economy and Society Index (European Commission, 2018). The Norwegian government is currently considering participation in the EU's 2021-2027 Digital Europe Program, expected to fund large-scale research, development and innovation activities in artificial intelligence and supercomputing. These technologies are key future enablers of analytics. But will Norwegian organizations in the private and public sector be ready to leverage them? Gürdür et al. (2018) evaluate the analytics readiness of Swedish organizations. Their results show that Swedish industries can be considered to be digitally mature in terms of general IT capabilities and infrastructure, but that advanced data analytics is still a *next* step towards true mastery of Industry 4.0.

The global interest in how organizations can improve through business analytics is reflected in the academic literature and in numerous private-sector reports. However, there exists no unambiguous roadmap towards analytics excellence. The overall aim of the research reported here is to assess the current level of digital maturity in Norwegian organizations and identify key steps for progressing from digital maturity to analytics maturity: where should Norwegian organizations focus their efforts to fully utilize the potential that business analytics provides?

At present, most Norwegian research on this subject is still limited to small-scale case studies focusing on specific organizations or industries. Such narrow focus can limit the generalizability and strategic value of the findings. Our intention is to provide a broader basis, allowing comprehensive benchmark assessments and showing the way forward towards analytics maturity and excellence. The research reported here will address three overall objectives:

- Assess the degree to which Norwegian organizations have adopted digitalization as a strategic orientation,
- Identify the main challenges Norwegian organizations must address on their path towards business analytics maturity and excellence,
- Develop recommendations how Norwegian organizations should proceed in order to achieve business analytics maturity and excellence.

## 1.2. Defining Business Analytics

The concept of business analytics is still evolving—a single, widely known, authoritative definition of business analytics is yet to be agreed upon (Power, Heavin, McDermott, & Daly, 2018). As a working definition, Power et al. (2018) suggest "business Analytics is a systematic thinking process that applies qualitative, quantitative, and statistical computational tools and methods to analyze data, gain insights, inform, and support decision-making" (p. 51). Originally, Davenport and Harris (2007, p. 7) defined business analytics as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris, 2007). The definitions are similar. There is one criterion, using data, and one objective, using the data for improved decision making in the organization. For simplicity, we will abbreviate business analytics as BA throughout the thesis.

## 1.3. Overview

The thesis consists of eight chapters. Following this introduction, the second chapter will present the theoretical foundations of our research and review existing empirical evidence. The third chapter will present our research questions and an overview of the three studies to be reported. Study 1 is a benchmark analysis of digital maturity in Norwegian industries, using representative survey data. Study 2 is qualitative and based on expert interviews, identifying key challenges Norwegian organizations face on their way towards analytics maturity. Study 3 is a follow-up survey Norwegian organizations, exploring how they address the challenges identified in Study 2 and trying to identify success factors. It is also used to explore our framework based on existing literature and findings in Study 1 and 2. Chapters 7 and 8 integrate and discuss the findings, present conclusions and recommendations, and make suggestions for future research in the area.

# 2. Theory and Previous Research

## 2.1. Maturity Models

In recent decades, business has increasingly moved from the real world to the digital realm. Digital technologies require companies to change how they think about products, customers, innovation, competition and much more. To put this in a systematic and organized manner, several maturity models have been developed. According to Martin Fowler, their purpose is to help subjects assess the current effectiveness and identify the capabilities needed to climb the model's steps (Fowler, 2014). In other words, it works as an evaluation tool to support users in improving their performance in whatever field in focus. For this thesis, two categories of maturity models are relevant. First, the digital maturity models of Deloitte and Capgemini provide an overview for understanding and approaching digitalization, a term sometimes misunderstood. Second, we go in-depth in one of the most important components of the digital age, analytics.

Maturity models have been around for decades, but digital and analytics maturity models have been criticized. One criticism is that maturity models tend to cover only specific parts of the given domain, failing to grasp the domain as a whole (Rajterič, 2010). If a company wants an accurate assessment of its maturity, Rajterič recommends using multiple models. However, another problem occurs from this, namely that models are not comparable as they use different approaches, metrics and criteria, which requires users to be attentive. Another problem is that maturity models tend to have specialized terminology, and in the case of analytics many of these have yet to reach a unanimous definition. Thus, they will be understood quite differently depending on the user's company, professional field and background. This is because maturity models have no explicit concept of who should use them, and how they should be used (Andersen, Lee, Mettler, & Moon, 2020). One aspect that tend to be quite explicit, however, is the linearity. Most, if not all, maturity models are built on the numbering and visualization of different stages of maturity. In complex fields like analytics, this can be grossly misleading (Widjaja, 2020). For instance, there is no certainty that higher levels of analytics bring more value, and the idea of completing each step before moving on sequentially can distract from the actual goal of providing decision support. Ali et al. challenged the influential position of maturity models further, questioning their ability to grasp analytics' contribution to business value (Ali, Mancha, & Pachamanova, 2017). They maintained that while maturity models can be useful, users must be careful to avoid myopia. Analytics maturity must be approached as a means to achieve business goals, rather than an end itself. Combining a strategy that specifically focuses on the company's broader ecosystem and its shareholders with analytics maturity is a necessity to optimize the gains from analytics.

### 2.1.1. Digital Maturity Models

There are several maturity models for digitalization, and nearly every consultancy firm seem to have its own. Forrester's, for example, is called Digital Maturity Model 4.0 (VanBoskirk & Gill, 2016). It presents four dimensions of digital maturity related to cultural, organizational, technical, and insights challenges. Depending on their score, companies are then either labeled as skeptics, adopters, collaborators or differentiators. In Forrester's view, any digital team should focus on three functions: developing their digital strategy, govern digital strategies across firms, and strive for operational excellence in their digital execution.

Another example was developed by David Rogers (Rogers, 2016). Rogers presents five domains of strategy that are affected by the digital age and require some response of digital transformation: customers, competition, value, innovation and data. Main takeaways from the model are to get away from traditional understandings of customers as mass markets, rather approaching them as customer networks, and exploring concepts of *coopetition.* While there are many others to choose from, our focus will be on Deloitte's Digital Maturity Model and Capgemini's Digital Mastery.

In 2018, Deloitte developed their Digital Maturity Model (Deloitte Digital, 2018). Here, they identified five dimensions that when combined gives a clear picture of how the company stands regarding digitalization: *customer*, *strategy*, *technology*, *operations*, and *organization* & *culture*. *Customer* is about how the company develops a digital partnership with the customers, that see them returning to the available channels for future needs. *Strategy* focuses on digitalization as a competitive advantage, and to what degree this is included in the overall business strategy. *Technology* refers to the creation, processing, storage, security and exchange of data to support the digital strategy. *Operations* evaluate how processes and tasks are designed to aid the company's effectiveness by using digital technologies. Last, *organizations* and *culture* reviews how the organizational culture, for instance governance and talent processing, enhances improved maturity. Figure 1 shows the five dimensions with their 28 sub-dimensions.

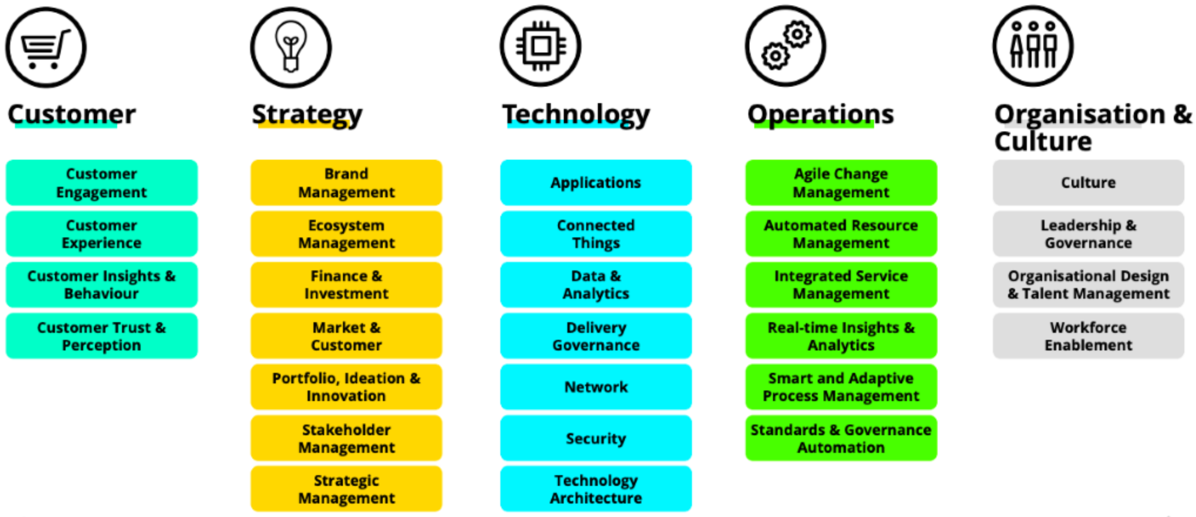


*Figure 1: Deloitte maturity model (Deloitte Digital, 2018)*

Next, we will review Capgemini's model of Digital Mastery (Bonnet, et al., 2019) shown in Figure 2. The two axes are digital capability and leadership capability. Leadership capability refers to creating an environment and culture that facilitates digital transformations. Thus, it includes factors like vision, sense of urgency, data governance, and executive skills. Digital capability refers to changes in customer experience, daily operations, innovation and more. In other words, aspects of leadership capability are prerequisites for digital capability, representing more concrete changes at company level.

Companies with low performance both in digital capability and leadership capability are classified as *beginners*, which typically have just started their digital journey. If the digital capability is good, but leadership low, the company is a *fashionista*. While these companies might have sophisticated digital functions and usage, a lack of leadership capability probably means they have not reached their full potential. Third, we have *conservatives*. These companies are characterized by a conscious approach on an organization level but lack the actual use and exploration of the opportunities offered by digitalization. Last, there are *digital masters* that have high digital capability and high leadership capability, enabling them to combine strong organizational culture with value-adding digital initiatives.

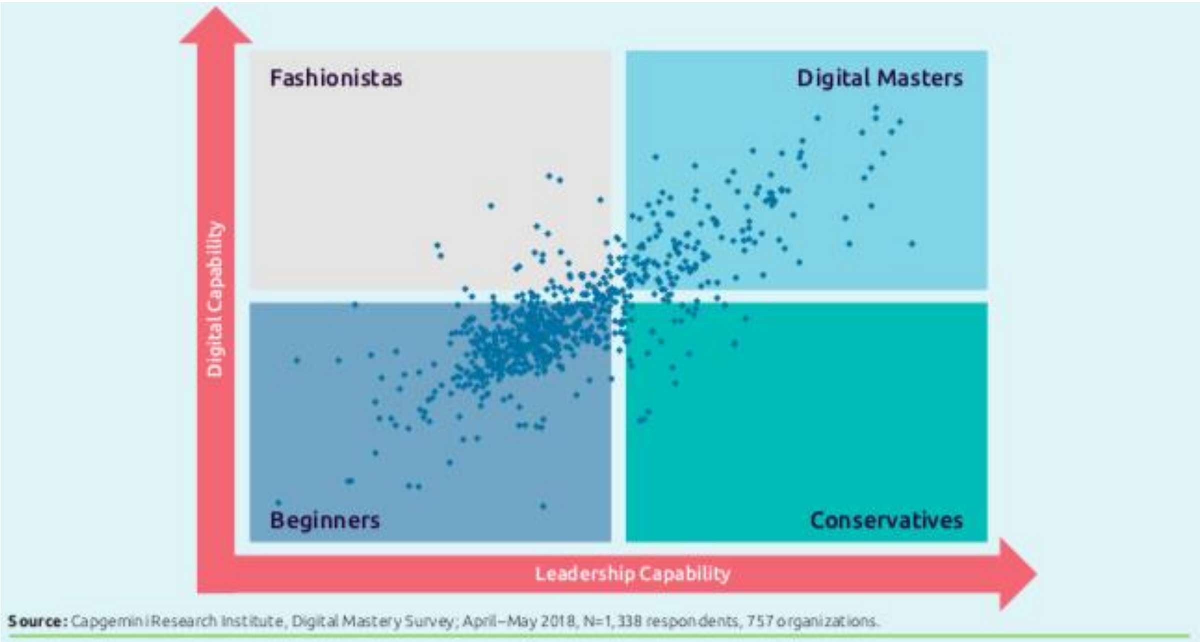


*Figure 2: Capgemini model of digital mastery (Bonnet et al., 2019)*

As shown by Capgemini's 2018 survey a minority fall in the latter category, with 39% believing themselves to have the needed digital capabilities, and 35% in the case of leadership capability - the combination of these being even rarer.

While both models provide valuable insight on digitalization, the simplicity and visual nature of Capgemini's model makes it an excellent tool for study 1. That is not to say, however, that Deloitte's will be ignored. In fact, this model shows how closely related digitalization is to BA. Customer understanding and behavior can be thoroughly explored through analytics. Insights in operations through sensors and other data gathering devices is increasingly beneficial, and what Capgemini has identified as a strategic opportunity that remains unexploited (Thieullend, Colas, Buvat, Subrahmanyam, & Bisht, 2017). Gartner believes that data and analytics are key to any digital transformation, as it is an integral part of turning information into assets (Pettey, 2019). In short digitalization without analytics is a losing proposition, as the latter supports and enables several parts of organizational development.

### 2.1.2. Analytics Maturity Models

Finding that analytics is not separated from digitalization, but rather an important part and contributor to it, this section will review analytics maturity models. As in the case of digitalization maturity models, there are many maturity models. An early example was Williams and Thomann's BI maturity model, which presented three stages of BI maturity (Williams & Thomann, 2003). Stage 1 is characterized by companies treating information like before, with a list of predefined data elements sent from businesses users to IT, with focus on *what* information they want. Moving to Stage 2, organizations rethink the role of information, tightening the bonds between information requirements and business goals. As such, the focus moves to include *why* the information is necessary. The final stage is recognized by companies searching for *how* to use the information, by looking into the overall business processes and organizational change required to support the new capabilities. This model might seem a little simplistic, and that could be the case as it was conceived in 2003 - a lot has changed since then.

Another widely used analytics maturity model is Gartner's Analytic Ascendancy model, which presents four categories of analytics (de Jong, 2019). First, it is used descriptively, asking the question of *what* happened. This is the easiest approach, for instance listing average sales per day. Next is diagnostic analytics, where the question becomes *why* something happened. A firm can explore why the sales have changed between two periods, for instance by reviewing correlations and patterns. Third is predictive analytics, where the goal is not only to explore the past, but also the future. Demand forecasting is a typical example, where firms use historical data to predict future production. Lastly, prescriptive analytics. This is the most difficult step to master, as it aims to suggest specific courses of action through feedback to learn and improve the model. An example is Spotify's recommendation system, which offers users suggestions based on previous data. Gartner's model also seems quite limited as it is purely concerned with the analytics output, rather than the complexities that enable this output. Thus, we will focus on two other maturity models.

First, the Data Warehousing Institute's (TDIW) Big Data Maturity Model (Halper & Krishnan, 2013). In their words, "big data maturity can be described as the evolution of an organization to integrate, manage and leverage all relevant internal and external data sources". Thus, their model has five stages of maturity as evident in Figure 3.

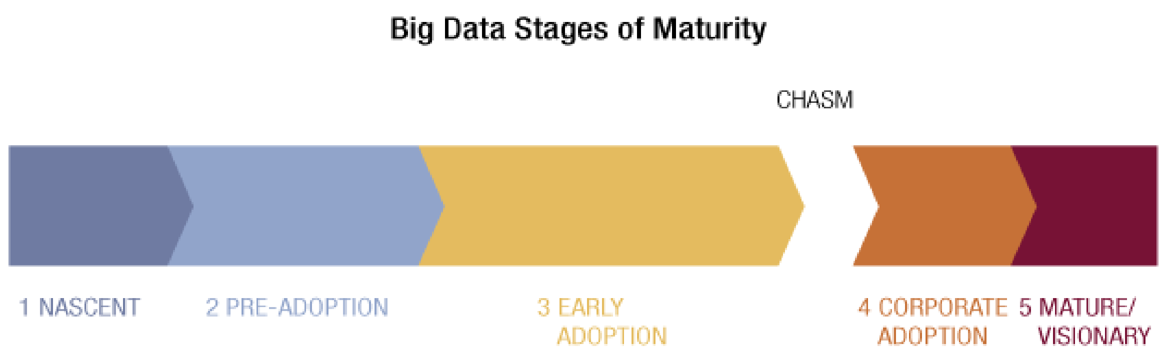


*Figure 3: TDWI's big data stages of maturity (Halper & Krishnan, 2013)*

Each step characterizes organizations, infrastructure, data, management, analytics and governance in various ways. *Nascent* organizations have low awareness of big data concepts and potential value and are recognized by pockets of enthusiasts rather than real executive support. While they will typically have some kind of data warehouse, there is lack of assessment about what data to gather and how to store it. Thus, data use mostly revolves around immediate results. Whatever analytics exist typically relate to specific departments and functions, such as marketing, leading to information silos.

Stage 2, *pre-adoption*, sees the companies prepare for further expansion through investments in new technology such as data lakes, and have one executive sponsor not on the business side. There is still a certain skepticism company-wide, and the mindset generally revolves around experimentation, but they realize that identifying the right business problems are crucial for success. Initiatives still relate to individual departments, and an enterprise-wide framework for data governance is evolving. Still, most data sources are internal, and metadata is lacking.

Stage 3 is perhaps the most time-consuming, *early adoption*. Typically, one or two proofs of concept (POCs) will have evolved at this point, attracting more interest and support from executives. A team is established to plan further, increasing bureaucracy. While different kinds of big data technologies are in place, a unified data architecture or ecosystem is still absent, keeping the company from using their full potential. Their content is typically data collected as files of various formats, with some metadata at the division level. Data quality and security become increasingly relevant, and while a company-wide big data management strategy is not present, at least data is not casually thrown away. Regarding analytics, the organization uses descriptive and even predictive analytics in its projects. Still, the deployment is often isolated to single departments.

Before progressing to Stage 4 of *corporate adoption*, there are barriers to cross that the authors call *the chasm*. One is funding. As most early big data projects are driven by IT, business involvement becomes critical at this point both to secure the necessary means and provide tangible business outcomes. Sharing data across the organization through a unified data architecture is important, and with this data governance. Combining employee skills in traditional warehouses and new data lakes technologies is important, especially since employees working with the latter tend to come fresh from university and lack business knowledge.

With these complex issues solved, companies enter Stage 4 where end-users get involved, gain insights and change how they work. The organization has usually embraced analytics as a tool for competitive differentiation, securing stable funding. The data infrastructure is recognized by a unified architecture using a range of technologies, which might include the cloud, with the goal of supporting the analytics. The same can be said for data management, which aims to make data sharing a collaborative activity and removing data silos. Strong data governance policies are in place, keeping the overall executive sponsor involved, and metadata is attributed at the divisional or company level. A center of excellence (COE) is formed, consisting of data scientists who might train other groups in the use of analytics. New data coming in can quickly be analyzed and integrated into the existing logical infrastructure.

Going to Stage 5, companies become *visionaries*. At this level, they are using big data programs effortlessly and as a budgeted and planned initiative. Executives have endorsed analytics as a critical standard for how they do business, and it is viewed as a crucial competitive advantage. Collaboration has become a central feature of the company data culture, and they are constantly searching for new ways to use analytics. The data infrastructure supports smooth integration of new data sources, primarily through the use of data lakes. Security and backup are perceived as vital aspects, and data is openly shared across the organization. The visionary label is hard to reach and is only achieved by a few companies.

One of the most influential books on the subject of BA since its release in 2007 is Davenport and Harris' *Competing on Analytics* (Davenport & Harris, 2007). In the book, the authors review different aspects of organizations and how they aid in creating what they refer to as *analytical competitors.* This is a drastic shift from the gut-feeling that have driven the majority of businesses, but a growing number see the necessity of moving in this direction. Analytical competitors can be found in several different industries, but they all have one thing in common: what truly differentiates them are the human and organizational aspects, not purely technological.

Analytical competitors have four primary attributes. First, the company's analytics must support a distinctive capability. In other words, they must support a competitive strategy. These capabilities depend on the business's industry. For some, it can be supply chains and pricing, for others customer predictions and customer loyalty. In the absence of such strategic capabilities the company cannot aspire to be an analytical competitor, since there is no clear plan for what analytics is actually supporting.

Second, analytical competitors have an enterprise-level approach to analytics. Analytics are not simply concentrated in one group or a random collection of employees in the organization, but managed at an organizational level with the goal that no process or business unit is optimized at the expense of others, unless it is strategically important to do so. This means avoiding information silos, ensuring that data and analysis are available throughout the organization. The consequences of neglecting this can be severe, as decisions will be made on narrow or incorrect data. Many companies have had an individual approach to analytics, often leaving this entirely up to individuals using isolated spreadsheets. While this may be considered a start, it is not an ideal way to manage analytics for an enterprise. These spreadsheets are error-prone and can create multiple solutions to an issue, perhaps causing more harm than good. There are several approaches to ensure enterprise management. IT groups can manage data and install BA software, a central analytical services group can assist executives in need of analyses, or a cross-functional business intelligence competence center can be established.

Third, there must be senior management commitment. A broad analytical approach needs to be supported by culture, process, behavior and skills for employees. These changes, in turn, must be led by committed senior executives. The list of such CEOs from analytical competitors is long: Jeff Bezos of Amazon, Reed Hastings of Netflix, Rich Fairbank of Capital One, and so on. Without this push from the top, it is not easy to make the cultural changes needed to become an analytical competitor. As Davenport and Harris state: "We know it is a bit of a cliché to say that an idea needs the passionate support of the CEO or other senior general managers, but in our research on analytical competitors, we simply didn't find any without such committed and broad support from the executive suite".

Lastly, analytical competitors have high aspirations for their endeavors. Several of Davenport and Harris' analytical competitors bet their futures on analytics-based strategies, often being drastic departures from existing industry practices. While incremental steps and tactical use of analytics can give rewards, these will be minor. To achieve major ones, a competitive and ambitious use is necessary. In sum, these four criteria are not independent from each other. Senior executive commitment is perhaps the most important one as it enables the others. By combining these four factors, Davenport and Harris identified five stages of analytical competition as shown in Figure 4.

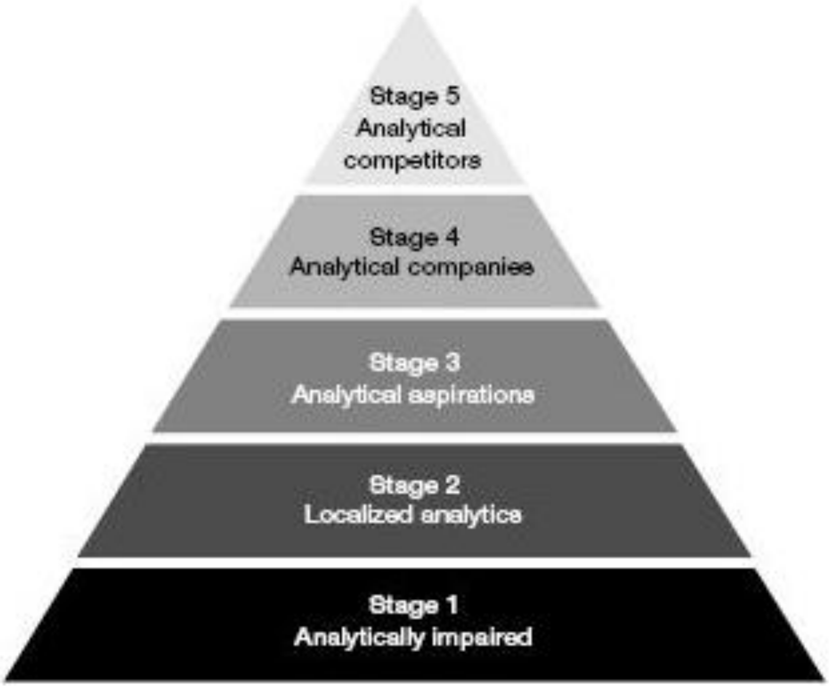


*Figure 4: Five stages of analytics (Davenport & Harris, 2007)*

Few companies make it to stage five, but that does not mean that analytics is wasted for the remaining. Individual insight can be beneficial. However, there are five features of analytical capabilities that characterize analytical competitive advantages. First, they must be hard to duplicate. As analytical competitors are distinctive due to their culture and processes rather than advanced software, this is a given. Furthermore, it must be unique to the company's strategy and market position: no glove fits all in this field. Third, analytical organizations can apply their analytical capabilities in adaptive and innovative ways, swiftly responding to different scenarios. Fourth, the organizations must be better than the competition in their use of data, even in industries where the use of analytics is extensive. Lastly, as with any competitive advantage, it must be renewable with continuous improvements.

Achieving any level on the analytical stage requires companies to build their analytical capabilities, which is far from easy. If the data quality and managerial support is absent there is hardly any choice in pursing analytics at all. When these fall into place, however, there are three key areas of capability: organization, human and technology. While these have different content, they should all support the same goals. The organizational issues have been discussed previously, highlighting focus on distinctive capabilities, processes and culture. However, the latter to wholly depend on the humans. Part of this is obviously executive commitment and creating a fact-based mindset, but another aspect is managing analytical people. Davenport and Harris have two categories of analytical employees, professionals and amateurs. Professionals are typically organized in groups, maintain a close relationship with IT, and should make a point of keeping their communication to the rest of the organization simple enough to be understandable. Analytical amateurs fall between two stools; they know something, but not enough to use powerful statistical tools. Too often, they end up using spreadsheets with all the weaknesses that follow.

The issue of analytical professionals versus amateurs is perhaps smaller now than at the book's release in 2007, as software development has been considerable since then. This leads us to the last key area, technology. The choice of software is less important than the process. The architecture of successful BA must be a close collaboration between IT and business managers. While IT ensures the gathering of data, technology and processes, all efforts are wasted if it has no connection to the company, its strategy and the analysts involved.

| Stage | Organization | | Human | | | Technology |
|---|---|---|---|---|---|---|
| | Analytical objective | Analytical process | Skills | Sponsorship | Culture | |
| 1 Analytically impaired | Limited insight into customers, markets, competitors | Doesn't exist | None | None | Knowledge allergic—pride on gutbased decisions | Missing/poorquality data, multiple defines. Unintegrated systems |
| 2 Localized analytics | Autonomous activity builds experience and confidence using analytics; creates new analytically based insights | Disconnected, very narrow focus | Pockets of isolated analysts (may be in finance, SCM, or marketing/CRM) | Functional and tactical | Desire for more objective data, successes from point use of analytics start to get attention | Recent transaction data unintegrated, missing important information. Isolated BI/analytic efforts |
| 3 Analytical aspirations | Coordinated; establish enterprise performance metrics, build analytically based insights | Mostly separate analytic processes. Building enterpriselevel plan | Analysts in multiple areas of business but with limited interaction | Executive—early stages of awareness of competitive possibilities | Executive support for fact-based culture—may meet considerable resistance | Proliferation of BI tools. Data marts/data warehouse established/expands |
| 4 Analytical companies | Change program to develop integrated analytical processes and applications and build analytical capabilities | Some embedded analytics processes | Skills exist, but often not aligned to right level/right role | Broad C-suite support | Change management to build a fact-based culture | High-quality data. Have an enterprise BI plan/strategy, IT processes, and governance principles in place |
| 5 Analytical competitors | Deep strategic insights, continuous renewal and improvement | Fully embedded and much more highly integrated | Highly skilled, leveraged, mobilized, centralized, outsourced grunt work | CEO passion. Broad-based management commitment | Broadly supported fact-based culture, testing and learning culture | Enterprise-wide BI/BA architecture largely implemented |

*Figure 5: Factors of analytics (Davenport & Harris, 2007)*

The models of TDWI and Davenport and Harris have similarities and differences, the latter mainly being a result of their focus. TDWI has a more detailed approach to data and its infrastructure, emphasizing the need for data governance programs and sufficient funding. Davenport and Harris is more concentrated on the organizational approach, executive sponsorship and employee competence. However, they share several features. They both highlight executive support, formalized data governance, reducing silos to a minimum, making data available throughout the organization, using analytics for competitive advantages, integrating data sources, coordinating resources in business and IT, and ensuring a level of skills in-house. Therefore the input of both models will be discussed in this thesis, although Davenport and Harris will be in the center.

## 2.2. Components of analytics maturity

To present the existing research that is useful for our thesis, this chapter is organized based on the components described in the chapter above. This has been done to present the research in a tidy manner. Although the research relates to the categories set by the framework of Davenport and Harris, the intention is not to describe the latter researchers' concrete description of the categories, but to provide more research-backed insight to the categories.

Existing research providing insight into the different components of this chapter stems from different fields. Academic research on business analytics and business intelligence is limited, and because of its connection to digital transformation, data-driven organizations and similar topics, we have incorporated research from these fields. Osmundsen, Iden and Bygstad found in a literature study that the terms digital transformation, digital innovation and digitalization have much in common, *big data* being one of them (Osmundsen, Iden, & Bygstad, 2018).

Data-driven organizations (DDO) have been defined as organizations in which decision making is enabled by evidence – based on data – rather than intuition (Windt, Borgman, & Amrit, 2019). Carl Anderson argues that the typical use of data in organizations is limited to describing what has happened, without being prescriptive and proactive (Anderson, 2015). Furthermore, analytics cannot be data-driven if the data is never or seriously considered or acted upon. DJ Patil and Hillary Mason offer a more detailed definition, stating that a DDO is an organization that acquires, processes, and uses data in a timely fashion to create efficiencies, develop new products, and navigate the competitive landscape (Patil & Mason, 2015).

Defining digital transformation, on the other hand, is not easy, as the research community has yet to agree on an unambiguous definition. Berghaus and Back defines digital transformation as changes that affect many parts of an organization, where the outcome is significantly different to the original state (Berghaus & Back, 2017). Westermann et al. on the other hand, defines the term as the use of technology to radically enhance the performance and range of the business (Westermann, Tannou, & McAfee, 2017). Other definitions include that digital transformation is a process to become a digital organization, and the use of digital technologies to reformulate the business model, and as a transformation of business models and organizational structures as a result of innovative technologies, altering how business is conducted (El Sawy, Amsinck,, Kræmmergaard, & Vinther, 2016).

### 2.2.1. Organization

*Objective*

The first component presented by Davenport and Harris is the analytical objective. This is echoed by other researchers. Both Henke et al. (2016) and Canon Moreno (2017) presented similar frameworks to guide data analytics transformation, with the first prioritization being to "set objectives" and "Craft an inspiring vision for data analytics" (Henke, et al., 2016; Moreno, 2017). Successful BA implementations are achieved by organizations that ensure that BA and business objectives are aligned (McMurchy, 2008). Bharadwaj et. al. 2013 also proposes that a digital business strategy must be formed in order to embark on a digital transformation (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). The digital business strategy should integrate the IT strategy into the business strategy. This is further echoed by researchers on digital transformation, agreeing joining IT- and business strategy into a digital business strategy is central (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). Rupanagunta et al. highlights the challenge of an unclear business problem in their paper about the analytics and consummation gap (Rupanagunta, Padmanabhan, & Mony, 2012). The paper argues that clarity around the business' agenda drives better hypothesis generation, better analyses and insights.

However, research also point out that this is not easy. Organizations typically struggle to figure out how to use their data and defining clear objectives is not always possible (Ransbotham, Kiron, & Kirk, 2016). In a survey of C-suite executives and managers, the most acknowledged challenge was to set up right visions and strategy (Henke, et al., 2016). The corresponding research also revealed that the lack of references for data analytics transformation strongly contributed to this challenge. Thus, organizations will often launch pilot projects to gradually gain understanding of the feasible possibilities, with the goal that a vision and strategy will become clearer after some experimentation. The latter also pointed out that long term programs often require early gains to maintain momentum. Other digital transformation research suggests that the objective could describe a future state and that the rest of the process should be approached from front-to-back, supporting the idea of experimentation (Kane, Palmer, Phillips, Kiron, & Buckley, 2015). This is repeated by Rupanagunta et al., stating that “more often than not, creation of analytics is an iterative process” (Rupanagunta, Padmanabhan, & Mony, 2012). About where to start a digital transformation, SAP found that most leaders of successful digital transformations focus on transforming customer-facing functions first (SAP Center for Business Insight and Oxford Economics, 2017).

*Process*

The second component is process. Berghaus and Back emphasizes the importance of defining processes and the infrastructure regarding information systems (Berghaus & Back, 2017). This is repeated by Berman, who adds that in order to implement a digital business strategy, integration planning for physical and digital components is necessary (Berman, 2012). Bygstad notes a need of gaining control over mazes of information that arise in silo systems (Bygstad, 2017). This is repeated by Canon Moreno, stating that business analytics processes often require “coordination of different areas of a siloed organization” (Moreno, 2017). Kiron et al. offer a further explanation of the occurrence of silos, indicating that these groups, or enthusiasts, often find innovative ideas with analytics, but lack the abilities to extend those into the organization (Kiron, Prentice, & Ferguson, The Analytics Mandate, 2014). The researchers argue that, on one hand, their knowledge of a certain business need allows them to target focused initiatives that could demonstrate business value. On the other, their distance from c-suite and managers blocks visibility and support for the initiatives.

Many studies suggest that a digital transformation should be organized top-to-bottom (Berman, 2012; Bharadwaj et.al, 2013; Westerman et. al., 2014). This is broadly supported by the research community, because it sets unambiguous direction for the whole organization and reduces the formation of silos. On digital transformation strategies, Matt et al. (2015) points out a challenge of different strategies in different areas of the organization: “IT strategies usually focus on the management of the IT infrastructure within a firm, with rather limited impact on driving innovations in business development. To some degree, this restricts the product-centric and customer-centric opportunities that arise from new digital technologies, which often cross firms' borders" (Matt, Hess, & Benlian, 2015).

### 2.2.2. Human

*Skills*

About forging a DDO, many researchers argue that the best organizations recognize that people are at the center, rather than focusing on which technology is used. The important questions are who control the data, who they report to, and how it is being used. (Anderson 2015, Patil & Mason, 2015). Windt et al. points out that a lack of analytical skills in people remains a major challenge in order to become a DDO (Windt, Borgman, & Amrit, 2019). A digital transformation requires the acquiring of skills and competence (Berghaus and Back, 2017, Westerman et al. 2014). However, it is unclear if this should be acquired internally, externally or just in general. Westerman et al. (2014) adds detail, stating that the digital transformation requires customization of competence. Competence and skills are acknowledged as very important, but many researchers do not describe what types of skill that needs to be obtained and how to acquire it.

One way would be to upskill the current workforce. A Capgemini report listed what they found were the key considerations for a successful upskilling strategy (Crummenerl, et al., 2018). The components of this strategy include "align learning to organization strategy, enable leaders to communicate successfully and manage change, assess your tech investments and extent the impact on the workforce, define the skills you need and when you need them, make upskilling a win-win for people and the organization". Matt et al. (2015) also notes the importance of upskilling for a digital transformation, stating that although the current workforce might have a less tech-savvy mindset and lack the required capabilities to cope with upcoming changes, it is often challenging to find and employ new highly skilled and focused staff members. To cope with the challenges that arise when embarking on organization-wide transformation, a solution could be the hiring of external consultants. Stated rather famously by Wendell French, consultants are considered the *agents of change* (French, 1999). Matt et al. (2015) challenge this as digital transformations require skills not only necessary for the actual transformation, but also for the new work practices that it pioneers. This is repeated by Henke et al. (2016, p. 5): "while it is possible for organizations to outsource their analytics activities, business translator roles require proprietary knowledge and should be more deeply embedded in the organization". Wolf et al. also recommends that knowledge must be tied to the company as far as possible (Wolf, Semm, & Erfurth, 2018).

Upskilling, outsourcing or acquisition of workforce are ways to obtain the necessary skills, but what are they? Anderson (2015) listed numerous skills that an analyst needs to get the most out of the data: numeracy, detail-attention, method, critical questioning, confidence, curiosity, good communication, patience, pragmatism, and business acumen. Other researchers also emphasize data literacy as a key skill. A Gartner report from 2019, put data literacy in employees as one of the two biggest blocks for organizations to forge a DDO (Rollings, Duncan, & Logan, 2019). Data literacy is defined as the ability to read, write and communicate data in context. This includes an understanding of data sources and constructs, analytical methods and techniques applied, and the ability to describe the use case, the application and the resulting value. Researchers thus seem to agree that the competence of people is a major factor for creating a DDO.

*Culture*

Research on DDO also includes research on data driven culture (DDC). Kiron et.al defines DDC as patterns of behavior and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information play critical roles in the success of their organization (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 2011). Anderson (2015) adds that many organizations generate reports and have dashboards, but although these activities are part of a culture using data, this does not make them data driven. The importance of culture is also emphasized in digital transformation. Westerman et al. (2014), points out the necessity of adapting culture. Other researchers also agree that a change in organization culture must correspond with the development of digital strategies and digital business models (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Berman, 2012). Bharadwaj et al. (2013) adds that cultural transformation is the interplay between all the systems of the organization. Berghaus and Back (2017) highlights the need for cultural transformation to facilitate and embrace collaboration in the entire organization.

A Capgemini report defines seven key attributes for a digital culture: innovation, data-driven decision making, collaboration, open culture, digital first mindset, agility and flexibility, and customer centricity (Buvat, et al., 2017). It also lists the challenges in implementing the digital strategy. The main challenges address that leaders tend to neglect or misunderstand the need of a digital culture in the planning of a digital transformation, that the existing culture and work practices are too deeply ingrained to change, and that employees are not sufficiently empowered to change and innovate the way they work. These challenges are repeated in much research. Among them, Canon Moreno (2017) states that "organizational and cultural challenges stem from the fact that data analytics implies a different way of running a business and making decisions - particularly for companies with a strong legacy of intuition-based decision making. In many organizations data is seen a by-product of business and often not looked at as an asset. Changing these paradigms takes time and significant effort".

Henke et al. (2016) touched upon the term of the business translator role in the topic of skills, and further defines the term in the context of challenges arising with distancing between departments. The study proposes the creation of business translator roles to help bridge the gap between data science and business units and therefore facilitate implementation of analytics insights. Further recommendations related to roles for solving cultural challenges are given by Aiken & Gorman (Aiken & Gorman, 2013). Their research suggests that a CDO (Chief Data Officer) should be given the same importance as a C-suite function like CFO's (Chief Financial Officers), and that this structure "would impose a much-needed bias towards data-centric development practices."

Wolf et al. (2018), offers a detailed explanation of digital cultural challenges with proposed solutions. First, their research finds that organizations usually have two competencies that must be brought together, namely enthusiasm and wisdom. The competencies are usually found in young, more tech-savvy employees and older, more experienced employees, respectively. Organizations must therefore focus on diversification in general, and age in particular. Furthermore, the research finds that fragmented knowledge prohibits success, and that information and knowledge must be exchanged as transparently across departments as possible. Lastly, organizations must achieve a collaboration culture. The authors note that this could stem from inadequate incentive systems and a lack of tolerance anchored in the corporate goals. Employees might also be worried about their own spaces and feel protective of their capabilities and responsibility. The latter is also repeated by Canon Moreno (2017), who indicates that employees do not want to share their "keys to the kingdom", as this might make them replaceable and lead to a tougher internal competition with other employees.

Lastly, Kreutzer, Neugebauer & Pattloch finds that it is worth celebrating successful steps of a transformation at all levels (Kreutzer, Neugebauer, & Pattloch, 2018). This will show the organization what is possible and achieved and enable trust of the seemingly impossible.

*Sponsorship*

Sponsorship or support from management is considered one of the absolute necessities for success. Young & Jordan found evidence, on general project management, that management support is the most important success factor for a project and cannot be considered as just "one of many" (Young & Jordan, 2008). This is echoed by research on digital transformation, stating that the transformation is not possible without support from management (Westerman et al. 2014, Berghaus & Back 2017, Bharadwaj et al. (2013). Matt et al. (2016) states that because transformation affects the entire organization, resistance of some sort is bound to occur in some departments, and it is therefore necessary with total sponsorship for the cause in order to push the transformation through. Rupanagunta et al. (2012) also stresses the importance of executive endorsement for successful use of analytics.

However, there are numerous challenges to sponsorship. Ransbotham et al. point out that an organization's capability to produce increasingly sophisticated analytics outpaces management's abilities to understand them (Ransbotham, Kiron, & Prentice, Minding the Analytics Gap, 2015). A Capgemini report found increasing gaps between managements and employee’s perception of different scenarios (Buvat, et al., 2017). Management and leaders claimed much higher values in questions measuring topics ranging from culture and innovation to endorsement and empowerment, than did their employees. This shows that, albeit leaders believe they show and execute support and sponsorship, employees might not feel the same way, and therefore not propose new initiatives.

### 2.2.3. Technology

Collecting, storing and analyzing data require significant input from organizations and humans to succeed, but combining these factors with technology is crucial.

While data gathering can be plagued by different issues, data quality seems to be the most severe. In its data management report, Experian found that 95% of organizations notice impact from poor data quality (Experian, 2019). While poor data quality can reflect a number of reasons, the biggest contributors are human error and too many data sources. While bad data is at best inconsequential, in that it is either ignored or does not provide any reasonable support, it can prove disastrous if the wrong end result is actively used in decision making. According to IBM, poor data quality costs the US economy $3.1 trillion per year (IBM, 2020). Furthermore, poor data quality is unfortunate as it also brings distrust from the users, which will hurt the digital transformation.


*Figure 6: Data quality dimensions (Bluwave Analytics, 2019)*

While data warehouse and data marts have dominated data storage for decades, new solutions to meet the increase in data volume have been developed, the most popular being data lakes (Sulmont, 2020). As opposed to data warehouses, that require a certain amount of data processing, data lakes are designed to tackle any kind of raw data. The most important difference, however, lies in the schema. While warehouses work on a previously defined schema, data lakes can be filled with data that can be analyzed without premonitions. This provides great scalability, but at the cost of a consistently high level of skill from its users. Note that the integration of data lakes, warehouses, cloud solutions and more are rapidly changing. Thus, the required skills and capabilities are constantly altering, typically relieving companies of the most demanding technical tasks.

*Table 1:* Data lakes vs data warehouses

| | Data lake | Data warehouse |
|---|---|---|
| Type of data | Unstructured and structured data from various company data sources | Historical data that has been structured to fit a relational database schema |

| | | |
|---|---|---|
| Purpose | Cost-effective big data storage | Analytics for business decisions |
| Users | Data scientists and engineers | Data analysts and business analysts |
| Tasks | Storing data and big data analytics, like deep learning and real-time analytics | Typically read-only queries for aggregating and summarizing data |
| Size | Stores all data that might be used—can take up petabytes | Only stores data relevant to analysis |

Analyzing data can happen in a lot of different ways, but the goal should always be to provide insight – to turn data into information. While Microsoft Excel remains perhaps the most widespread tool, dashboards are becoming more commonplace. The latter can be designed either top down or bottom up (Chuppala, 2012). Top down means that analytics are based on a strategy derived from the top of the company's hierarchy. Based on these directives, departments will aim to deliver precise answers to whatever predefined questions are given. Bottom-up, on the other hand, takes the opposite approach, giving different departments freer reigns to design their own dashboards based on what metrics they believe to be most helpful and answer questions that may not be anticipated.

While the limited research on the topic has yet to define a best approach, top-down has both dominated empirical studies and been considered the optimal solution (Chadha, 2016). Some case studies show that bottom-up can be equally useful when there is a lack of corporate strategy, bringing issues to their right place in the managerial hierarchy.

With the growth in data volume, more sophisticated data analysis has become available to a growing number of companies through machine learning. One of the world's leading companies in the field, SAS Enterprises, says that "Machine learning is a method of data analysis that automates analytical model building (…) It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention" (SAS Enteprises, 2020). There is a plethora of possible alternatives: supervised learning, unsupervised learning, classification, clustering, etc. While this may seem intimidating to many firms, there is no doubt that it can provide significant value. For instance, McKinsey reported that some banks in Europe showed a 10% increase in sales of new products, 20% savings in capital expenditures, 20% increases in cash collections, and 20% declines in churn after replacing old statistical-modeling approaches with machine learning techniques (Pyle & José, 2015).

The increasing complexity of data gathering, storage and analysis, has made data governance central for any organization wanting to succeed in BA. According to Newman and Logan, data governance is "the collection of decision rights, processes, standards, policies and technologies required to manage, maintain and exploit information as an enterprise resource" (Newman & Logan, 2006). Khatri & Brown expands on this, defining the five decision domains of data governance as data principles, data quality, metadata, data access and data lifecycle (Khatri & Brown, 2010). Thus, it is clear that data governance is important for any organization to proactively manage their data. By providing an enterprise-wide data governance framework with clear policies and procedures, firms can ensure that all aspects of data are aligned with the firm's strategy and goals.

## 2.3. Analytics Maturity and Market Orientation

Already in 1994, Narver and Slater predicted that the nature of competitive advantage would change dramatically (Slater & Narver, 1994). Building on the works of Kohli and Jaworski, they expanded on the concept of market orientation (Kohli & Jaworski, 1990). To adjust for these changes in competitive advantage, companies had to change to this market-oriented approach, characterized by customer orientation, competitor focus and cross-functional coordination. As the authors note, "thinking in terms of market (not marketing) is essential in the highly competitive arenas of today" (page 22). If anything, this rings even more true today and is also echoed by Davenport and Harris, who note that as previous sources for competitive advantages like geography and protective regulation are no longer available in a global market, what is left to compete on are effective business processes and good key decisions. In many cases, the goal of these decisions is to support the features of a market-oriented approach.

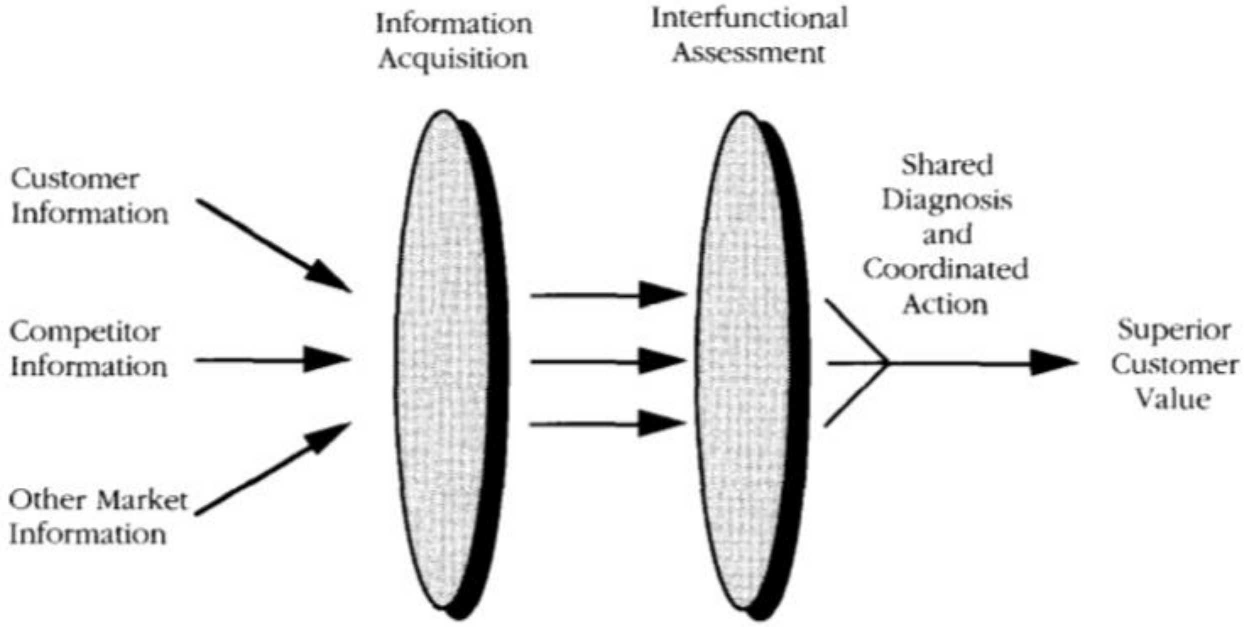


*Figure 7: Market orientation (Narver & Slater, 1994)*

Customer orientation is at the heart of market orientation, and requires the firm to know more than just the immediate target buyer. Rather, firms have to understand the buyer`s entire value chain and possible changes. Considerable time must be allocated for this purpose, and the firm should always strive to improve customer satisfaction and deliver superior customer value. Narver and Slater emphasize the importance of developing internal skills and employees, but also in continuously involving customers to forge strong customer loyalty. These ideas are not unlike what Rogers and other digital maturity model present, where different aspects are aligned to support the idea of increasing customer value (Rogers, 2016). What has changed are the available tools. While Narver and Slater describe employee programs that encourage workers to visit customers monthly to keep up-to-date on their needs, BA has changed the game completely. The end goal, however, is intact.

Competitor focus is the second component of market orientation, referring to which competitors and technologies providing threats to the firm. Understanding competitors' tactical and strategical strengths and weaknesses is crucial in order to create superior customer value. Once again, this is echoed in for instance Rogers (2016).

However, competitors cannot be understood as participants in a zero-sum game. Changing supply-chains and floating industry lines has affected how firms should understand their competitors, and the concept of *coopetition* has emerged to describe how competitors increasingly often work together for mutual benefit. However, the importance of developing shared perspectives of competitive threats, as well as rapid and dynamic responses, remains an important feature.

The last element of market orientation is interfunctional coordination. Since any point of a buyers value chain is an opportunity to create value, enterprise-wide coordination of resources is valuable. This is a central part in developing agile organizations, for instance building value by low time-to-market. Gathering cross-functional teams to work with BA is crucial, as both business knowledge and technical skills are required for success.

While Slater and Narver primarily considered market orientation as part of organizational culture, Kohli and Jaworski (1990) understand it as the implementation of a marketing concept. According to the latter, market orientation consists of three activities: intelligence generation, intelligence dissemination and responsiveness.

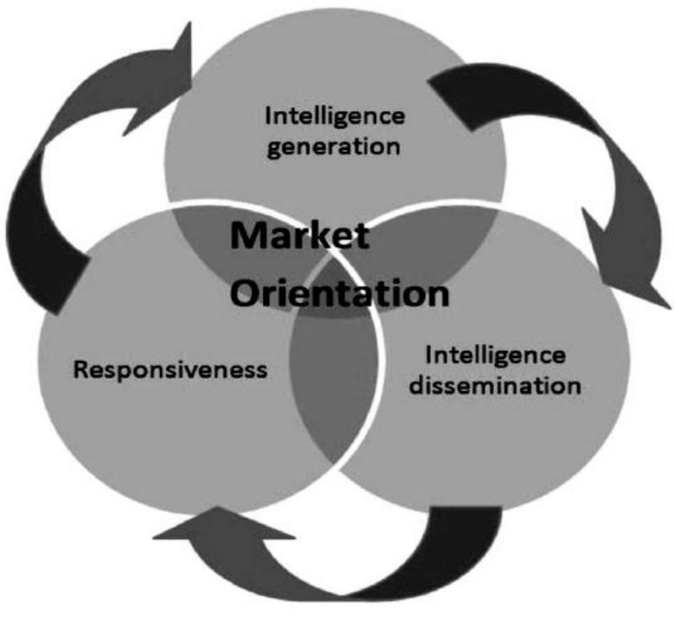


*Figure 8: Market orientation (Kohli & Jaworski, 1990)*

Intelligence generation is the gathering of different information sources deemed useful for the firm. Kohli & Jaworski were clear that this is not limited to customers, but had to cover the broader picture. Current needs and circumstances are not enough, there has to be a predictive feature as well, with new products sometimes requiring years of development before reaching the shelfs. While time to-market has been significantly slashed in most industries, *big data* has provided enormous amounts of information. The need to combine external and internal data for information is tough for any company, along with predictive analytics. It is clear that the hardest part is not gathering data, but using it for intelligence and insight.

Thus, the second component of intelligence dissemination becomes central. Responding effectively to information requires all departments to move in the same direction. Ensuring information flow and aligning different organizational components thus become crucial. While this was previously done through newsletters and the likes, a large number of alternatives are now available. However, the mission of information flow is intact. A common challenge in this regard are data silos, which limits information access and restrains synergies. These can occur for several reasons, sometimes being legally required, but should be avoided.

Lastly, there is responsiveness to market intelligence, i.e. to what degree they can turn information into action. This can be understood as the actual value creation: customer segmentation, product and service offerings, distribution, promotion and more. Quickly responding to market trends and preparing for what is to come is crucial for any company.

While these elements look attractive enough, Kohli and Jaworski define some antecedents that enhance market orientation. One is senior management factors, such as low risk aversion, high education and positive attitude to change. Another is interdepartmental dynamics, interaction across organizational departments. By lowering the conflict level, tightening connectedness and fostering openness to initiatives from other groups, market orientation is more likely to succeed. Lastly, the firm`s organization-wide characteristics are assumed to work in different ways. For instance, while formalization and centralization might lower intelligence generation and dissemination, it will improve response implementation.

As shown in Chapter 2.2, the same three elements appear in relation to BA. Support and involvement from senior management, for instance, was shown to be crucial. Ensuring interdepartmental dynamics to avoid information silos and cooperation across departments and functions is also necessary, particularly in combining the business and technology side of analytics. Lastly, the formalization of analytics strategy and data governance programs, for instance, are important for succeeding with analytics.

Combined, the two presented approaches to market orientation encapsulates central aspects of digitalization and analytics. As is evident, the principles and strategic goals of market orientation remain influential in today`s digital and dynamic environment. Therefore they have even been adopted by different maturity models. In essence, BA provide tools that support the elements of market orientation. Thus, they aid in providing an overarching platform for the following studies. Their influence on the studies differ. The culturally centered approach of Narver and Slater will be most influential in Studies 1 and 2, while Kohli and Jaworski's focus on how to realize value from insight is present in Studies 2 and 3.

## 2.4. Empirical Research on Analytics Maturity and Excellence

So far, this chapter has reviewed different components of digitalization and analytic. However, the actual implications of high maturity on profitability has yet to be demonstrated in detail. Furthermore, understanding what industries and companies invest in these capabilities will be an interesting addition to this thesis.

### 2.4.1. Analytics and Profitability

Any business wants its decisions and processes to increase profitability, or else they would rather invest money elsewhere. While this traditionally has been fairly easy to read into the bottom line, for instance through reduced production costs, modern digital and analytic tools tells different story, as insight is notoriously difficult to value.

After all, how do you quantify the value of awareness? Several studies have explored this and provided different insights.

The idea of IT-related capabilities adding value is not new, and several studies have confirmed this. Masli et al. found that firms with superior IT capabilities were able to outperform their competitors until 1999, when the advantage seems to have disappeared (Masli, Richardson, Sanchez, & Smith, 2011). However, firms that maintained high levels of IT capabilities between 1988 and 2007 continuously delivered better results than the rest. Another study showed that enterprise resource planning systems in particular have a similar effect (Kallunki, Laitinen, & Silvola, 2011). The latter also found that more formal than informal types of management controls increase performance, which may come in the form of analytics. Analytics is also a central tool in planning and providing decision support, which is increasingly important with the changing dynamics of business. Comparing future preparedness data from 2008 and performance data from 2015, Rohrbeck & Kum found that future-prepared firms had 33% higher profitability than the average, and even more impressively had 200% higher growth (Rohrbeck & Kum, 2018).

Analytics is often understood as a sub-category of digital transformation, an endless journey that seems both long and hard. However, it does seem to pay off (SAP Center for Business Insight and Oxford Economics, 2017). While SAP reports that only 3% have completed digital transformation projects across the enterprise, these companies show significantly better results than the others. For instance, 80% say that digital transformation has increased profitability, versus 53% of other companies. In the case of market share, the number is 85% to 39%. Their focus on technology as a competitive advantage is a defining feature, with 93% sharing this mindset as opposed to 72% for all others. Interestingly, leader focus on human skills is another central feature. In total, 34% reported that talent attraction and retention would be a leading growth factor over the next two years, and 31% of decision makers said investment in staff digital skills would be key in increasing revenue in the coming years. This shows that companies share the sentiment that digital transformation is about more than technology. Lastly, note that they spend a lot of time and resources to build analytical capabilities, with as much as 94% of the leaders investing heavily in big data and analytics, against 60% of others. Furthermore, Ferraris et al. found that developed analytics capabilities, in both technological and managerial sense, increased firm performance (Ferraris, Mazzoleni, Devalle, & Couturier, 2019). Another study focused more specifically on the capability-business alignment of analytics, i.e. to what extent analytics strategies are aligned with the firm's overall strategy (Akter, Wamba, Gunasekaran, Dybey, & Childe, 2016). Their findings on analytics as a predictor for financial performance again showed a strong positive relationship, with strategy being the most significant part of analytics.

Digital maturity has also been shown to have a positive effect on financial performance in several studies. One such study, based on the previously presented Capgemini Digital Maturity framework in 2.1, found that digital maturity certainly matters (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2017). Digitally mature companies in either of the two dimensions perform better than their competitors. Companies that perform higher on the vertical axis are better at deriving revenue from their physical assets, due to their somewhat experimental approach to digital measures. This does not always transform into profitability, though. Companies with stronger management capabilities are actually more profitable, proving that strategic alignment and firm governance play a role in the overall picture. The same trend is the case for company market valuation. While there are some differences in what measures companies with high scores on one axis outperform in, there is no doubt that the digital leaders dominate. They are 26% more profitable, generate 9% more revenue through physical assets, and have 12% higher market valuation ratios.

Isik et al. tried to clarify what BI success means (Isik, Jones, & Sidorova, 2013). Due to its inherent nature, it is not straight forward to deduce the value. Somewhat obvious, they find that BI success relates to the positive value added from the investment. What this really means depends on who you ask (Williams, 2011). For CFOs and financial management professionals, BI success is about getting a precise understanding of the relationship between operational performance and financial results, easy access to data for planning, forecasting and budgeting, and lastly better information for managing working capital. For a COO and operations management professionals, focus is on information regarding cost analysis, customer service, product quality, and historical data for demand management and capacity planning. The CMO and marketing professionals need information about individual customers for customer segmentation, campaign targeting, customer service and customer retention. CIO and BA teams will emphasize their ability to meet the demands of business users, moving beyond standard reports, and their role in improving business performance through supporting a data driven culture. However, it has been proven hard to provide a definitive approach to measuring BA success in the same way as most other properties, namely its impact on the bottom line.

McKinsey has been at the fore of such studies for several years, and a 2014 publication explored how analytics boosts corporate performance (Bokman, Fiedler, Perrey, & Pickersgill, 2014). They found that extensive use of analytics had a major effect on their sample's corporate performance. In fact, companies with extensive use of customer analytics performed 126% better than their competitors on profit and 132% better on ROI. The difference in growth is even more staggering, with extensive analytics users seeing 186% higher sales growth. Furthermore, these companies really seem to grasp the idea of the modern customer. By using customer analytics, customers of analytical companies are more than nine times more likely to be loyal and 19 times more likely to provide above-average profitability. Tightly connected to the last measure is the ability to migrate customers to profitable segments, which is 21 times more likely. All these aspects clearly demonstrate that analytical companies vastly outperform their competitors in customer related features. Lastly, McKinsey finds that the analytical champions have three things in common: seeing analytics as strategic rather than supporting, C-level executives have a hands-on approach to analytics, and the internal skill level is high.

### 2.4.2. Industry Differences

While it is quite clear that digital and analytics capabilities increases company performance, the extent of these advantages might be different between industries as their circumstances differ greatly. However, Westermann et al. found that digital maturity matters in every industry, albeit in different ways as they are not equally affected (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2017). Industries like pharmaceuticals and manufacturing are lagging behind, while high technology firms lead in digital maturity. Banking and retail, being faced with electronic commerce in the early 2000s, also score high in both digital and leadership capability. Still, it is paramount to note that while there are significant differences in the industry maturities, they all have digital leaders. This means that even the weak industries should feel an urgency to improve their capabilities, as this is a long-lasting endeavor. Digital beginners need years to even catch up with the digital leaders, and the sooner this journey starts, the better.

McKinsey did a similar analysis for digitization, using 27 indicators in the three categories of digital assets, digital usage and digital workers (McKinsey Global Institute, 2015). Digital assets measure investments in hardware, software, data and IT services. Digital usage looks at companies' digital engagement with customers and suppliers through payments, marketing and design processes. Lastly, digital workers measure the degree to which companies provide their employees with digital tools to increase their productivity. The most advanced sectors were knowledge-intensive sectors like information and technology, media, professional services, and finance and insurance. At the opposite side of the scale are industries like agriculture, construction and hospitality. The study found that digital usage and digital labor have the most impact on the industries' rating. For instance, workforces from companies in leading sectors are 13 times more digitally engaged than the rest.

Another study by Remane et al. explored the digital maturity in traditional industries (Remane, Hanelt, Wiesboeck, & Kolbe, 2017). Based on a survey on digital transformation, they did a cluster analysis which showed some interesting results. The industries weakly affected and poorly prepared for digital transformation were typically from the health, electronics or automotive industry, comparatively smaller than the others, and had very low IT skills. While no particular industry was identified in cluster five, which understood the implications of digitalization and prepared accordingly, these firms were more profitable, had lower revenues, high IT budgets and employees with high IT skills. In sum, the best indicators of digital transformation impact and readiness were company size, profitability, IT budget, and IT competency.

Looking at a mature industry like finance, a 2018 study explored the relationship between digital innovation and profitability (Giaretta & Chesini, 2018). Measuring the digital innovation through six variables, among these R&D and Software & Databases, for European banks between 2000-2015, they found that investments in digitalization had a positive effect on bank profitability. One relationship proved especially strong, namely that between R&D and bank income.

### 2.4.3. Who Invests in Analytics?

As shown, digital transformations in general, and analytics projects in particular, can be costly. While the research on what drives investment in analytics is quite limited, one study found that company size is positively correlated with analytics investment (Liberatore, Pollack-Johnson, & Clain, 2016). The same study notes the importance of momentum and using the scalability inherent in analytics, as companies tend to build on existing analytical capabilities. This is in line with Xavier et.al, who showed that existing understanding of analytics increases investment, and these companies tend to have rather large turnover (Xavier, Srinivasan, & Thamizhvanan, 2011). Lismont et.al explored analytics maturity, identifying four clusters (Lismont, Vanthienen, Baesens, & Lemahieu, 2017). A defining feature of each cluster was their number of employees. The cluster *No analytics* had a median of 10 employees, while *Analytics bootstrappers*' median was 1200, with 4.5 data scientists. The third cluster, *Sustainable analytics adopters,* had an average of 15 data scientists and 3500 employees in total. Lastly, the *Disruptive analytics innovators* had 10 000 employees and 30 data scientists.

### 2.4.4. Digitalization and Analytics in Norway

While the use of BA in Norwegian companies is fairly unsolved question, there are several reports and studies on the level of digitalization and digital maturity. Note that these terms have very different meanings for companies and individuals. According to Siemens 2019 report on digitalization in Norway, digitalization is "about using technology to renew, simplify and improve" (Siemens, 2019). When asking executives and employees in Norwegian companies, however, Siemens get a wide array of responses. On the question "what terms do you primarily associate with digitalization", where the respondents could provide more than one term, more than 80% noted automatization. Following this was flow of information, big data and internet of things, all around the 50% mark. A term like business intelligence is in the lower half, with only 26% of the respondents. This is not to say that BA is neglected, but it gives an idea of what companies mean when they use the term digitalization and perhaps where their investments are heaviest. This rings even more true when reviewing Visma's Digital Index 2019 (Visma, 2019). Of the thirteen processes they recommend Norwegian companies digitalize, more than half relate to automatization of processes regarding invoices.

Although the terms may not directly touch on BA, these types of reports can certainly aid in providing a rough understanding of the digital state in Norwegian companies. One aspect previously stressed in this paper is a sense of urgency, a feeling of necessity in furthering the company's digital capabilities. Siemens reports a medium sense of urgency in Norwegian companies, and a quite interesting paradox. While 74% view digitalization as very important in five years and are making plans to meet this, only 55% find it very important to act immediately. This is supported in Visma's report, which shows that 25% of their respondents believe digitalization will provide minor or no contributions to their company's competitiveness.

Another essential contributor in creating data driven organizations and analytics maturity is support from C-level suites. When asking what the businesses consider the biggest hurdles for digitalization, prioritizations is the number one response. While it does not necessarily have to, this can be interpreted as a lack of support from management. After all, they decide how the company should use and develop its resources. This could stem from a lot of reasons: lack of technological competence, vision, a fear of change, and more. However, it is reasonable to assume that in most cases it is simply deemed not to improve the bottom line. This is supported by the second biggest hurdle being cost. Investments in digitalization are costly, and the majority do not bring immediate returns. Previously we have shown that BA-initiatives pay off, and this is the case also for Norway. A study performed by Statistics Norway showed that the average value creation per hour is 14,7% higher in companies with widespread use of IT (Rybalka, 2008).

A third issue these studies present is a lack of organizational competencies within different areas of digitalization. The discrepancy between acknowledging the lack of and need for this competence is significant. While 40% in Visma's report believe competence is among the three biggest hurdles to digitalization, only 14% believe their company's need for said competency is momentous. This demonstrates a possible lack of insight and again underlines the missing sense of urgency. There is no doubt that the required skills, both from executive and employee, are rapidly changing. Gaining these skills can come in two ways, either recruitment or further developing existing employees. According to Siemens' report, the latter is slightly more prioritized with 65% planning to increase the competency level with existing employees to 59% planning to recruit new employees with digital competency.

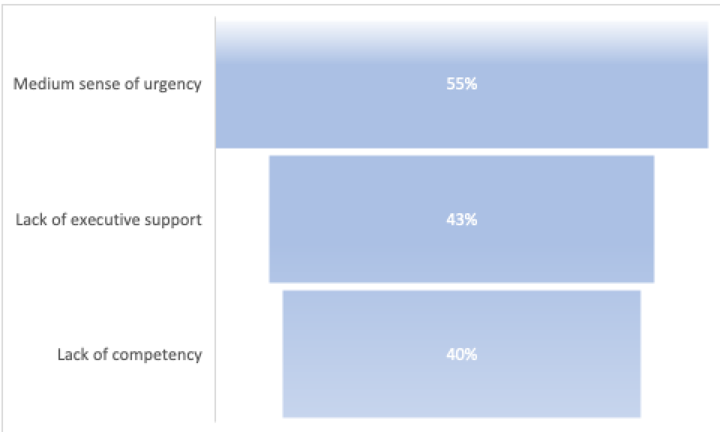


*Figure 9: Challenges with digitalization*

SINTEF, an independent Norwegian research organization, released a report named "Learn from the best - how to achieve competitive advantages through digitalization" (Knutstad, et al., 2020). By involving 33 hand-picked companies, coined as "pioneers", they present different successful practices and approaches in Norwegian businesses. One such example is the production company Øglænd System. Facing an oil crisis, affecting a significant market segment, Øglænd was required to change its way of thinking. Since then, they have focused on improving through incremental steps, focusing on predictive maintenance and automating orders. They keep updated through workshops with different employees present, who are generally keen on identifying technological possibilities - especially the younger generation. This is further substantiated by the biorefinery Borregaard, which has a company policy that all processes before, during and after investments in new digital technology must include young employees with digital skills. They represent skills and insight somewhat lacking in the older generation, which typically make up the executive team, and this support is essential in improving their decision making.

SINTEF finds that the respondents generally use inclusive decision processes where both employees and executives are active participants, with the acknowledgement that this broad approach stimulates ownership and motivation for the following implementation. These workgroups investigate needs, consequences, and financial implications. Depending on the investments' nature and size, the decisions are made in different hierarchical levels of the organization. Furthermore, they find that a long-term plan is of great importance in succeeding with digitalization - some businesses have integrated this in their overall company strategy, while others have separate approaches. There is reason to believe that the Norwegian working model can aid Norwegian companies in succeeding with digitalization. In short, this working model is recognized by different parts, i.e. employers and employees, cooperating in business development. Among other things, this has resulted in mutual trust, flat organizations and worker's rights to influence their own work. The businesses in this survey acknowledge that this is a helpful and important framework for technological development. As previously discussed, all companies rely on their employees for success in any technological project and should always aim at involving them to create a feeling of ownership. An example of this integration of employees is found in the furniture producer Ekornes, which seats their engineers in different departments to facilitate a close working relationship to processes and operators. This is to avoid traditional patterns of silos and divisions, ensuring that the organization works towards similar goals.

Another essential criterion for success is the company's access to digital expertise. This can stem from a number of sources: internal resources, consultants, technology suppliers, research institutions or academia. One business specifically focused on creating its own dashboard solution, using a Microsoft platform, using in-house resources. This way, they were able to improve internal capabilities throughout the process. The ambition was that this would help them constantly improving visualizations and other functions provided by the tool, which they state businesses often have trouble using to its full extent. Combining internal expertise with core competencies in production processes seems to optimize solutions, but not all companies have this option available. In fact, most businesses can gain from focusing on developing their own core competencies and recognize areas where they require external expertise. Mapping out the digital competency at different levels and parts of the company can greatly ease the job of correctly identifying where this is needed. Furthermore, building close connections to external suppliers is important to ensure the quality of solutions, and this is typically easier done with a relatively close geographical proximity.

On the point of executive involvement, the report provides some interesting observations. Some companies have challenges with their leaders not comprehending the extent and complexity of digital projects. They cannot simply hire consultants, provide them with a project scope, and get a polished product in return. Digitalization involves the entire organization and its levels, demanding that humans work together to reap the rewards. Several executives acknowledge this, especially the issue of treating technology development projects as isolated ventures rather than part as a more holistic organizational advancement.

# 3. Research Questions

The global interest in how organizations can improve through business analytics is reflected in the academic literature and in numerous private-sector reports. However, there exists no unambiguous roadmap towards analytics excellence. The overall aim of the three studies reported in the following is to assess the current level of digital maturity in Norwegian organizations and identify key steps for progressing from digital maturity to analytics maturity.

Our first objective is to assess the degree to which Norwegian organizations have adopted digitalization as a strategic orientation. This will be addressed in Study 1. The empirical basis will be a large survey of Norwegian organizations conducted in collaboration with Digital Norway. Specifically, we will address the following research questions:

- Are there distinct patterns of strategic orientations that distinguish digitally mature industries from others?
- Do these strategic orientations coincide with a higher focus on the development of analytics capabilities?

Our second objective is to identify the main challenges Norwegian organizations must address on their path towards business analytics maturity and excellence. This will be addressed in Study 2. Here, the methodology will be qualitative, based on expert interviews. Specifically, we will address the following research questions:

- What are the main challenges faced by Norwegian companies on their path towards BA maturity and excellence?
- What company characteristics facilitate BA success?

Our third objective is to develop recommendations on how Norwegian organizations should proceed in order to achieve business analytics maturity and excellence. This will be addressed in Study 3. We will use survey methodology again, but with a much smaller and more targeted sample of organizations than in Study 1. Specifically, we will address the following research questions:

- How does companies understand and use BA today?
- How should companies approach BA in order to ensure rewards and impact?

# 4. Study 1: Digitalization as a Strategic Orientation

## 4.1. Method

Through the generosity of the organization Digital Norway, a non-profit organization working to help Norwegian businesses succeed with digitalization, we gained access to a detailed survey on the digital maturity in Norwegian companies. It had 22 questions, spanning six topics: introduction, management, competency, renewal, customers and competition. The survey was written in Norwegian, and the authors of this thesis are responsible for all translations.

### 4.1.1. Participants

In total, the survey had 1 682 respondents. Due to missing data, particularly on company industry and number of employees, 534 of these were omitted, leaving 1 148 responses. The respondents can be divided by two different axes, their industry or the number of employees. The survey covered nineteen different industries including retail, industry, public administration, information services, and more. Thus, the companies were sorted after their industry and size. In the absence of revenue data, size was assessed using the number of employees, using the definitions provided by the Confederation of Norwegian Enterprises (NHO). Thus, small companies have less than 20 employees, medium companies have between 21 and 100 employees, and all companies with more than 100 employees are considered to be large. The final distribution is available in Appendix 1.

### 4.1.2. Procedure

The Digital Maturity Survey was distributed through industry organizations and has a wide variety of respondents. The survey was completed both individually and in groups. While some of the individual respondents used minutes, the groups typically used several hours, implying lengthy discussions. Removing the respondents that used more than a workday of nine hours, the average answering time was 19 minutes and 47 seconds.

#### 4.1.3. Measures

The questions included in the survey cover a wide range of topics within digitalization, with inspiration from the Digital Transformation Playbook (Rogers, 2016), Deloitte Digital Maturity Assessment (Deloitte Digital, 2018) and the Exponential Quotient survey (OpenExO, 2020), combined with the organization's knowledge and experience, including its owners such as the Municipal and Modernization Ministry of Norway, Telenor, DNB and AkerBP.

All the questions were answered on a graded Likert-type scale ranging from one and seven, where seven represented the strongest agreement. For instance, question 7 reads "The business is actively working on questions related to digital threats". Explanations given for score one and seven were respectively "we do not experience that our company is exposed to these threats" and "to secure data, systems and equipment against internal and external threats, we implement what we continuously believe to best practice for working routines, employee training, and supplier control".

As described in Chapter 2.3, digitalization can be understood as an indication of the overarching strategical positioning of the company, i.e. whether or not they follow a market-oriented approach. Customer insight, cooperation across organizational functions, and different sources of information in decision making are examples of how this manifests itself. This is reflected in the survey`s indexes and questions in (see Table 2).

In order to reduce the amount of the noise in the data, the 1148 original complete responses were aggregated by industries, resulting in 57 data points. Table 2 shows means, standard deviations, minimum and maximum values for the distribution of the average industry values.

*Table 2: Survey items, index measures and descriptive statistics of the distribution of by-industry averages*

| Item/index | N industries | Max | Min | Mean | SD |
|---|---|---|---|---|---|
| Norwegian companies need to adapt as a result of digitalization over the next five years to remain competitive | 57 | 6.78 | 4.00 | 6.16 | 0.47 |
| Digital technologies will create new opportunities for your business over the next five years | 57 | 6.67 | 3.50 | 5.87 | 0.58 |
| Your company's vendors offer solutions that use digital technologies in new ways | 57 | 6.33 | 2.80 | 4.86 | 0.70 |
| *Index: Recognition of digital opportunities* | 57 | 6.33 | 4.00 | 5.63 | 0.47 |
| The board of directors of the company is a driving force for the company's strategy to use digital technologies and systems | 57 | 6.20 | 2.33 | 4.08 | 0.72 |
| Available data and insights from internal and external sources are used when making strategic decisions | 57 | 6.00 | 1.71 | 3.60 | 0.84 |
| The company emphasizes qualitative and forward-looking indicators to drive change and improvement | 57 | 6.00 | 2.00 | 3.60 | 0.72 |
| The company is actively working on issues related to digital threats | 57 | 7.00 | 1.50 | 4.79 | 1.15 |
| *Index: Consistent strategy formation* | 57 | 5.75 | 2.63 | 4.02 | 0.59 |
| The company has access to resources with expertise in new digital technologies | 57 | 6.00 | 2.67 | 4.25 | 0.81 |
| The company encounters few obstacles when it develops services based on data from its own sources | 57 | 6.00 | 2.33 | 4.22 | 0.74 |
| Experiences from development activities are shared across the business in a structured way | 57 | 6.00 | 2.40 | 4.06 | 0.72 |
| The company emphasizes the development of employees' expertise and skills in digitalization | 57 | 5.71 | 2.67 | 4.28 | 0.61 |
| *Index: Implementation capabilities* | 57 | 5.75 | 3.00 | 4.20 | 0.58 |
| The company uses modern forms of work in innovation projects | 57 | 6.00 | 2.72 | 3.99 | 0.65 |
| Responsibility for innovation is distributed and rooted in the business | 57 | 7.00 | 1.91 | 4.28 | 0.86 |
| The company works systematically to eliminate or simplify manual and repeatable tasks | 57 | 7.00 | 3.00 | 4.48 | 0.76 |
| The company uses external resources to carry out administrative tasks | 57 | 6.00 | 1.80 | 3.49 | 0.81 |

| | | | | | |
|---|---|---|---|---|---|
| *Culture of innovation and work processes* | 57 | 6.50 | 2.98 | 4.06 | 0.60 |
| The company analyzes available data and insights to ensure that customer needs are met | 57 | 6.00 | 2.67 | 4.20 | 0.68 |
| The company adapts marketing and sales to the channels used by existing and new customers | 57 | 7.00 | 3.00 | 4.57 | 0.85 |
| The company works systematically to understand how customers are affected by new digital technologies | 57 | 7.00 | 2.00 | 3.98 | 0.85 |
| To ensure that the customer's needs are met, customers are actively involved in the company's product and service development | 57 | 7.00 | 2.67 | 4.34 | 0.76 |
| *Index: Customer centricity* | 57 | 6.50 | 3.15 | 4.27 | 0.62 |
| The company develops and tests products and services that the market has not explicitly requested | 57 | 5.17 | 2.00 | 3.96 | 0.67 |
| The company develops and tests products, services and delivery methods that compete with the company's existing offerings | 57 | 5.20 | 1.75 | 3.51 | 0.69 |
| The business involves external players in product and service development | 57 | 6.00 | 3.00 | 4.30 | 0.61 |
| *Index: Product development* | 57 | 5.00 | 2.87 | 3.92 | 0.53 |

#### 4.1.4. Reliability and validity

Prior to the analysis, all data were rescaled to the 0-1 range using the range normalization:

$$X_{normalized} = \frac{x_i - \min(X)}{\max(X) - \min(X)}$$

Table 2 shows the indexes, their questions, content, and reliability coefficients based on Jöreskog's rho. The reliability the index measure *recognition of digital opportunities* is 0.39, which is lower than the rule of thumb of 0.5. However, as we found no negative correlation between the underlying questions, we decided to keep the index as is.

With the theoretical foundation from the survey deriving from The Digital Transformation Playbook (Rogers, 2016), Deloitte Digital Maturity Assessment (Deloitte Digital, 2018) and the Exponential Quotient survey (OpenExO, 2020), and the survey itself being created by industry experts and affiliates from Digital Norway, we find little ground to question the content validity of the underlying questions.

Intercorrelations between the index measures are shown in Table 4. With the exceptions of *implementation capabilities* and *culture of innovation and work processes* ($r$ = 0.70), there were no alarmingly high intercorrelations between the index measures. Hence, their discriminant validity can be judged as moderate to high.

*Table 3: Reliability of composite index measures*

| Index | Variables from survey | Content | Reliability (Jöreskogs rho) |
|---|---|---|---|
| Recognition of digital opportunities | Average of question 1-3 | Future implications | 0.39 |
| Consistent strategy formation | Average of question 4-7 | Role of digitalization in strategy | 0.60 |
| Implementation capabilities | Average of question 8-11 | Digital capabilities and experiences with implementation | 0.88 |
| Culture of innovation and work processes | Average of question 12-15 | Working processes and innovation approach | 0.74 |
| Customer centricity | Average of question 16-19 | Customer relations and focus | 0.78 |
| Product development | Average of question 20-22 | Product and service development | 0.77 |

*Table 4: Intercorrelations of index measures*

| | | | | | | |
|---|---|---|---|---|---|---|
| Recognition of digital opportunities | 1 | | | | | |
| Consistent strategy formation | 0.28 | 1 | | | | |
| Implementation capabilities | 0.48 | 0.59 | 1 | | | |
| Culture of innovation and work processes | -0.04 | 0.31 | 0.71 | 1 | | |
| Customer centricity | 0.27 | 0.40 | 0.65 | 0.63 | 1 | |
| Product development | 0.34 | 0.53 | 0.61 | 0.56 | 0.70 | 1 |

## 4.2. Results

### 4.2.1. Segments of Industries with Distinct Maturity Patterns

Segments of industries with similar digital maturity patterns were identified by means of hierarchical cluster analysis (Ward's method), using SAS JMP Pro 15. The dendrogram is shown in Figure 10.


*Figure 10: Dendrogram*

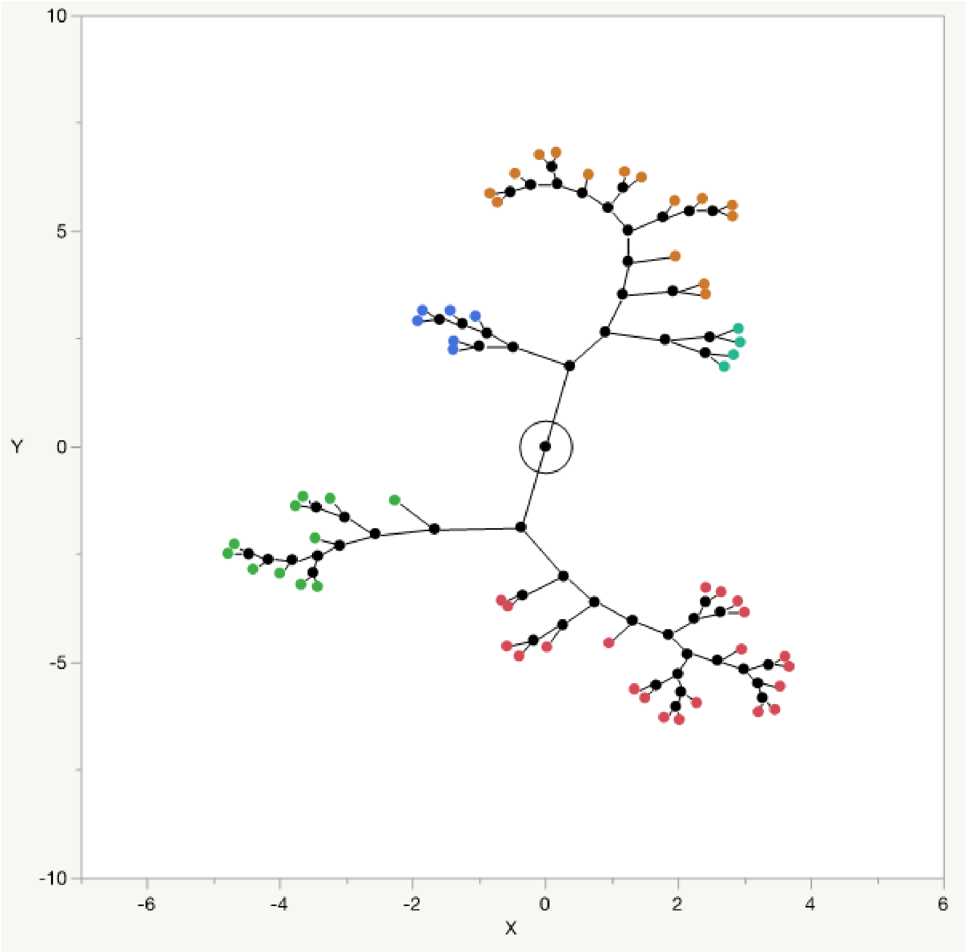


*Figure 11: Cluster constellation plot*

To decide on the number of clusters, we used the Cubic Clustering Criterion (CCC) as a guideline. While the CCC usually performs well in discovering the "true" number of clusters (SAS, 2017), it has the weaknesses that it is based on the (rather strong) assumption that clusters obtained from a uniform distribution on a hyperbox are hypercubes of the same size. In most cases, this will obviously be false. However, it is only a minor limitation when there are not too many clusters. The CCC recommended six clusters. However, one of the clusters in the six-cluster solution only had only one member and had to be regarded as an outlier cluster. Hence, we decided on a five-cluster solution.

A constellation plot of the five-cluster solution is shown in Figure 11. The circle in the center of the plot represents the midpoint between all segments. The colored dots represent the cluster members, corresponding to the dendrogram above. The distance between the observations shows how similar they are. Clusters 4 and 5 are closely related, with Cluster 3 joining them later. Clusters 3 and 5 are the tightest-connected clusters.

Figure 12 shows cluster profiles on the six index measures we had used as active segmentation criteria. The different segments reveal very different states of digitalization: the industries in Cluster 1 acknowledge that changes and new opportunities are arising but are facing challenges in how to respond. They are particularly poor in terms of *culture of innovation and work processes*, which addresses how internal processes are organized. The industries in Cluster 2 can be considered digital leader industries. They have a clear understanding of how changes driven by digitalization affect Norwegian companies and their specific industry. Simultaneously, they have built the means to benefit from these changes. Industries in Cluster 3 have a similar understanding of the implications from digitalization but have low scores in all areas, scoring lowest in three out of five measures of digital maturity.

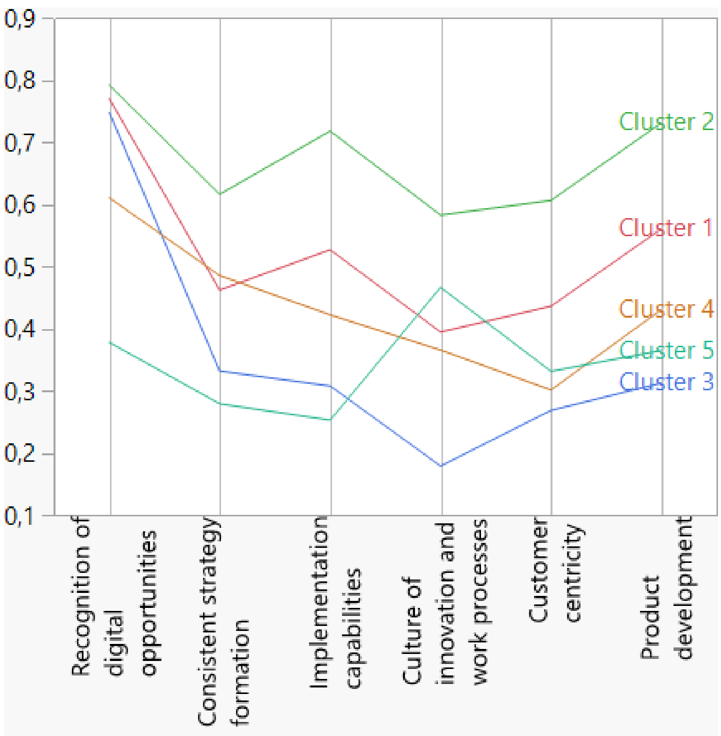


*Figure 12: Cluster means*

*Table 5: Distribution of industry clusters*

| Cluster (color) | Characteristics | N industries | Percent |
|---|---|---|---|
| Segment 1: Responding conservatives (Red) | Acknowledge challenges and opportunities and have a decent response | 21 | 37% |
| Segment 2: Digital leaders (Green) | Digital leaders who feel the urgency and reap the rewards | 11 | 19% |
| Segment 3: Bystanders (Blue) | Acknowledge the challenge but have significant issues dealing with them | 6 | 11% |
| Segment 4: Relaxed conservatives (Orange) | Semi-acknowledgement of the challenges with relaxed measures | 15 | 26% |
| Segment 5: Freeloaders (Turquoise) | No feeling of urgency but manage to float along | 4 | 7% |

Industries in Cluster 4 semi-acknowledge the changing circumstances, and currently have mediocre capabilities. Industries in Cluster 5 shows little sense of urgency but manages to keep afloat in most of the measures.

For Cluster 2, it is worth noting that more than 50% of the industries in this cluster are dominated by large organizations, which may indicate that there are advantages that in size. However, this seems to be the case only in the private sector. Large organizations in education, health and welfare services, and public administration, all dominated by the public sector in Norway, score quite poorly while they do acknowledge digitalization's impact. Further looking at the sense of urgency, it seems that clusters dominated by small and medium companies score lower on *recognition of digital opportunities* than the rest.

Table 5 shows the absolute and relative number of industries in each cluster, together with a short label and a heuristic characterization of each cluster.

### 4.2.2. Differences in Analytics Capabilities

Based on the questionnaire, we created another index for *analytics capabilities*. This was made by averaging eight questions that directly relate to analytics capabilities, namely questions 4, 5, 8, 9, 10, 11, 15 and 16. They touch on aspects such as the role of management, the use of data in strategic decisions, the availability of data and upskilling.

As Figure 13 shows, the analytics capability scores are fairly similar across clusters. Cluster 3, 4 and 5 generally perform at the lower half, while Cluster 1 and especially Cluster 2 have notably higher scores. Thus, there is a clear tendency that businesses with a high digital maturity also have high capabilities in the specific area of business analytics. Note that the average score for all industries are lower than the average when including all questions. This indicates that business analytics remains a challenging part of digitalization, compared to the other components covered in the survey.

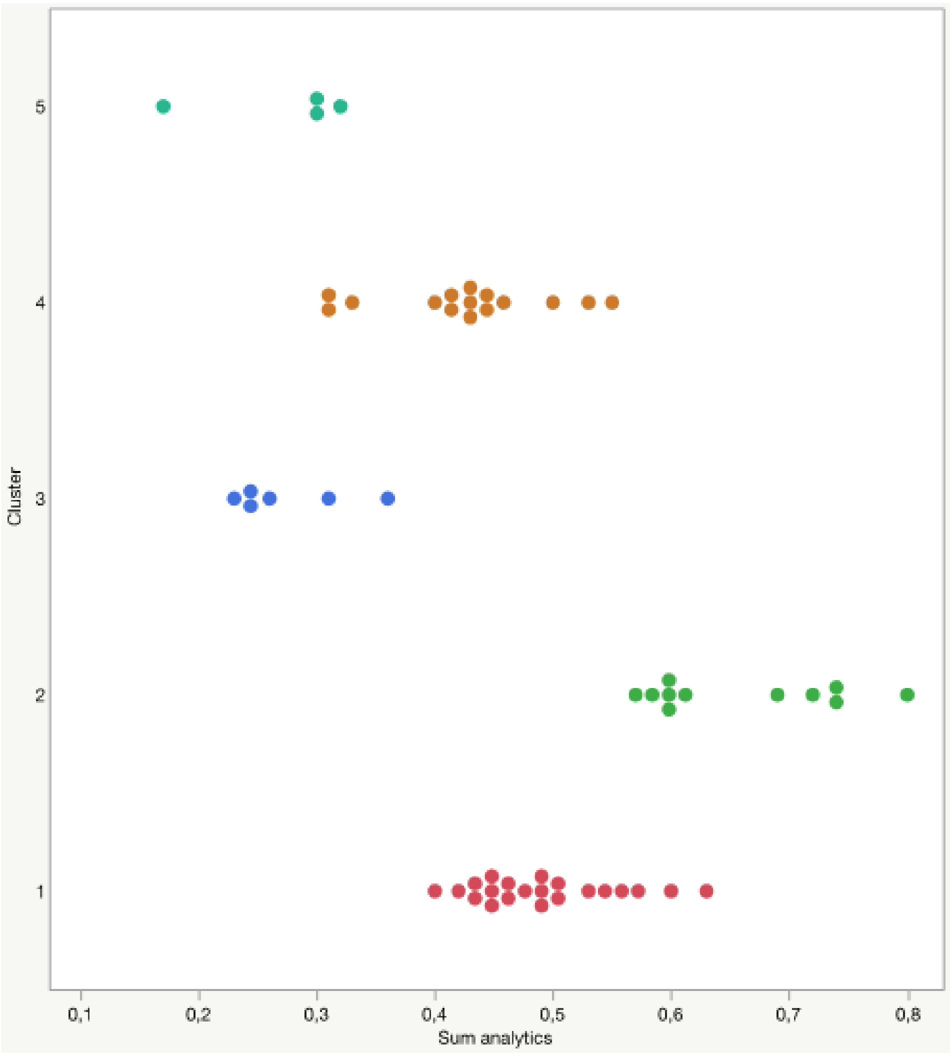


*Figure 13: Within-cluster distributions of analytics capability scores*

### 4.2.3. What Differentiates between Maturity Clusters

While five clusters have been identified, we have limited insight into how the different features affect their separation. A useful approach for this is doing a discriminant analysis, which summarizes group differences and dimensionality with respect to the original variables. As opposed to logistic regression, which aims to identify which category that observations fit in, discriminant analysis has fixed classifications and the variables **Y** are the realizations of the observations (Hastie, Tibshirani, & Friedman, 2008). This analysis uses linear discriminant analysis (LDA), which has two assumptions of the data. First, that it the data Gaussian (i.e., that each variable has normal distribution) and secondly, that the variables have the same variance. As can be seen in Figure 14 these are sufficiently fulfilled by our data. LDA then estimates the probability that a new set of inputs belong to each class, and the class that gets the highest probability is the predicted one. Bayes theorem is then used to estimate the probabilities. Note also that the analysis was performed with specified priors' proportional occurrence, rather than equal probabilities.

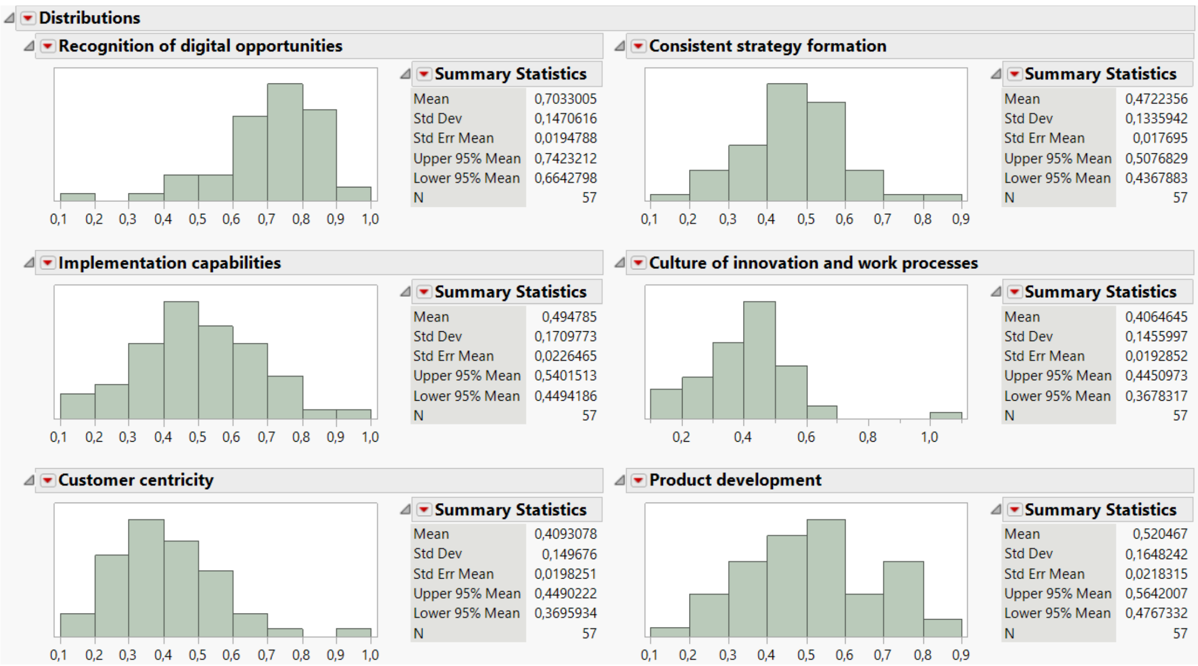


*Figure 14: Univariate distributions of index measures*

*Table 6: Classification table*

| Actual Cluster | Predicted Cluster | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| 1 | 21 | 0 | 0 | 0 | 0 |
| 2 | 0 | 11 | 0 | 0 | 0 |
| 3 | 0 | 0 | 6 | 0 | 0 |
| 4 | 1 | 0 | 0 | 14 | 0 |
| 5 | 0 | 0 | 0 | 0 | 4 |

Figure 15 shows the canonical biplot. Function 1 had a much higher eigenvalue than all remaining discriminant functions, discriminating best between the clusters. *Recognition of digital opportunities* and *product development* had the highest coefficients on Function 1. For Function 2, these were *culture of innovation and work processes* and *implementation capabilities*. The discriminant coefficients are available in Appendix 2.

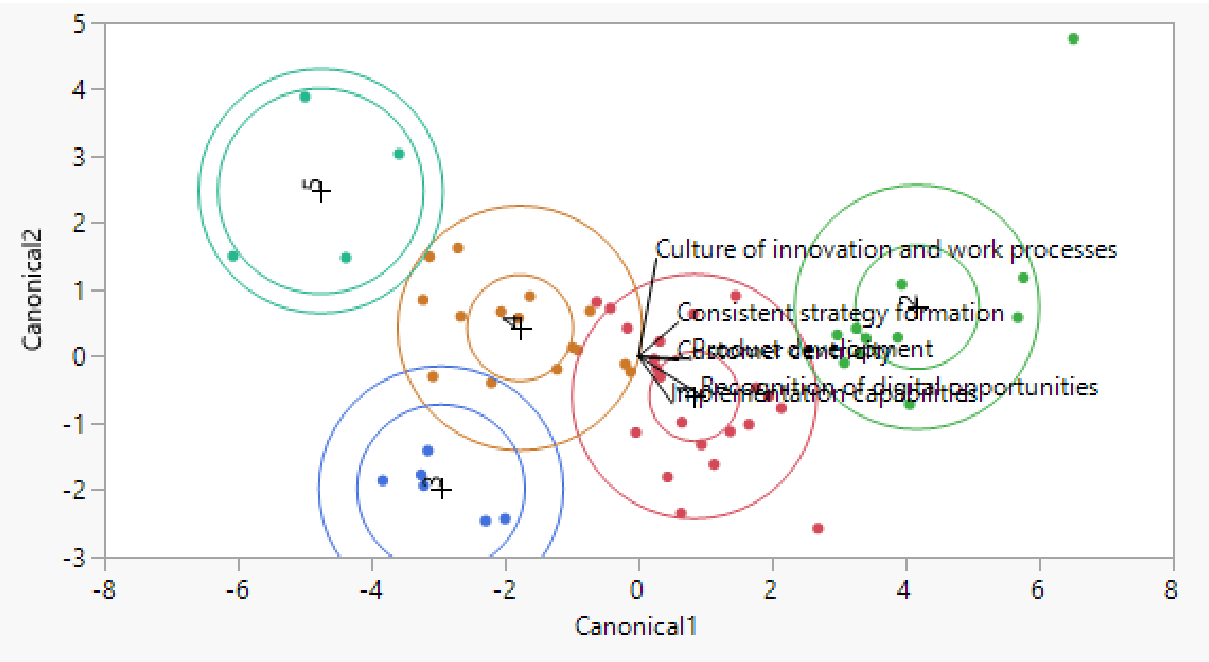


*Figure 15: Canonical plot*

## 4.3. Discussion

Relating these results to an existing framework, we look to Capgemini's four groups of digital mastery from Chapter 2.1.1. For the different sectors and sizes used for our analysis, the digital mastery diagram matrix is represented by Figure 16. When plotting the clusters, the result is shown in Figure 17. The score for leadership capability was calculated using the average from three indexes: *recognition of digital opportunities, consistent strategy formation,* and *implementation capabilities.* The digital capability score is an average of the remaining three: *culture of innovation and work processes, customer centricity* and *product development.* It is important to stress that the axes scales have been adjusted slightly to better reflect the differences between the units and relative state of Norwegian businesses. Furthermore, the calculated scores on each axis are not a perfect duplication of Capgemini's framework, but rather a simplified approach with the goal of adding to the overall understanding. As is apparent, the majority of Norwegian industries seem to fall in the category of conservatives, which is characterized by solid leadership capabilities but weaker execution. The next-largest categories are digital masters and beginners, which are on opposite sides of the two axes. Digital masters have high digital and leadership capabilities, while beginners have low scores in both. One industry has particularly impressive digital mastery, namely *large property services.*

The cluster distribution, it is a natural extension of the different industries. Cluster 2 reaffirms their role as digital masters, outperforming the others in both leadership capability and digital capability. Cluster 1 and 4 are conservatives, with decent leadership capability but lacking digital capability. Lastly, Clusters 3 and 5 are beginners with low leadership capability and low digital capability.

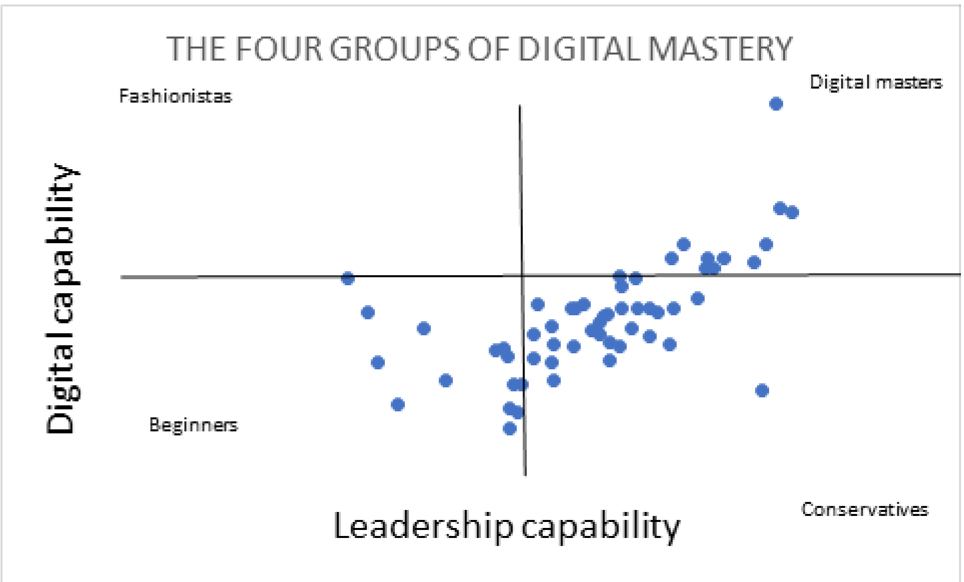


*Figure 16: Digital mastery by industry*

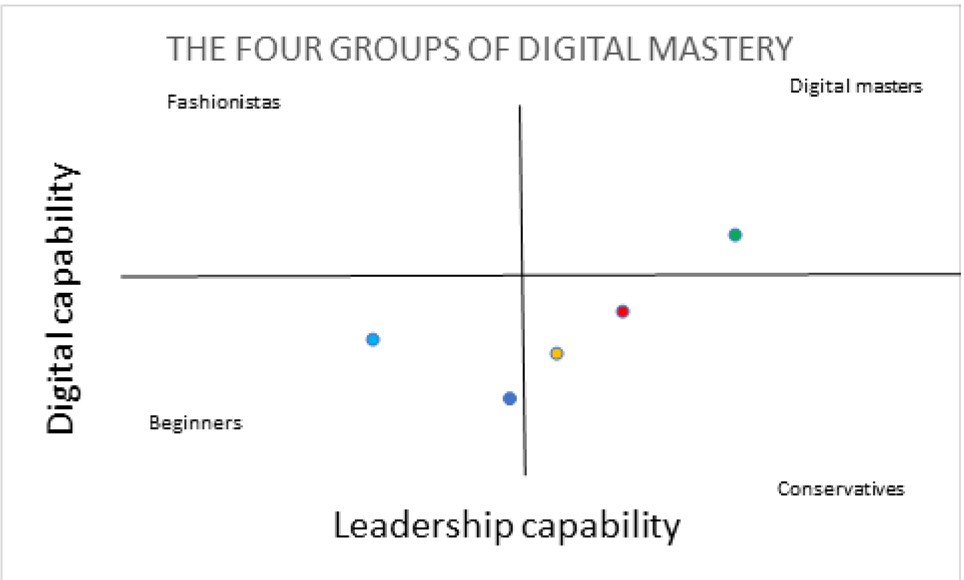


*Figure 17: Digital mastery by cluster*

This study found interesting patterns in industry and enterprise sizes. First, note that size does seem to matter. Cluster 2, digital leaders, has more than 50% large industries. The same trend can be seen in the second most digitalized cluster of responding conservatives, where 76% of the companies are either large or medium. While proof of analytics project sizes and success rates are absent, studies suggest that company size and analytics investments have a positive relationship (Liberatore, Pollack-Johnson, & Clain, 2017). The fact that BA projects tend to demand heavy investments and organizational change to maximize its potential, does seem to have an effect on the SME segment.

Enterprise sizes are one thing, but patterns in industries can also be expected. As shown in Chapter 2.3.2, knowledge-intensive sectors tend to score higher in digital advancement. This trend is echoed in our results. One such industry has all its representatives among the digital leaders, namely information and communication. This is as expected given that the companies involved typically provide consultants, IT services, software, and similar services. Professional and technical activities also have two representatives in this same cluster. Others are more surprising, such as construction, education and property services. They do remarkably well in several categories, and it is not easy to pinpoint why, but as they perform quite poorly in McKinsey's study it is certainly an interesting find. Broadening our view to include Cluster 1 of Responding conservatives, the industry variation increases significantly. While one industry has all its enterprise sizes gathered in one cluster, namely Water, drainage in Cluster 4, all the others vary. Based on our analysis, it thus appears that companies operating in knowledge-based industries or with high revenue tend to have a higher digital maturity.

# 5. Study 2: Challenges in Achieving Analytics Maturity and Excellence

While the quantitative data presented thus far does provides a decent overview of the BA maturity of Norwegian businesses, it is always helpful to complement with qualitative data. Through interviews with five industry experts working closely in the field, we have been able to focus on specific findings and go in-depth in our research questions. This allows us to elaborate on observations made in existing literature, as described in chapter two. Additionally, certain findings in the previous two analysis are further explored through these conversations. Drawing on the experts' real life experiences and thoughts, we broaden the analysis and comprehension.

## 5.1 Method

There are many ways to organize interviews (Saunders, Lewis, & Thornhill, 2016). After reviewing the alternatives, we decided to conduct semi-structured interviews based on a loose interview guide. In the case of this study we have a clear idea of what we want to explore, but in line with our explorative design still want to focus on the informant's knowledge and experiences as this can provide valuable new insight. A semi-structured interview allows for flexibility and adaptation to the given context of each interview, and some of the questions might be dropped based on the situation. The complexity of our questions and topic necessitate a more open interview form. As we were able to complete all our interviews using Microsoft Teams, rather than in written form, this was advantageous.

### 5.1.1. Key Informant Selection

On the basis of our research questions, we mapped and contacted a number of potential sources. In the end, we interviewed five people from different Norwegian consultancy firms and organizations. While the discussion on sample sizes in qualitative research appears never-ending, there seems to be an agreement that between 20 and 30 is a good base. However, this will always have to be adjusted for the given research, both in light of its design and available resources (Adams, Khan, Raeside, & White, 2007). All of our informants operate in the same field, offering data consultancy services and advice to the Norwegian market. Due to Covid-19 it was more difficult to arrange interviews then we had hoped. In the end we managed to organize insightful interviews with several knowledgeable and experienced people, listed in table 5**.** We aimed at a certain level of heterogeneity in our sampling, as recommended by Harsh Suri, to ensure a comprehensive understanding of the phenomenon (Suri, 2011). Thus, some informants work with small companies, some with larger ones; some are business developers, some are engineers; some are consultants, some are non-profit based advisors. There are primarily two traits all share, their gender and expertise.

*Table 7: Key informant interviews*

| Informant | Position | Interview date | Interview duration |
|---|---|---|---|
| 1 | Advisor in NGO | 23.04.2020 | 1:04:31 |
| 2 | Software engineer II | 01.05.2020 | 1:08:21 |
| 3 | Manager | 11.05.2020 | 1:03:20 |
| 4 | Head of data and analytics | 13.05.2020 | 1:07:11 |
| 5 | Manager | 26.05.2020 | 0:59:15 |

### 5.1.2. Interview Guide

Semi-structured interviews do not necessarily require a very detailed list of questions, but an idea of what to ask *about* before beginning the interview. We decided to create an interview guide to help us during and after the interviews. This way we were able to gather our thoughts, develop concrete ideas of what we wanted to explore and more easily analyze the different responses. Whilst creating an interview guide, and during the interview for that matter, it is important to ensure that language is appropriate and understandable for all parts, avoid questions that take on multiple issues, and ensure that the questions are comprehensible for the informants. Based on this, we drew up an interview guide building on existing literature and our research questions, available in Appendix 3**.** During none of the interviews did we make use of all the questions. As the study progressed some themes proved more fruitful than others, and some questions were never touched upon as our study progressed. In any case, the interview guide proved helpful, ensuring a smooth and focused conversation. The informants were not given access to the interview guide beforehand.

### 5.1.3. Reliability and Validity

While unstructured interviews are a great source for data and information, there are problems associated with its quality. Four issues related to our data will be discussed, namely data reliability, potential bias, generalizability and validity. Furthermore, there will be comments on the classification of data.

Due to the nature of semi-structured interviews, it is quite hard to reproduce the exact same results; there are many factors that determine how humans act in conversations. However, there is an argument that this is not really the main goal (Saunders, Lewis, & Thornhill, 2016). Interviews are intended to reflect reality at the given time, often in dynamic circumstances. Due to the complexity of our subject, we cannot compromise the quality of the conversations by aiming for absolute reliability. Thus, the reliability of our data is not very strong. To ensure the study's rigidness and dependability, we have clarified the research process in detail. This will help others understand the findings in detail.

As in any type of human conversation, there is a risk of bias. In this case, we refer to the way interviewers use comments, tone or non-verbal communication (Saunders, Lewis, & Thornhill, 2016). Unconsciously, we may communicate a bias to the informants, whose answers could be affected. The same goes for how the answers are interpreted at a later stage. To keep the interviews unbiased, we performed trials with each other and external resources to learn and adjust our interview guide. The opening of the interview was of specific focus, as this is typically the most important part. Being clear on what information we are looking for and how this will be used is important to gain the informant's confidence and should preferably be done beforehand. Lastly, allowing the informant to talk freely and pick up on their points, rather than constantly changing subject or question, aided to ensure the conversation flow.

Qualitative research often suffers from a concern about its generalizability, as it typically reviews a small number of cases, often just one. In our case, we interviewed five experts with both current and historical knowledge of how Norwegian companies work with their data. While their backgrounds differed, we noticed several similarities in their answers. This implies some degree of generalizability, but as our sample size is so low it is hard to strongly uphold this claim.

Lastly, we must assess internal validity, i.e. the strength of our conclusions, inferences or propositions (Adams, Khan, Raeside, & White, 2007). Are we measuring what we think and are supposed to? Data from unstructured interviews can achieve high validity by following some guidelines (Saunders, Lewis, & Thornhill, 2016). Researchers should focus on using clarifying questions, probing meaning and exploring responses from different sides. In addition, using open questions, meaningful follow-ups and avoiding bias are helpful to ensure the data's validity. These aspects have all been areas of focus during our process, and thus we consider the data's validity to be high.

## 5.2. Results

The purpose of the interviews is to get a better understanding of the experts' perspective on the topics we are exploring in the thesis. We have chosen to present the empirical findings thematically, based on the components of maturity from Davenport and Harris' framework (2007), and the further theory presented in Chapter 2. Although some of the results presented in each finding might be relevant for the other findings, we emphasize the context in which the informant presented its case. The results presented in this chapter do not reflect all the topics discussed during the interviews, but shows the key takeaways that best relates to our research questions.

### 5.2.1. Organization

***Setting objectives, goals, and plans for BA is a major challenge, but customer needs are a good place to start***

All the informants addressed that organizations often struggle at the starting point. Numerous reasons are stated as to how initiatives are formed and realized, but they all fall into two categories. Either, management wants to be innovative and feel a certain pressure from customers or competitors, or there is an internal enthusiast that wants to improve something. In both cases, setting an objective is not easy. Informant 3 states that organizations that want to do something just to do it, often fail to improve where it should improve, and often end up creating something that is too far from how the organization currently operates. All the informants share that the enthusiast mostly has an idea that solves an actual problem, but that it often is limited to one department or team, and that the solution might interfere with work practices across other units of the organization. Solutions to one department is not always transferable to the whole organization. This often leads to the involvement of consultants early on. Informant 1 stressed that all BA initiatives must come from a need:

> *"We always recommend businesses to start with a customer-driven requirement - start digitalizing where you can solve a specific problem or improve the bottom line. By succeeding in these areas and taking small steps, businesses will be aware of the available gains and be better equipped to handle larger projects in the time to come."*

Informant 4 repeats that if the organizations do not have a something critical to solve with BA, the best starting point is to find something that affects the customers, in order to search for the right objective. The consultants share that when they can set the objective, they usually start off with something that provides a visible value quickly.

***BA must be rooted in the business side rather than the IT side***

When Informant 4 was hired as head of BI and analytics for a multinational company, his first concern was that the position was part of the IT department. This only reinforced his feeling that BA is way too heavy in IT. In the end, the impression was that they were pushing bottom-up from IT instead of responding to needs from the business side:

> *"You lack some sort of mandate getting in-depth on the business side, finding the right stakeholders and people willing to do something more. When we created a reporting self-service tool that people loved, we used way too much time to find the right people to get this going. We practically had to look for potential user cases to sell - that is anything but easy".*

The other informants shared similar reasons for how BA initiatives should be organized. Informant 2 shared his feeling that IT to some degree is still considered to be a support department, rather than providing value. Informant 3 believed that BA was closer to corporate governance than being isolated business cases, and that the insight from data is like the insight an organization gets from its accountants. It should provide an overview of other aspects that is not provided in the accountant's book. However, he also said that the overview should be business critical, and that the responsibility for this must be rooted in the business side of the company. All informants agreed that BA initiatives and responsibility is a business function, but that IT must support the initiatives the same way it supports other functions. Furthermore, informant 5 defined three roles as necessary to succeed with BA initiatives and develop a data-driven organization. A functionary that represents the business side of the initiative, a technologist that represents IT, and lastly a person representing DevOps. Lastly, informant 4 stated:

> *"The most successful projects I have been part of are the ones that started outside of IT."*

***Silos disrupts companywide change***

Especially a challenge in large companies, the informants point to silos and the formation of silos. The consultants shared examples of silos in work practices and reporting practices. Informant 2 told of frustration in different departments working with different software, while Informant 4 presented a case in which his former employee measured sales data differently across teams. He noted that when you do not accurately know what a fundamental measurement, such as sales data, means, the KPIs become meaningless. Collaboration and sharing across teams also become difficult, because they are not speaking the same language. Informant 1 painted a less negative picture about the effects of silos:

> *"Silos could also present more use cases to the organization. If one department is successful with a new reporting system, over time, this might be implemented across all departments. If a strict company policy prevents teams from experimenting within, new and proven solutions might not see daylight."*

However, he also noted that this reporting system could have negative effects on other departments, and therefore be ineffective for the organization as a whole. Informant 4 pointed out that organizations need a centralized information system department to prevent silos and shadow systems, business processes not under the jurisdiction of a centralized information systems department. The informant also underlined that BA initiatives that stem from the thought of doing something are not rare and typically the result of silo-thinking where someone from a department has an idea of something they can do better. This is challenging for consultants, as it takes a lot of time to learn how businesses work with data and what is required to provide the solution.

### 5.2.2 Human

***Organizations neglect or underprioritize upskilling***

A recurring topic from the interviews was competence and its importance for successful BA initiatives. Several informants pointed out that clients would often end a project right after the technical solution was implemented, and thus the possibilities and intended improvements are never realized because the involvement of users in the process is greatly neglected. Some of the informants noted that if upskilling is part of the initial plan of a project, but resources are cut from the project, it almost always affects training first. Informant 5 viewed an organization's emphasis on training as an indicator of whether it has a long- or short-term perspective on its BA initiatives. He outlined the concept of training in this context:

> *"On the operational matter, the users must be taught how to maneuver new systems and read reports with new measurements. The other part is the backend, where someone must know how to maintain the new system and overlook the data flow".*

He further went on to explain that organizations typically fail to recognize the value of the latter. Other informants presented similar nuances of training. Informant 4 stated that, albeit sounding clichéd, employees must 'dream' beyond what is currently available. He followed this up by presenting data literacy among workers as the most important competence to obtain, so that employees can read data, discuss it and plan for future use. Informant 3 shared some thoughts about the challenges of hiring these competences:

> *"Potential candidates might not find it very interesting to sit with the same problems every day, fighting with reluctant executives, seemingly getting nowhere. The necessary skills and candidates simply may not be available."*

***Outsourcing is great for initiating projects and introduce new work practices but critical business services or processes must be kept in-house***

As most informants were consultants, this finding could be biased. Several competences that consultants represent where listed during the interviews. Among them was implementation capacity, program roll-out experience, and being up to date on the newest technology developments. Informant 5 pointed out that using consultants for operational tasks are not efficient, but using them for discovering and implementing efficient ways of running the operational task is.

> *"Unless the organization is continuous in development, it is not necessarily sustainable to keep these competences in-house, regarding BA and data. Organizations do not want to tie up capital by full-time hiring the competence that we offer."*

Other informants shared experiences where consultants had discovered critical business services or processes, and in those cases, even the consultants urged the organizations to seek full-time positions to keep core-competence in-house. Informant 4 added that, prior to his current position as a consultant, he was an internal enthusiast in a large organization. Eager to inspire a new BA initiative, he used consultants to share different use-cases and success stories related to his project, enabling the executives to endorse it and set a companywide objective.

Informant 1 believed companies and BA suppliers should increase their focus on cooperation rather than the typical model of consultancy contracts that bill every hour and product. Businesses want to focus on their own core competencies and outsource most other services. Obviously, this is not entirely negative, and the informant emphasized that this is helpful in creating agile organizations with the ability to readjust swiftly:

> *"In-house capabilities may in fact create new obstacles for the organization."*

***Better communication between IT and business is important***

The informants mentioned many aspects of cultural challenges but struggled to present solutions for how to facilitate cultural changes in an organization. Informant 4 highlighted teamwork and understanding across business and IT functions as crucial for a successful initiative:

> *"A person from a business function might have an idea of how to cut costs through automating reports or something, but a lot of times these reports never get automated because the need is never communicated to IT. At the same time, IT can be sitting on a gold mine in the form of great technology, but not know how to implement it because the needs of the business and corporate governance are uncertain to them."*

Informant 5 agreed, stating:

> *"There has to be someone operating as a bridge between IT and business, and however cliché this might sound, there needs to be mutual respect between the two."*

Informant 1 emphasized that culture also affects management support. Employees might feel that their ideas are not needed, because they trust that someone higher up knows better. This can block initiatives and hinder the organization to growing through the enthusiast.

Informant 4 also emphasized trust, but in another sense. He believed that lack of trust in the provided information is key. However, this does not only relate to poor data quality, but the fact that there can be other mistakes. If one or two people know the data well enough to make their own customization in Excel, and the system shows something different that is wrong, it is hard to rebuild this trust. He went on:

> *"They lose control over their reports and might feel threatened by the new software. This is another problem caused by the distance between developers and business."*

***Sponsorship is vital but rarely a major challenge because of high capabilities among leaders***

All informants emphasized the importance of higher up endorsements for initiatives to succeed. Many reasons and consequences where presented, such as that management sponsorship makes sure that there are sufficient resources for a project, or that the initiative will not reach its full potential. Informant 3 summarized this through the example of an enthusiast's initiative:

> *"There must be someone from the executive team that owns or sponsors this. If the enthusiast does not have a director behind him it will not be big enough, it will not be properly adopted, and it will not be used."*

Informant 4 also noted that lack of sponsorship is usually the biggest reason for silo formations, as initiatives that are not implemented company-wide could still be implemented in the enthusiast's department or team, depending on the level of influence that the enthusiast has. The informant also noted that executives are more business-savvy than tech-savvy, and that this would affect how the enthusiast approach executives when trying to get support:

> *"You cannot go in there with your most tech-savvy people to present how awesome TensorFlow and Python is. In these discussions it is especially useful to present a number; having an example from a similar business has also proved very helpful".*

Albeit being an acknowledged success factor, the informants noted they rarely face challenges from insufficient sponsorship and support from C-level. They point out that leaders often hold high BA competences, and that they have a mature attitude towards innovation and change projects. Informant 3 explained this with an illustration:

> *"They know that you will not get in better shape by buying running shoes – you actually have to start running".*

He was certain that managers became significantly more interested in all available help to run their business.

### 5.2.3. Technology

***Technical aspects are overprioritized***

During the interviews, all our respondents downplayed the importance of technology. They all shared the same belief, that technology is the easiest to obtain. They also emphasized that technology is improving so rapidly, there is no final optimal solutions. Some of the informants even claimed that organizations are often too focused on the technical part, forgetting about all the other aspects of a successful BA initiative.

Informant 5, whose employer is especially focused on the development and facilitation of the latest technology trends, talked about the technological competencies that need to be developed for BA environments to help organizations grow. The first is the shift towards enterprise architecture, which will enable a view of the whole organization. The second is the shift toward cloud-based infrastructure.

> *"In earlier years, we would manually build Hadoop clusters, which obviously costs a lot of resources. Clients want insight, not infrastructure. In the cloud there are premade Hadoop-clusters, so that you can focus on bringing value to the client instead".*

Lastly, he emphasized the potential of reaching solutions in artificial intelligence:

> *"Traditionally, a BA solution is access-to-data through an SQL-based warehouse. But a more modern way is through API. Data platforms will prevail data warehouses. API facilitates for a pragmatic access to the data, which makes it possible to build more sophisticated data platforms, which again can feed artificial intelligence tools with a continuous flow of data. There exists a lot of POC's on artificial intelligence, but it is rarely utilized. The problem is that there has not been a steady flow of data".*

Informant 4 agreed that both in artificial intelligence and predictive analytics such as machine learning, there are lots of POC's, but many never see daylight.

The only aspect that the informants agreed on as upmost importance, is data quality. However, they point out that this often correlates highly with silos, and that aspects such as culture and organization are factors that influence data quality.

Data quality is always a concern when it comes to analytics. Informant 3 believed this may sometimes be slightly exaggerated; if the focus on data quality becomes too finicky, the company will quickly lose agility and speed:

> *"If you are trying to get the quality to the same level as in an accounting system, that may prove too ambitious. [… ] Where we work a lot on data quality, is when it is an obstacle to providing a complete picture".*

In other words, where people and systems do not follow the same rules. Even if the rules are similar, people will always make mistakes, and it is rarely worth it to investigate and correct every single one.

### 5.2.4. Industry differences

***Banking and finance slightly ahead***

The informants hesitated to put one industry over another. However, most of the respondents mentioned that the banking and finance sector was probably most ahead. Informant 5 also noted the public sector as an example of a forward-thinking sector:

> *"A lot of the public organizations are developing artificial intelligence and building huge and sophisticated data platforms to embed BA into the organization".*

In his opinion, the public organizations obtain high competence and assertiveness. He notes that the focus on data initiatives in public organizations might be two-folded. His characteristics apply solely to the centralized and core-activities of public functions, and he acknowledges that regional offices and smaller functions do not allocate enough recourses and do not obtain the competence to complete successful analytics initiatives. The other informants did not have the same admiration for BA in the public sector.

In Informant 2's experience, heavy industry organizations often have an immature perspective on its IT function. He said that although organizations in this industry develop sophisticated hardware for their operations, internal IT was often viewed as a support function, and BA initiatives were often overlooked.

In summary, the informants agreed that pointing out industries are tough, as they all see individual organizations in all industries being both above and below their respective benchmarks.

***BA initiatives work best in and for larger organizations***

Informant 1 noted that SMEs rarely see the use of BA:

> *"As opposed to large companies in sectors like banking and finance, SMEs face a challenge in identifying what the usefulness really is. SMEs usually have fewer and bigger clients, which tend to decrease the value of low threshold initiatives"*

He also noted that there are financially challenging to embark on such initiatives:

"While larger companies tend to have different C-suites and significant data departments working together, similar positions in SMBs typically have more functional roles closer to production. In other words, big companies have professionalized how they work with capacity building and training. In addition to this, they have the finances to pay for the skills they lack. Small companies do not have the resources to hire McKinsey".

Both statements were supported by the other informants. Informant 3 presents a rule of thumb he uses to assess whether potential clients have the resources to create something meaningful with BA.

> *"BA projects should equal around one thousandth of revenue. If revenue for example equals 800 million NOK, BA initiatives should be around 800 000 NOK. If the project is under 500 000 NOK, it leaves very little room to really do anything".*

He also explained that this was supported by the fact that such companies typically have few systems and somewhat simple business models, which does not necessitate a lot of staff to keep track - this often changes when the scope gets widens.

Informant 5 clearly saw a general trait in the difference between what he calls mature and immature ventures:

> *"Immature ventures have to fall in love with something you deliver. You must blow them away for them to realize the value of data and analytics".*

He said that immature organizations were often smaller companies and start-ups, who tends to have a file-and-forget approach to analytics initiatives. Larger organizations, often more mature, show commitment on the opposite level.

> *"The larger companies have higher requirements to your deliverables, but they recognize that there is no magic formula, and few quick-fixes and turn-key-solutions".*

He also noted that larger organizations are used to introduce new processes and work practices into the organization, and thus understands the scope of what it takes and how to achieve it on an organizational level.

Informant 3 also noted the difficultness of demonstrating value with BA. This is also echoed by the other informants. Knowing that an increase in revenue is due to BA is not easy. It could be a result of market trends or simple luck. However, he does believe that all initiatives can have positive repercussion, even if they do not provide any immediate reward. Informant 4 put this as a challenge to get started with BA initiatives, as a value creating objective is hard to assess.

## 5.3 Discussion

Many of the findings presented in this study corroborates some of the theory presented in Chapter 2. This section aims to compare the findings from this study with the theory.

### 5.3.1. Challenge 1: Setting objectives, goals, and plans for BA are major challenges but customer needs are a good place to start

As presented in Chapter 2.2.1 about the objective, researchers echo our informants' perception of the importance and challenge that is to craft an objective for BA. Henke, et al., 2016 found that organizations often end up experimenting rather than working from a clear vision and was supported by Rupanagunta et al. (2012). The informants did not emphasize experimentation *per se*, but they noted that taking small steps might be useful. This will help organizations keep momentum even though a clear objective is not at hand. This is supported by Liberatore et al. (2016), who found that it is important to keep momentum and using the scalability inherent in analytics, as firms tend to build on existing analytical capabilities. However, Informant 1 recommends always to start with customer-facing functions. This recommendation is backed by the findings in SAP's report (2017), stating that leaders of successful digital transformation always focus on customer-facing functions first.

In summary, this is both a challenging and important factor for BA initiatives that can be solved if organizations look to customer needs and functions first, and experiment from there.

### 5.3.2. Challenge 2: BA must be rooted on the business side rather than the IT

Matt et al. (2015) found that distance between business and IT restricts the product-centric and customer-centric opportunities that arise from new, digital technologies. However, our finding suggests that the distance must be reduced, but that the responsibility must lay on the business side. The theory presented in Chapter 2 does not clearly indicate that BA initiatives should be rooted in the business side, but it emphasizes the importance of a combined strategy between the two. In the theoretical foundation presented in Chapter 2.2.2 about culture, Aiken and Gorman (2013) suggested moving the CDO outside IT to give the role a broader influence in the organization. The CDO will in many cases be the head of the BA initiatives, and so this supports our informants' perception.

### 5.3.3. Challenge 3: Silos disrupt company-wide change

Canon Moreno (2017), presented in Chapter 2.2.1, found that business analytics processes often require "coordination of different areas of a siloed organization". This supports the notion of our informants' perception. Informant 1 proposed that silos could present use cases. This is supported by the research presented by Kiron et al. (2014). However, both the latter theory and the informant acknowledges that this is rarely successful.

### 5.3.4. Challenge 4: Organizations neglect or underprioritize upskilling

The theoretical foundation for this discussion on skills is in chapter 2.2.2. Broadly regarded as a critical factor by the researchers, competence is also of mayor importance according to the informants. Both sides view competence similarly. This can be exemplified with the skill of data literacy, which is stressed by Rollings et al. (2019) as well as Informant 4. Interestingly, in our informants' experiences, Norwegian organizations have almost no focus on upskilling or training. Furthermore, upskilling of the workforce is necessary as employing the necessary skills is challenging. Both Informant 3 and Matt et al. (2015) presented similar arguments on why it is difficult to hire full-time BA competence.

In summary, competence is important, but training is neglected. This needs to change if organizations seek to enhance their maturity level.

### 5.3.5. Challenge 5: Outsourcing is great for initiating projects and introducing new work practices, but critical business services or processes must be kept in-house

Our informants meet resistance from researchers regarding this topic. This not surprising as the informants represents outsourcing services and could therefore be biased regarding this topic. Among the researchers, Henke et al. (2016) state that BA knowledge must be deeply embedded in the organizations. This is supported by Wolf et al. (2018), and Matt et al. (2015). The latter claims that organizations must keep in mind that there is a time after the transformation, and related competence must be kept for that time too. On the other hand, Crummenerl, et al. (2018) proposed a framework for a successful upskilling, where one aspect is to "define the skills you need and when you need them". The informants proposed different competences that they provided, but they acknowledged that certain competences need to be kept in-house. As indicated by the latter researchers, the skills consultants provide might not always be needed, but organizations might need them at certain points.

#### 5.3.6. Challenge 6: Better communication between IT and business

The informants strongly emphasized better communication and collaboration across the two functions. IT presents solutions to business, as stated by Informant 4, and the functions must know this to effectively implement BA solutions that will improve the organization. Wolf et al. (2018) repeats the importance of this, arguing that knowledge and information must be exchanged transparently across departments. Henke et al. (2016) proposed a solution to this, namely the introduction of business translator role that can work as bridge between the functions. This solution was also presented by informant 5. However, as presented in the part of competence in chapter 2, as well as in this discussion part, hiring business translators are difficult.

Wolf et al. (2018) also presented the obstacle of collaboration as a result of inadequate incentive systems, and that employees might be protective of their information. A solution might therefore be to implement better incentive systems for employees to be willing to give up their "keys to the kingdom" for the greater good.

#### 5.3.7. Challenge 7: Sponsorship is vital but because of high capabilities among leaders rarely a major challenge

The informants and the researchers share the belief that executive support is undoubtedly one of the most important factors for successful BA initiatives. However, our informants downplayed sponsorship as a real challenge, stating that they rarely face trouble getting initiatives in with the executive group.

#### 5.3.8. Challenge 8: Technical aspects are overprioritized

Data quality is the only technical aspect the informants felt worthy of presenting as a success factor. Informant 5 also presented solutions of how to reach artificial intelligence, but generally through all the interviews, the emphasis was to pull focus away from technology, to focus more on crucial factors. However, a key takeaway is still data quality, which both the research, in Chapter 2.2.3 and informants states the importance of. Another is the shift towards enterprise architecture, presented by

Informant 5. Khatri and Brown (2010) echoes this, and notes that an enterprise-wide data governance framework helps organizations to reach their strategic goals with data. Arguably, this supports the factor of getting the whole organization to pull in the same direction and helps to reduce silos.

### 5.3.9. Challenge 9: Banking and finance slightly ahead

Comparing with the empirical evidence presented in chapter 2.3.2. Westerman et al. (2017) supports the finding, as their research found that banking obtains high scores in digital and leadership capabilities. The same goes for McKinsey Global Institute (2015), as their findings also suggested that finance organizations were most advanced on the field.

### 5.3.10. Challenge 10: BA initiatives work best in and for larger organizations

As presented in chapter 2.3.1, there is much empirical evidence that BA enhances company performance. So says our informants, but informant 3 points out that it is not easy to demonstrate this for organizations. This is supported by Isik et al. (2013), emphasizing that it is not straight-forward to deduce the value of BA.

Empirical evidence in chapter 2.3.3 supports the finding. Lismont et.al (2017) presented four clusters of analytics maturities. The average number of employees in the organizations for each cluster grew exponentially the more mature the cluster in the model became. Liberatore, Pollack-Johnson, & Clain (2016) found a similar effect between the number of employees and investment in BA. The informants agreed that BA is best suited for larger companies, as they often have many products and customer segments across divisions. The need for better analysis and big data solutions is obviously more needed for organizations that create a lot of data, than for smaller organizations.

# 6. Study 3: How to achieve Analytics maturity and excellence

Through existing literature and this thesis own studies, we propose a conceptual framework for an analytical approach. Building closely on the work of Kohli and Jaworski (1990), a modern understanding of today's situation is presented through the six components of executive support, strategic clarity, BA skills, data governance, information flow and BA impact.

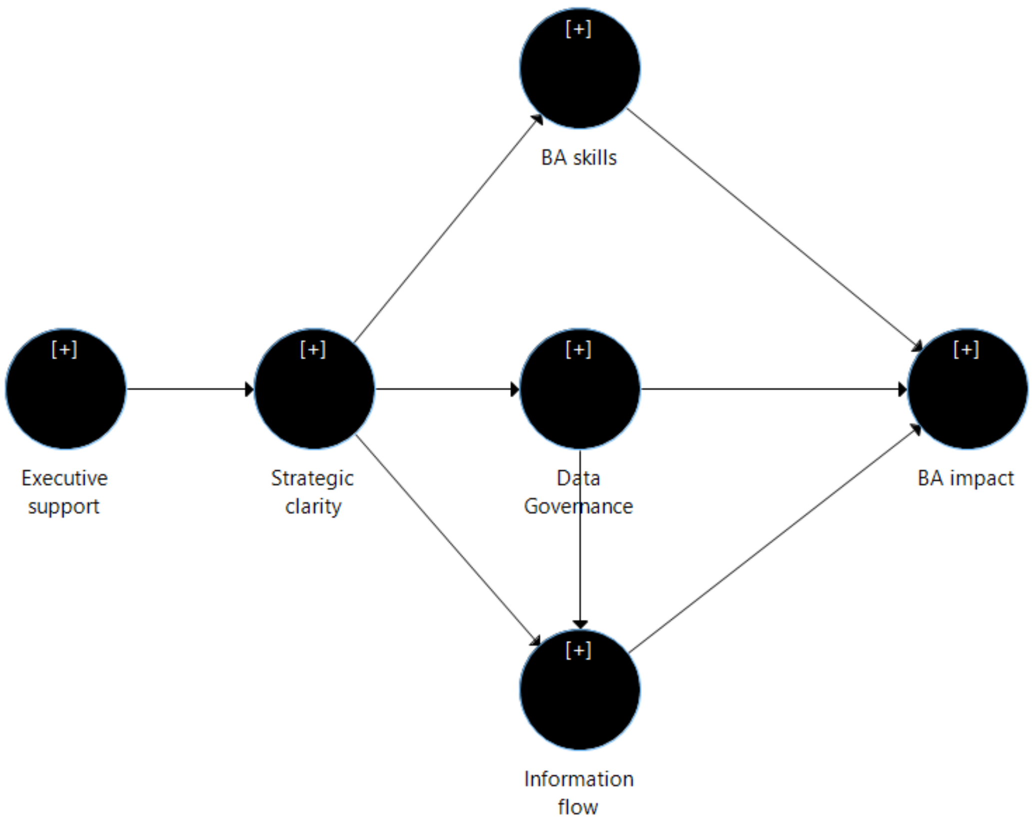


*Figure 18: Enterprise-wide BA framework*

Executive support has been shown to be essential for analytics, both in existing literature and our own studies. While it can be helpful in isolated initiatives, its main contribution is to ensure that analytics is considered in a holistic manner, with a clear firm strategy. Through strategic clarity and an enterprise-wide approach, companies will have a clearer understanding of the skills needed, how to prepare data governance programs, and how to ensure information flow. Combined, these three aspects will assure that BA has an actual impact.

While some of these aspects are novel, others build directly on Kohli and Jaworski. As Figure 8 showed, their view on market orientation had three components. In our model, intelligence generation has been replaced by data governance. Generating data is not exactly a main issue anymore. There are a plethora of sources available, both internal and external. Data governance, however, cover much more than simply creating the data. It relates to the firm's data quality, data lifecycle, data access and much more. While actual data collection was pivotal thirty years ago, these are real concerns of data generation today.

Kohli and Jaworski's second component of information dissemination is reflected in information flow. While some aspects remain important, for instance hall talk, analytics-related information is typically available in data form. This is affected by data governance, which stipulates accessibility to data. However, this is not isolated to data access. As shown in Study 2, BA projects tend to end up as shadow systems that are developed and implemented with single units in mind, rather than the firm as a whole. This greatly weakens analytics coordination across departments and prevents synergy effects.

Responsiveness is perhaps the hardest element to include, as measuring the effects of analytics is difficult. However, Kohli and Jaworski define responsiveness as actions taken in response to knowledge derived from intelligence generation and dissemination. Thus, analytics responsiveness can be understood as the degree to which analytics has contributed to changes in a company's business model. This could come from a number of places. CRM is a good starting point, but new products and offerings are also very concrete uses. In addition, there are numerous areas where analytics could contribute, for instance operations.

There are three additional components to the presented framework. Study 2 found that executive support is considered an essential antecedent to analytics, again quite similar to Kohli & Jaworski. Without sponsorship from senior management, analytics projects and impact tends to be severely restrained. This is further underlined both in existing research and in the Davenport-Harris framework for analytical competitors (2007). With adequate executive support, analytics should be incorporated in and interact with the firm's strategy. Having a clear idea of why the organization wants to approach analytics is key to mapping what skills are required, how data should be handled, and how to align the organization's departments. In the words of Davenport & Harris, there needs to be an understanding of what the analytical objective is. Is the goal to provide analytically based insights in some areas, or aim at analytics to be a competitive advantage? These two approaches have very different implications for the complexity going forward. The framework's last component is BA skills. Due to the complexity of BA, the requirements for skills and competence are demanding. This has been a significant challenge for companies, and greatly limits the window of opportunity. Recognizing what skills are required for whatever ambitions the firm has is crucial, both for performing current tasks and developing new areas for analytics.

It is noticeable that cultural aspects are largely absent from the proposed framework, as seen in for instance Narver and Slater (1994). This is primarily due to the inherent complexity and challenges in measuring culture, which basically permeates all the present components.

## 6.1. Method

For our third analysis, we wanted to delve deeper into the specifics of business analytics. Thus, we created our own survey comprising 32 questions. Surveys can be structured in many ways, and the choices made have significant implications on the result. The first question one should ask, is if a survey is really needed (Adams, Khan, Raeside, & White, 2007). As surveys typically have quite low response rates, the issue of generalization becomes quite pressing. In fact, Adams et al. "tend to advocate that surveys are the last resort and are meant for those who lack imagination" (2007). While this certainly rings true in a lot of business and management thesis, we believe that it has a value for our. By combining the results from our survey with secondary data from Digital Norway, other reports, and our own interviews, we should get a good overview of the situation in Norwegian companies.

### 6.1.1 Participants

Since our survey is fairly specialized, we decided to target certain company positions and employees. Working from the professional network platform LinkedIn, we first searched for CDOs, CTOs, data analysts, business analysts and similar positions. Moving on we extended our search slightly, but since we wanted to make sure we hit the right people, it was not always easy to find new candidates. As we learned through one of our later interviews, employees working with data in the SMB-segment typically have more functional roles closer to production. Thus, their working titles are not as specialized as in bigger companies. This is a plausible explanation for the significant majority of companies with a annual revenue above 375 million NOK. Furthermore, the sample is overweight in some industries. Again, this is likely to be a result of the data gathering process. The survey was open between 21.04.2020 and 21.05.2020. In the end, we had 47 respondents. The industry distribution is shown in Figure 17.

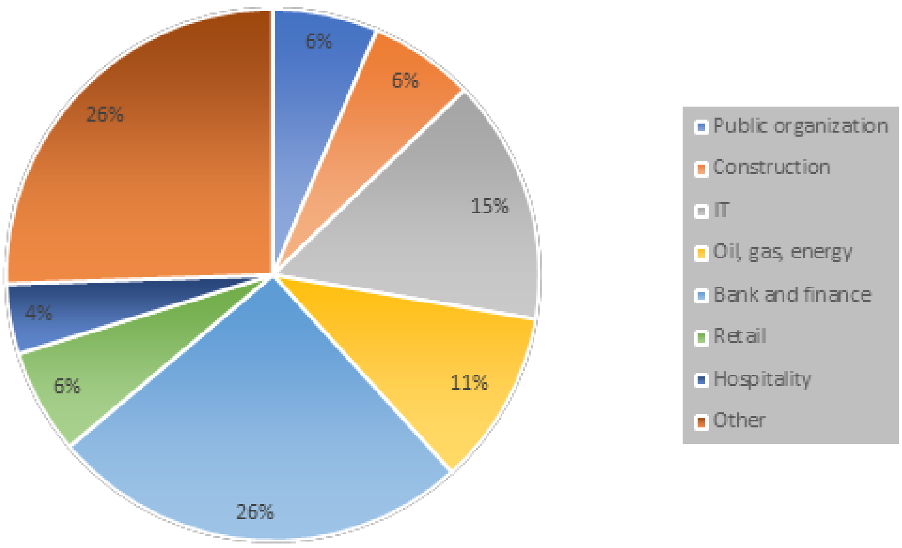


*Figure 19: Distribution of participating companies across industries*

### 6.1.2. Procedure

The data were collected through an online survey platform. With the accessibility of the internet it is hard to find a competing approach, even though certain companies still use telephone. Using the web provides great scalability, less work for the interviewer, and easy access to respondents.

In creating our survey, we followed general design principles. We made sure that the questions were founded not only in existing literature, but also maintained a practical approach to BA. Through talks and reviewing reports on Norwegian companies we ensured that the themes, terms and questions were designed with the goal of being comprehensible for the respondents. We aimed at keeping them clear, short and unambiguous, in addition to offering our own term definitions when appropriate. Second, for analysis purposes the scale, when used, is consistently going in one direction. Third, we decided to keep all questions closed. This clearly has some disadvantages, as it is almost impossible to develop alternatives that hold for all respondents in complex subjects. Additionally, creating responses that are mutually exclusive and exhaustive is a hard task we have approached to the best of our abilities. However, there are some advantages to closed questions. Processing the answers becomes a lot easier and less time consuming, and it is easier to compare observations. When fit, the respondents had the opportunity to select several alternatives in response to a question. Looking back, leaving open fields for alternatives like *Other* would allow respondents to clarify. Perhaps all who answered *Other* on a given question, at most 32% in our case, share an experience that we simply did not consider beforehand.

### 6.1.3. Measures

For *executive support*, there are two underlying variables; whether executives are analytics initiators and an assessment of executive BA skills. Second, *strategic clarity* measures the level of interaction between company strategy and BA and is thus a single observed latent variable. Moving on, *BA skills* is constructed by an assessment of the general BA competence, excluding senior management, and in what way the company has systematic BA training of its employee. Next, *data governance* is built on an assessment of the company's data governance framework, in addition to a variable measuring the important factor of data quality. Then there is *information flow*, again based on two variables: to what extent employees have access to the data they need, in addition to overview over data, also beyond what they have direct access to. Lastly, *BA impact* is whether predictive analytics has been a main driver for product or service offerings, if it has changed how the firm approaches customer segmentation, and how the company uses analytics.

*Table 8: Constructs, measures and reliability*

| Construct | Measures | Reliability (Jöreskog's rho) |
|---|---|---|
| Executive support | Does executives drive/initiate BA development? | 0,55 |
| | How do you assess the general level of competence within BA at management level? | |
| Strategic clarity | To what extent is there interaction between BA and the company's strategic plan? | n.a (single item) |
| BA skills | Do you have systematic training of employees within BA in the business? | 0.68 |
| | How do you assess the general level of competence within BA at the rest of the organization? | |
| Data governance | To what extent do you have a functioning data governance framework? | 0.71 |
| | How would you rate your company's data quality? | |
| Information flow | To what extent do employees have an overview / opportunity to view the company's data, also beyond what they have access to? | 0.41 |
| | To what extent do users have access to data they need? | |
| BA impact | Have predictive analytics been a main driver for changes in the company's product and / or service offerings over the past three years? | 0.87 |
| | Are you working with new customer segments from analytics? | |
| | How does the business use BA and for what purposes? | |

*Table 9: Discriminant validity (heterotrait-monotrait ratio of correlations)*

| Construct | BA impact | Data governance | Executive support | Information flow | Strategic clarity |
|---|---|---|---|---|---|
| BA impact | | | | | |
| Data governance | 0.800 | | | | |
| Executive support | 0.773 | 1.085 | | | |
| Information flow | 0.631 | 0.858 | 0.855 | | |
| Strategic clarity | 0.683 | 0.352 | 0.634 | 0.113 | |

### 6.1.4. Reliability and validity

The constructs' reliability and validity are provided in Tables 8 and 9. Similar to Study 1, the reliability of the index measures was assessed using Jöreskog's rho. Discriminant validity was assessed through the SmartPLS built-in discriminant validity tool, which uses the HTMT criteria as defined by Henseler et al. with a threshold of 0.90 (Henseler, Ringle, & Sarstedt, 2014).

One of the most important aspects to address regarding questionnaires are the data's content validity (Saunders, Lewis, & Thornhill, 2016). There are challenges that apply specifically to surveys of this kind. One is the internal validity, whether we are measuring what we intend to measure, which appears to be an oxymoron - if we knew the reality of what we are measuring, there would be no need to measure it. However, this is solvable by using other sources to support and illuminate answers found in the questionnaires. In this case, the other two analyses and previous research. Another is content validity, the extent to which the survey's questions provide adequate coverage of the questions we aim to explore. Again, it is fairly hard to give an objective assessment of the content validity. However, we have extensively used previous literature combined with talks to industry experts in developing our survey. Our ambition for the survey was to cover previously unexplored questions, and in this process, we are sure we have missed certain features. Still, the questionnaire content has been thoroughly discussed and revised, and the validity is medium high.

Reliability, the consistency of the data, is another area. An obvious weakness in this is that we use individuals as representative for the companies. Even though the survey has been targeted at certain respondents, subjective readings of both the survey's questions and the companies mean their response can differ considerably from any colleague. In our case, this seems to be especially true for IT departments, who tend to have somewhat separate experiences. Also, we must not forget that we are dealing with humans whose feelings can play a part. For instance, if they recently had a frustrating situation with a dataset, that might impact their response. Typically, this is handled by correlating results from questionnaires collected under nearly equivalent conditions, measuring consistency of responses across a subgroup of questions or using alternative forms of the same question as check questions. We have not employed any of these precautions. Combined, these aspects demonstrate that the reliability of this data is not very strong.

Furthermore, the data's generalizability should be assessed. This refers to the degree of which our data and research say something about our phenomenon outside of the respondents. Since this sample size is so heavily skewed towards companies with a significant revenue and certain industries, its value in this regard is limited. Even if we limit ourselves to large companies, the Norwegian business finder Proff shows that nearly 2000 companies had revenue over 375 million NOK in 2018. They operate in a wide variety of industries, and it is challenging to collect any data accurately describing them. Thus, the generalizability of the results will be much lower than for Study 1.

## 6.2 Results

Based on the framework proposed in the introduction to this chapter, we estimated a partial least squares (PLS) path model using SmartPLS. PLS is a multivariate technique, using a component-based approach to produce path coefficient estimates for structural equation models. It is essential to stress that the goal of this analyses is data exploration. As the sample size is quite low, we do not expect the results to be significant. However, we can still explore what tendencies and implications can be found in our dataset.

### 6.2.1. Saturated Path Model

First, a saturated model was estimated with the maximum number of connections between latent variables, as shown in Figure 20. While the theoretical fundament for this model is weaker than our proposed framework, it is always useful to start here. *Executive support*, which in our hypothesized model primarily affects strategy, has positive impact on all factors with the exception of BA impact. *Strategic clarity* is the only other construct with more explanatory power than we hypothesized, also having a direct positive affect on *BA impact.*

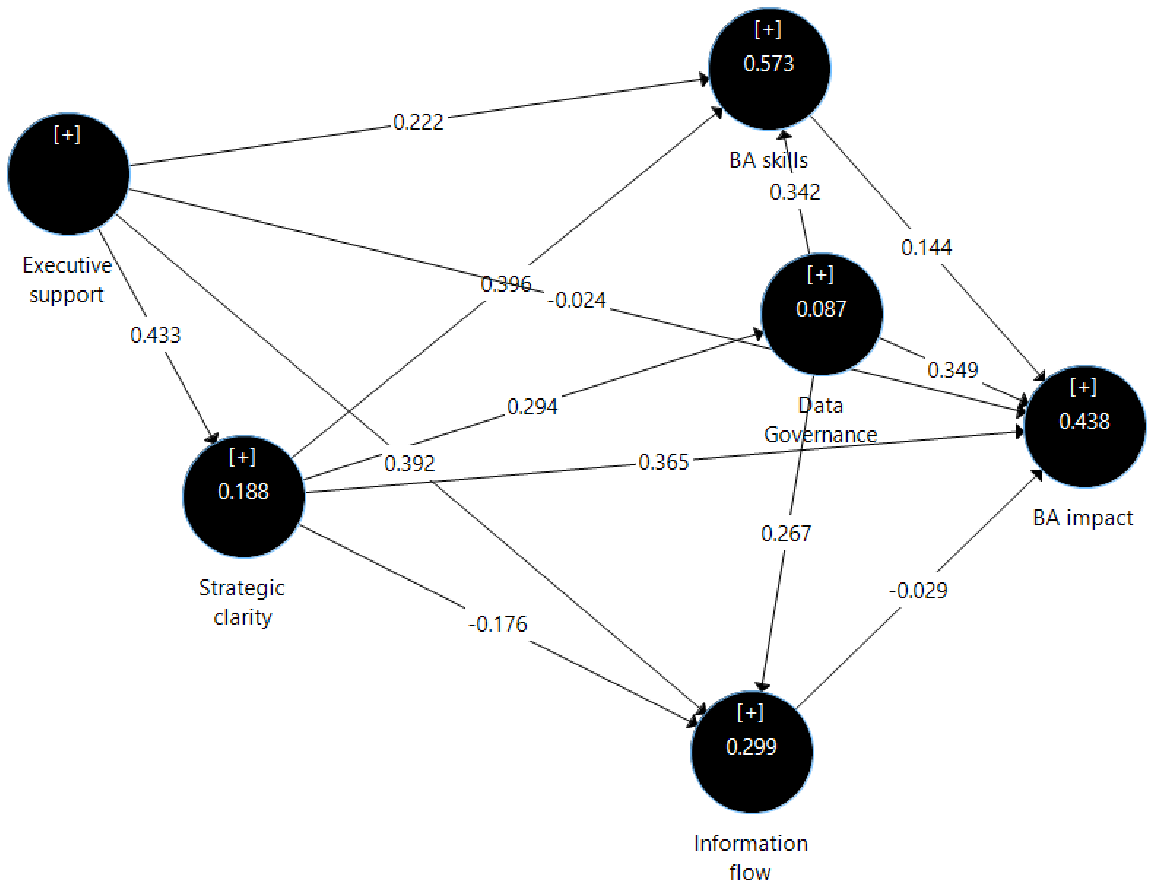


*Figure 20: Saturated PLS path model*

### 6.2.2. Restricted Path Model

In a second step, we restricted the model in accordance with our hypothesized model. The new estimates are shown in Figure 21. The results show the coefficients of each connection between the latent variables, and the corresponding R2 values of each construct. While the R2 values are quite low, there are indications of the relationships and their strength. Most of the connections correspond with our assumptions, except for those related to information flow. For our sample, strategic clarity has a very weak negative effect on information flow. This is somewhat surprising, but it is worth noting that information flow is the most likely variable to be affected by cultural factors. This could also explain why Information flow also has a negative relationship with BA impact. Furthermore, our measures for BA impact could well have positive scores even with the existence of silos, as they do not measure the bottom-line impact of analytics but rather its effect on the company's business model.

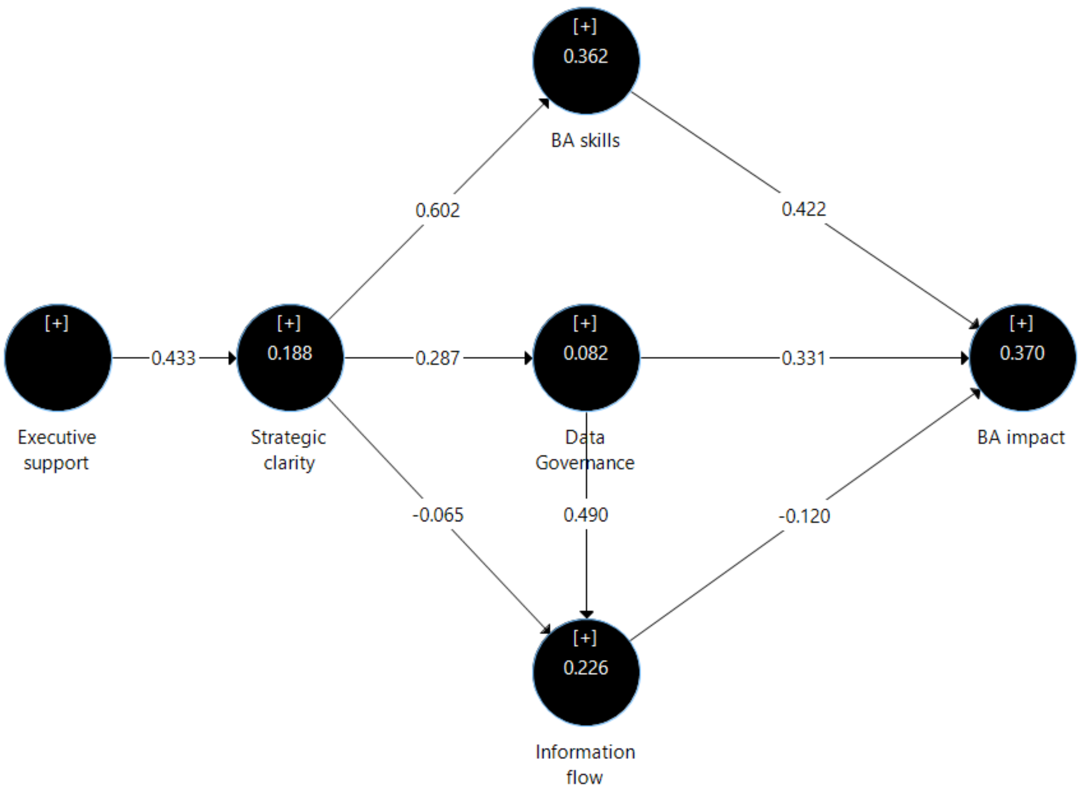


*Figure 21: Restricted PLS path model*

In other words, departments can have changed service offerings or customer segments without it having affected the bottom line positively. It is worth repeating that these results must be interpreted and understood as explorative rather than hypothesis testing.

#### 6.3.3. Additional Descriptive Results

The purpose of Study 3 was to illuminate the use of BA in Norwegian companies, and there are several interesting findings. Davenport and Harris' framework has once again been used for this analysis. Thus, finding 1 and 2 is associated with BA objective and process, finding 3, 4 and 5 relate to skills, sponsorship and culture, while finding 6 is linked with technology. Some findings still blur the line between the different components, but simply had to fit somewhere. It is important to repeat that the limited sample size implies that this study cannot be used as a general assessment for Norwegian companies, but it can give important implications and indications. The survey and the results are available in its entirety in Appendix 4.

***Passable analytical approach and standard analytics use***

Analytics is a versatile and diverse toolbox that can be used in many ways. Any organization with ambitions in analytics should strive for an enterprise-wide strategic approach. This is helpful to avoid silos, develop a data-driven culture, ensuring focus on analytics, and more. From our sample, 13% report that analytics is fundamental for the company's overall strategy. The same number has a defined strategy for analytics, while the remaining 74% have looser interaction between analytics and strategy.

When it comes to how they perceive the use of BA and its objective, 23% consider it to be a differentiating capability. The same number uses BA proactively to achieve a set of firm objectives. Combining these, we can say that 47% of the sample uses BA actively. Most companies, however, view BA as a tool for decision making and occurring problems. These can be understood as passive BA users.

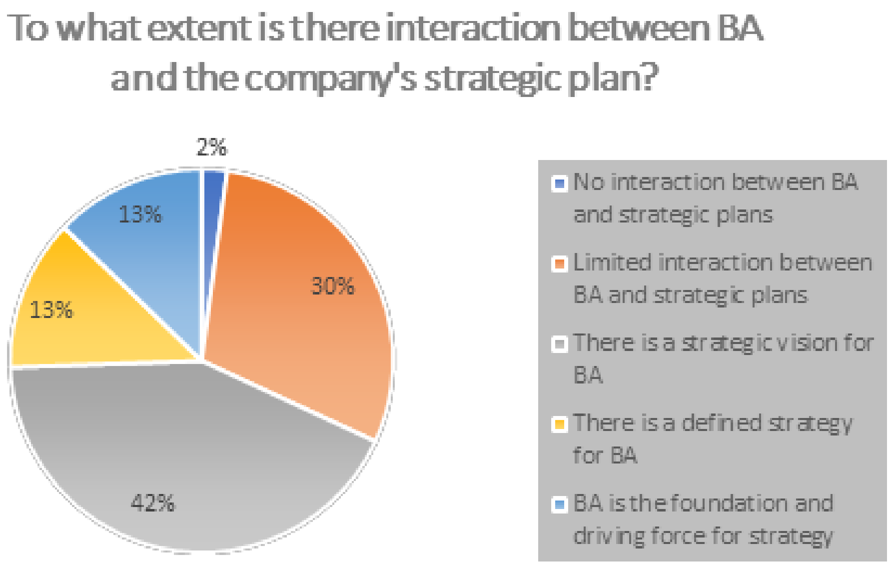


*Figure 22: BA and strategy interaction*

Looking further into how the companies primarily classify their analytics use, almost 50% have dashboard or scorecard solutions. This is not surprising, as dashboard solutions provide a feasible alternative to organize and visualize KPIs and other company data. Almost 40% use predictive analytics, based on our given definition "Predictive analytics aims to provide predictions of future outcomes based on historical data and analytical techniques such as statistical modeling and machine learning". The remaining companies use very few analytics tools, and primarily relies on *ad hoc* reports. This indicates that our companies are quite sophisticated in their analytics use, which may stem from the sample's skewedness. For instance, a 2017 survey found that fewer than a quarter of firms used predictive analytics (Dresner Advisory Services, 2017). The number using predictive analytics in our sample is actually 75%, but around half of these do not consider it their primary analytics focus.

The firms using predictive analytics have different goals. Most common is using it for market forecasting, which typically aims to predict future demand. A significant number also uses analytics for customer insight, production and logistics, and isolated analysis. Forecasting and logistics use addresses a specific business area and is increasingly important with the growth of lean and agile value chains, as a consequence of digital technologies (Wyciślak, 2017). Customer insight is typically one of the first areas to be explored through analytics and can lay good groundwork for later expansion. As shown in 2.2.1, most leaders of successful digital transformations focus on transforming customer-facing functions first (SAP Center for Business Insight and Oxford Economics, 2017).

Looking more specifically into customer relations, almost 65% of the companies report that they have some kind of automated measures. More than half use them in relation with fitting marketing campaigns, while 45% use them for upselling. Lastly, 38% have automated measures in the face of customer churn, such as automatic messages or offers. Customer segmentation is another popular area for analytics, for instance through clustering in the same fashion as study 1. While the majority of companies, 56%, have used analytics for customer segmentation, only 15% primarily work with the new segmentations. In most cases, the segmentations have been combined with existing knowledge and perceptions. There is no reason to think that segmentation through analytics automatically identifies the best ways to approach the customer base. While it can certainly identify patterns and groups unknown to the company, combining these results with business knowledge and experience is probably the best approach to exploit the results.

***Silos remain a significant challenge for analytical processes***

The biggest challenges faced in our sample is limited BA skills with users, poor data quality, silos due to different BA use, no formal procedures in BA use, and limited data access. While limited BA skills are somewhat isolated, there is no doubt that the issue of silos is amplified by the lack of formal procedures and limitations in data access.

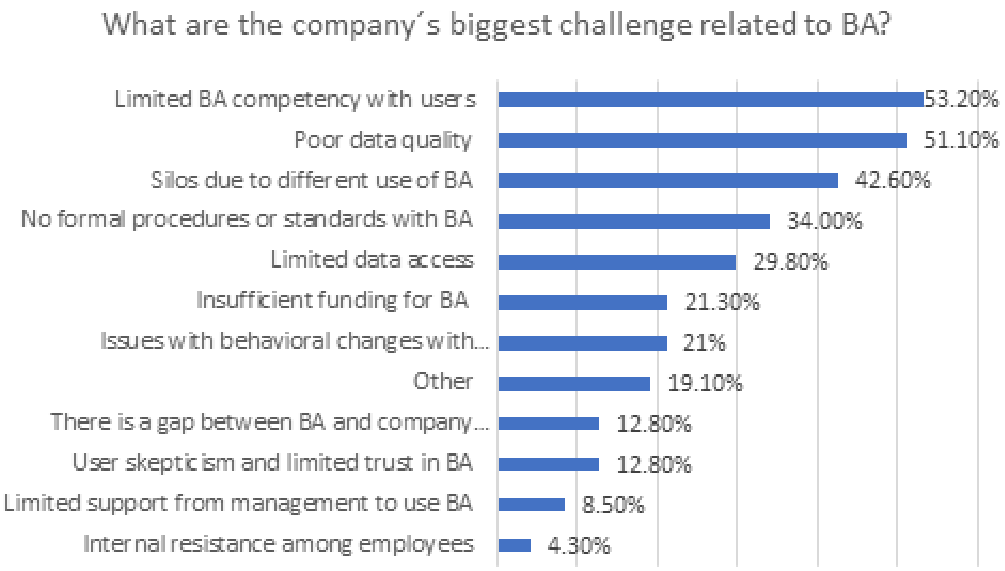


*Figure 23: Greatest BA challenges*

Silos are another big challenge to any organization's analytical capabilities. It limits information flow, reduces cooperation, creates shadow systems, and much more. This does not only arise from lack of data availability. For instance, study 2 found that enthusiasts play a big part. Looking at the primary drivers for BA for our sample, individual initiatives from enthusiasts dominate, with 83% of the companies noting it as a primary driver. Employees from IT, another source of silos, is a driver in 60% of the companies. Executives also score quite high at 62%, which probably mitigates some of the silo risks. However, there is no indication that our samples silo problems stems from enthusiast's BA initiatives. In fact, it is hard to pinpoint exactly what causes the silos. Nevertheless, it remains a significant challenge that all companies should avoid in their analytics processes.

***BA competence is not terrible but upskilling should have higher priority***

The important role of skills in creating data-driven organizations was shown in Chapter 2.2.2 and this should be an area of focus for more companies. However, the assessment of general BA competence is not terrible. In fact, less than one in five report a poor or very poor competence level. This seems to demonstrate the complexity of analytics as a business field. While the general level of competence might be just fine, new and demanding challenges keep emerging all the time. The skill level of companies with significant interaction between BA and firm strategy is considerably better than the rest, with a score of 3.77 to 2.94.

Recognizing that limited BA skill in users are the biggest challenge, one would think that this would be an area of focus for all companies. However, this does not seem to be the case.

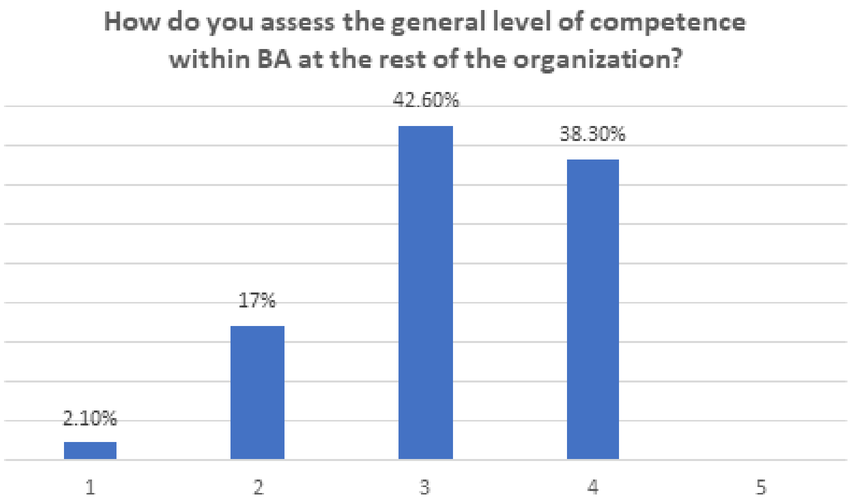


*Figure 24: BA competence*

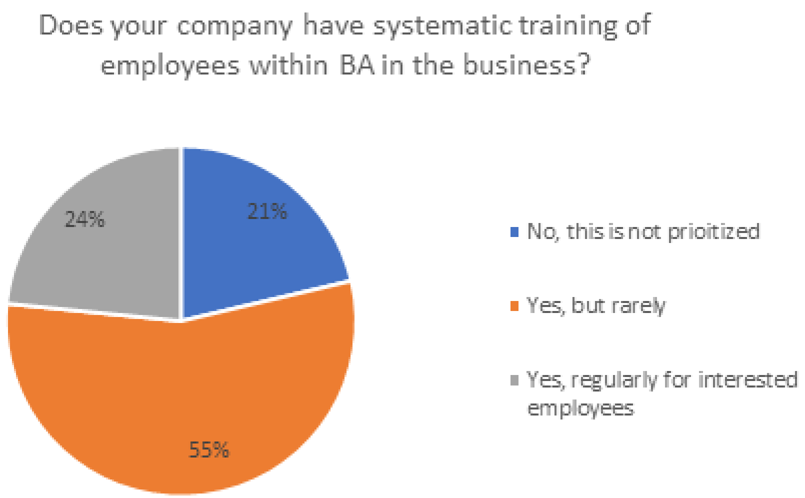


*Figure 25: Systematic BA training*

While most companies are aiming at improving this with internal upskilling rather than external recruitment, with 77% to 23%, focus on training does not seem too high. In fact, none of the companies have obligatory courses for their employees. 55% organize courses on an *ad hoc* basis, while the distribution between companies not prioritizing it and those regularly offering courses to interested employees is quite similar. None of the companies have obligatory courses for their employees. While it is hard to pinpoint exactly why this is, it shows a fairly lackluster effort to address the issue.

***Executives are involved***

One of the most important enablers for analytics is executive involvement and sponsorship. As we will show later, the sample's dedication to analytics through investments and change management are quite high, factors where executives can be expected to have weighty influence. However, executive involvement is also visible in several other areas. First, note that few respondents, 9%, feel that a lack of support is a big challenge with BA. In fact, it seems to be quite the opposite, with executives taking an active role both as users and initiators of analytics.

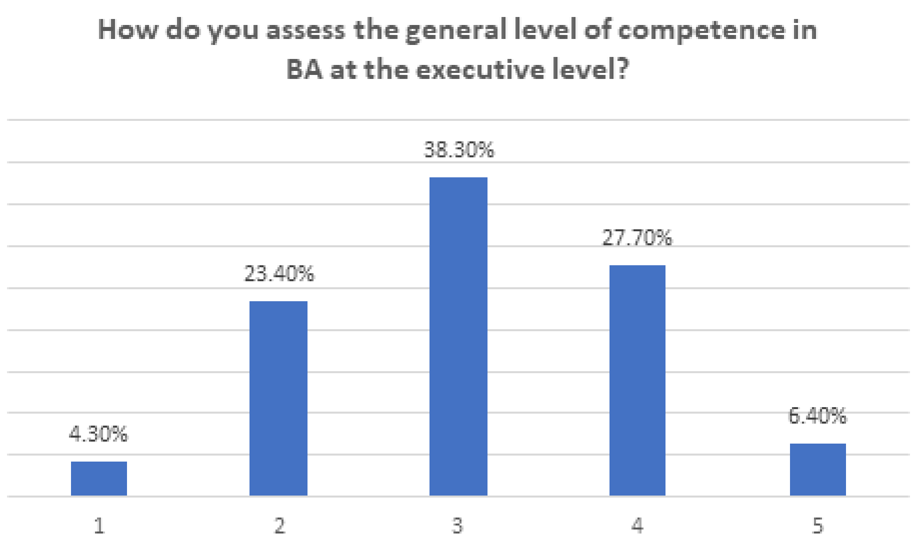


*Figure 26: BA competence, senior management*

As shown, 62% from the sample report that executives contribute in developing their company's analytics. Furthermore, 66% regularly use analytics-driven insights in decision-making. One main reason for this involved approach could be executive's BA competence, which in our sample seems solid. 34% have high or very high competence, 38% are mediocre and almost all the remaining 28% are low.

A possible and often sought after result of executive involvement is an enterprise-wide strategic approach. While this study has shown that the majority of companies has a somewhat loose interaction between BA and firm strategy, it is important to remember that most executives have limited time to handle such tasks. In fact, Microsoft found that more than 50% of executives from its data analytics survey spend over 60% of an average day on short-term activities like department meetings, customer issues, or project management (Prevedere & Microsoft, 2019). The same number reported they lacked time to devote to strategic planning. The fact that analytics is such a complex and hard area to get right is sure to complicate things further. This lack of time might be the reason why 26% of the companies in our survey primarily identify specific functions for predictive analytics through executive involvement. Still, they are the biggest makers of KPIs. In almost 50% of our sample, these are designed in a top-down manner, which typically contributes to organizational alignment and consistency.

***Cultural change seems to be present but is hard to spot***

Cultural changes are particularly hard to measure in a survey like this, as it requires many follow-up questions to uncover a complex phenomenon. However, there are some findings worth reviewing. Change management, an important part of developing analytics, seems to be a focus in our sample with 68% reporting high or very high focus on this aspect. Perhaps unsurprisingly, the interaction between BA and company strategy seems to be a decent predictor of how important change management is perceived. Firms with significant interaction between BA and strategy score 4.61, compared to 3.97 for the rest.

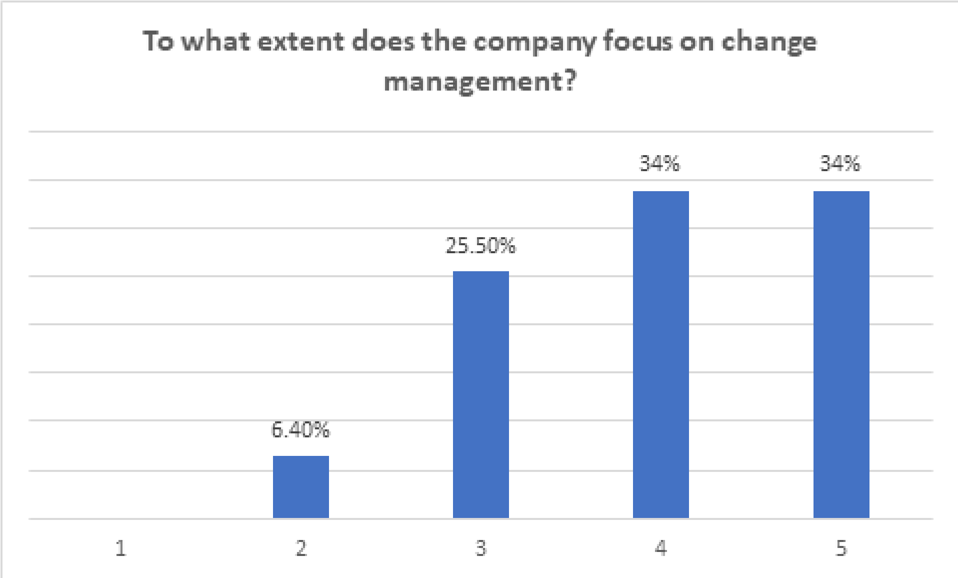


*Figure 27: Change management*

Furthermore, we find that the majority of companies have used BA as a main driver for changes in product or service offerings. For 34% it has even happened regularly, while 23% report occasional cases. While this may not directly link to the company's culture, it shows willingness to use analytics actively in renewing the company. Furthermore, only 9% report that a main reason why users do not rely on data is that it is not considered useful. Lack of skills and access to data are much bigger hurdles in this regard.

Lastly, investment plans might give an idea of company dedication to analytics and its role in creating data-driven organizations. Chapter 2.8 found that the sense of urgency related to digitalization in Norwegian companies is medium. In our sample, the sense of urgency for analytics seems slightly higher, with 77% of the companies planning considerable investments in BA the coming years. The 13 companies with significant interaction between BA and strategy have a higher degree of investment readiness, with 4.62 compared to 3.97. The same pattern is found in active users of BA, with 4.23 to 4.08. This is similar to existing research, such as Xavier et.al, showing that existing analytic capabilities tend to increase investments (Xavier, Srinivasan, & Thamizhvanan, 2011).

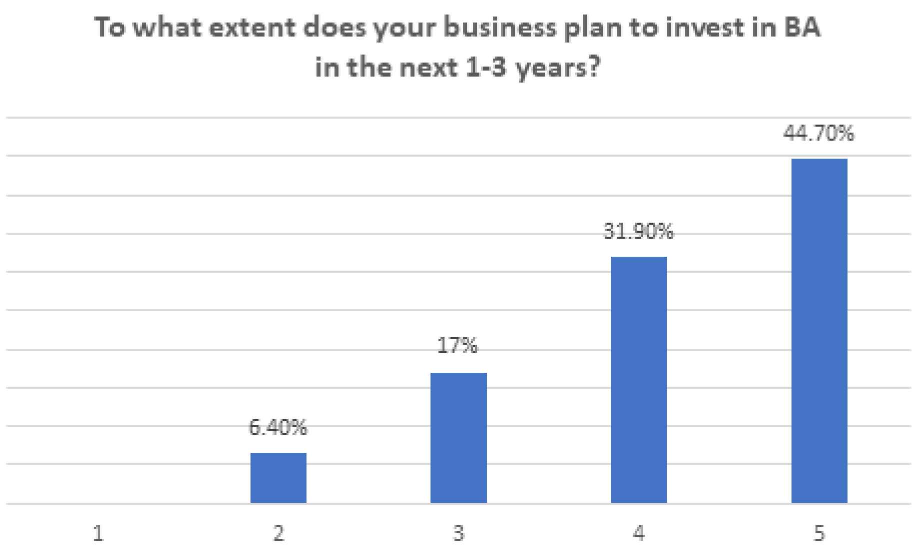


*Figure 28: Investment in BA*

Another important part of developing analytics is change management. Again, this seems to be in focus in our sample with 68% reporting high or very high focus on this aspect. Again, the interaction between BA and company strategy seems to be a decent predictor. The score for companies with significant interaction is 4.61 to 3.97 for the rest.

***Minority of data lakes, but decent data governance***

While data warehouses have and still represent leading data storage solutions, data lakes are growing every day and have become increasingly available through cloud services. Looking at the use of data lakes in our sample, 30% use the technology.

This is not far from the international trend. Market analyst BARC found that 12% of its surveyed companies in Europe and North America were using data lakes (Grosser, Bloemen, Mack, & Vitsenko, 2016). Even when including companies with pilot projects, which are not at all guaranteed to succeed, the number is 28%. Note that 72% from our sample have concrete plans to change their architecture in the next three years, which could mean the introduction of more data lakes solutions.

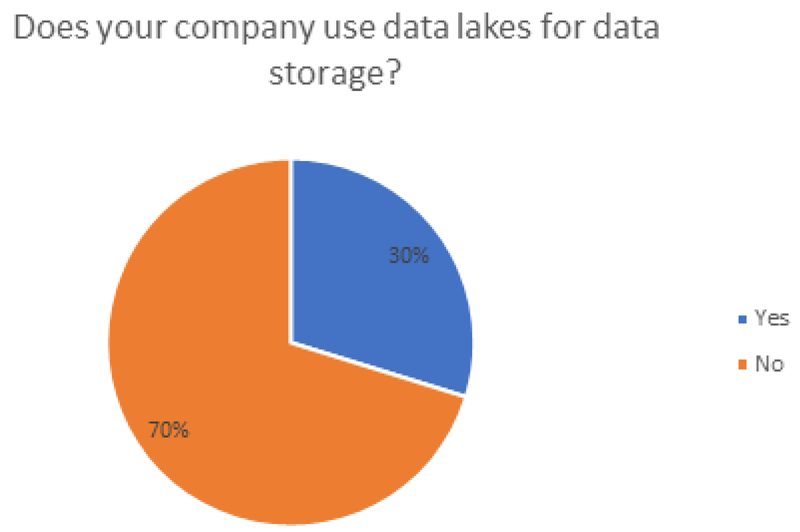


*Figure 29: Use of data lakes*

However, it is important to underline that data lakes are not for all. While they provide a remarkable scalability, they require significant attendance in relation to data stewardship, data governance, user skills, data quality and data retrieval. A study notes that while data lake technology may ease data acquisition, the more effort is required during data retrieval (Llave, 2018). This is probably the main reason why TDWI's maturity model introduces the concept after *the chasm*, underlining the importance of combining new employees with data lake knowledge and existing employees with experience from business. This is also a plausible explanation why companies with more 2 500 employees dominated data lake initiatives in BARC's survey; the demands on internal capabilities might simply be too high for smaller companies.

Whatever data architecture, data quality and data access are essential for enabling analytics. Data quality remains a significant issue, also in our sample. When asked about their biggest challenges with analytics, more than 50% reported poor data quality, making it second only to limited user analytic skills. This is echoed in the assessment of data quality. The majority of respondents, 57%, rate their data quality as mediocre to low, while 11% have very high data quality.

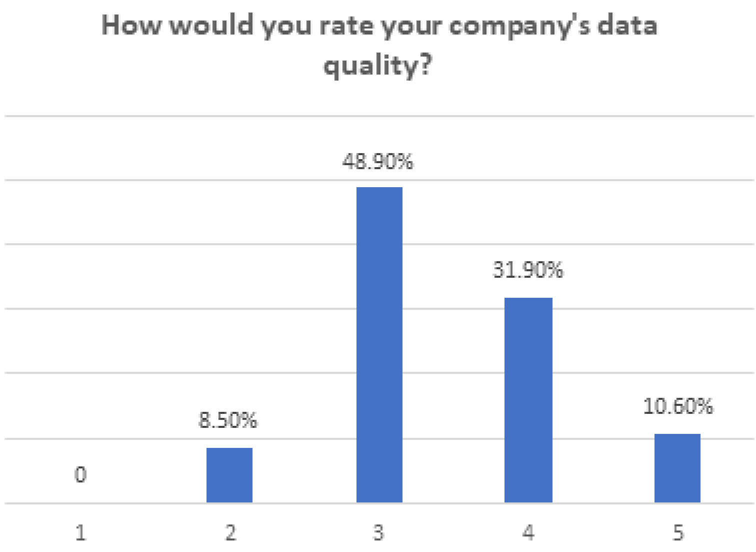


*Figure 30: Data quality rating*

Given the potential costs of wrong decisions and erroneous analysis, this remains an area of improvement. When looking at the data quality of companies using BA proactively or for differentiation compared to the others, they have better data quality scores with 3.64, compared to 3.28. While not insignificant, it seems like other aspects can explain more.

The issue of silos has been addressed several times and proves to be a challenge in our sample as well. Looking at the biggest challenges, silos due to different use of BA ranks third with 43% of the companies reporting it. A major part of this is data access, which ensures that information is available across the organization. In the case of our sample, this definitely seems to be part of the problem. Only 15% of the companies allow their employees to see nearly all data, with 49% not seeing any data they do not have access to. For 36%, the overview is limited to their own departments. Furthermore, 23% report that their employees have poor access to useful data, while 43% feel this is well maintained. 34% have mediocre access for their employees.

Given the challenges with data quality and access, it is interesting to see that the functionality of data governance is quite high. In our sample, 49% have very high or highly functioning data governance that works throughout the organization. Only 21% have low scores, while 30% report moderately working data governance. However, data quality and access are only two of the five aspects of data governance as identified in 2.2.5. It may be that the areas of data principles, metadata and data lifecycle are stronger.

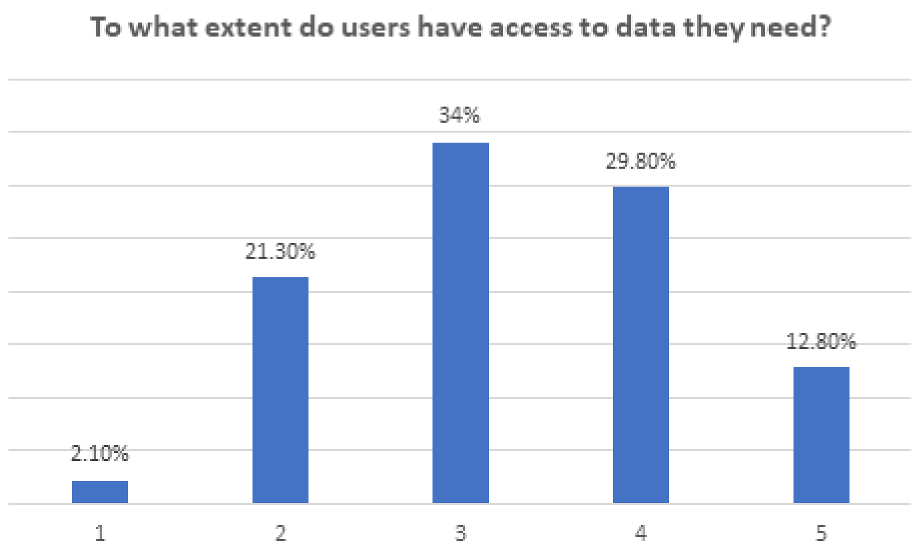


*Figure 31: Data access*

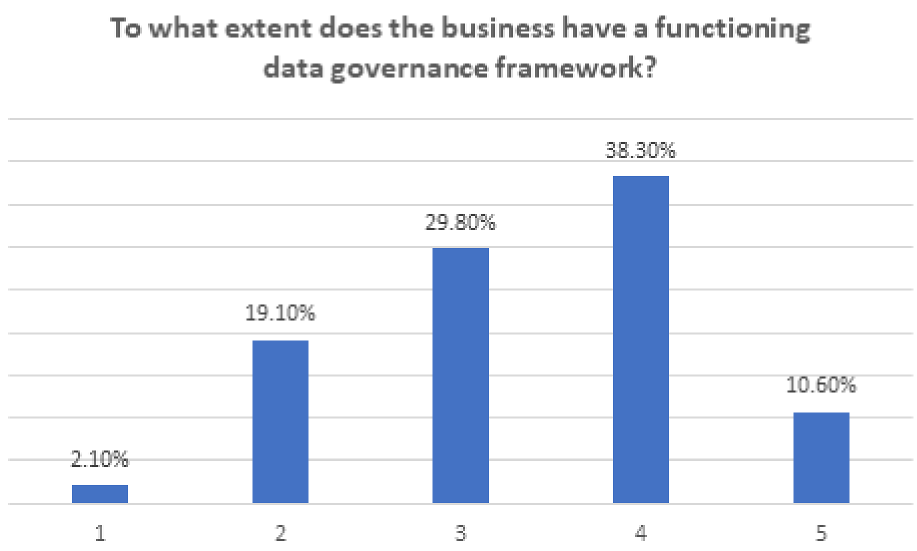


*Figure 32: Data governance framework*

### 6.3.4. Additional Predictive Results

While the findings in the previous section reveal some interesting points, they are descriptive and should be accompanied by a more sophisticated, predictive analysis. Using SAS JMP Pro 15, we performed decision tree analysis on the survey dataset. The JMP partition platform creates a decision tree based on the predictors and response values and is considered a data mining technique. In this case, it is chosen for several reasons. It easily handles large and complex problems; it is useful for exploring relationships without a good prior model; and the results are interpretable (JMP, 2020). In practice, the analysis provides us with a hierarchy of questions to help explain the response variable. The predictors and response variables can be either continuous or categorical. In either case, the split is chosen to maximize the difference in the responses between the two nodes of the split.

In order to perform a meaningful analysis, some of the variables were transformed. The scaled alternatives were changed into nominal variables, for instance *high* and *low*. For example, the question asking the respondents “How would you rate your company's data quality?” was answered by choosing a rating between one and five. For this analysis, however, the answers have been changed to *high* for ratings of five and four, and *low* for three, two and one.

***Active versus passive use of BA***

As first response variable, we chose the variable of “How does the business use BA and for what purposes?”. This question had four alternatives: *occurring issues, decision making, proactively to achieve goals* and lastly *differentiation.* One of the most important measures of analytics maturity is to what extent it is being used for predictive and prescriptive measures rather than descriptive and random analysis. Thus, we split the answers in two new groups. Answers of *occurring issues* and *decision making* are categorized as a passive approach to BA, while *proactively to achieve goals* and *differentiation* are viewed as active approaches to BA.

Using almost all the remaining variables as predictors, we performed our analysis in JMP as seen in Figure 33**.** Our analysis found that using BA for in-depth insight into customers best predicts whether or not companies use BA actively, with companies doing so being far more likely to have an active approach. The next split showed that if companies do not use BA for in-depth insight in customers, the general level of BA competence at management level had the biggest explanatory power. In the case where this is low, the majority of companies have a passive approach to BA. Furthermore, in the case where this is low, poor data quality has significant impact. Interestingly, the companies with poor data quality are more active users of BA than companies where poor data quality is not considered a BA obstacle. Lastly for this side of the tree, the analysis found that companies not using data lakes are unlikely to have an active BA approach; if they are using data lakes, it is much more evenly distributed.

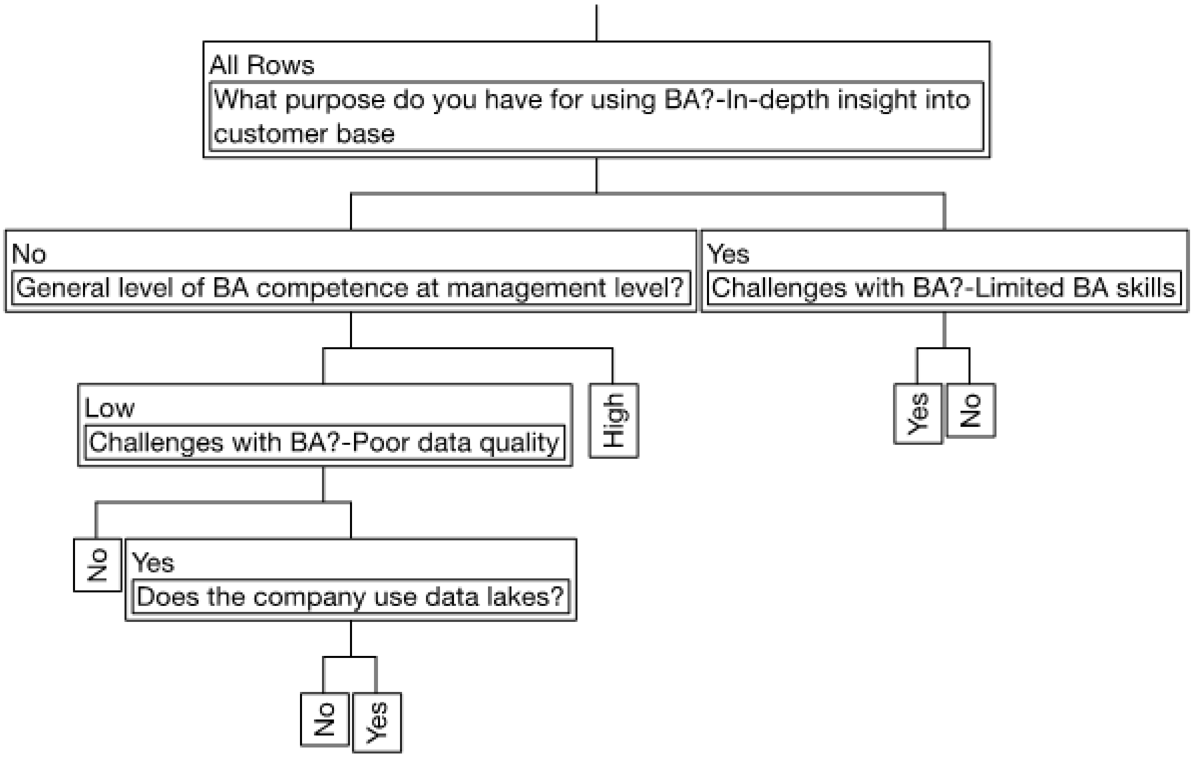


*Figure 33: Predicting active versus passive BA use*

Going down the other side of the tree, looking at companies using BA for in-depth insight into customers, the best predictor is whether challenges with BA stems from limited BA skills in the organization. Where limited BA skills was not considered a major challenge, almost all were using it in an active manner.

While the goal of this analysis is data exploration rather than creating an optimal prediction model, it is worth showing some statistical measures to comment on the model's fit. The misclassification rate is 0.19, implying that roughly one fifth of the observations are wrongly predicted on the basis of the five splits presented above. Furthermore, JMP provides a tailored generalized $R^2$ value for the analysis which in this case is 0.57. While our splits do indeed seem to offer a decent statistical fit, a lot of the variance remains uncovered. In other words, there are still plenty of differences between the surveyed units beyond what this analysis has unveiled.

***BA and strategy***

The same analysis was carried out with another response variable, namely "To what extent is there interaction between BA and the company's strategic plan?". This illuminates a more formal and overarching side of BA, which has less to do with its actual performance previously covered. Again, the answers were restructured into three alternatives: *high* for units with the highest score of 5, *medium* for units with scores of 4 and 3, and *low* with scores of 2 and 1. The decision tree is shown in figure 19. For this response variable, the best predictor is the general level of BA competence for the organization, excluding management. In fact, none of the units with *high* interaction between BA and strategy have low competence in BA. Splitting this group further, plans to change the data architecture in the next three years is a dividing feature. In the absence of such plans, 90% have low interaction between BA and strategy. Where such plans exist, however, all companies with BA challenges related to limited data access have medium interaction between BA and strategy. This is fairly interesting and might be an indication of the growing number of issues that arise from ambitions in the area of BA. Lastly, in instances without data access problems, the presence of data lakes is the best indicator. Companies implementing data lakes in their architecture are likely to have medium interaction between BA and strategy, while companies without data lakes typically have a low interaction.

Reviewing the other split on BA competence, where all the units with high interaction with BA and strategy are located, the next split relate to how BA related tasks are approached. In the case where this is internal, none of the units have low interaction between BA and strategy. Where it is both external and internal, however, there is a fairly clean distribution between *low* and *high* on the response variable. Lastly, in the case of internal handling of BA tasks, it becomes evident that most companies with high interaction between BA and strategy have incorporated data lakes in their architecture. For those who have not, all have a medium score.

Once again, it is worth having a look at the model's fit. The misclassification rate in this case is 0.15. The generalized $R^2$ for this model is 0.82, substantially higher than the previous. Once again, it is important to underline that there are sure to be differences outside of what is uncovered in this analysis.

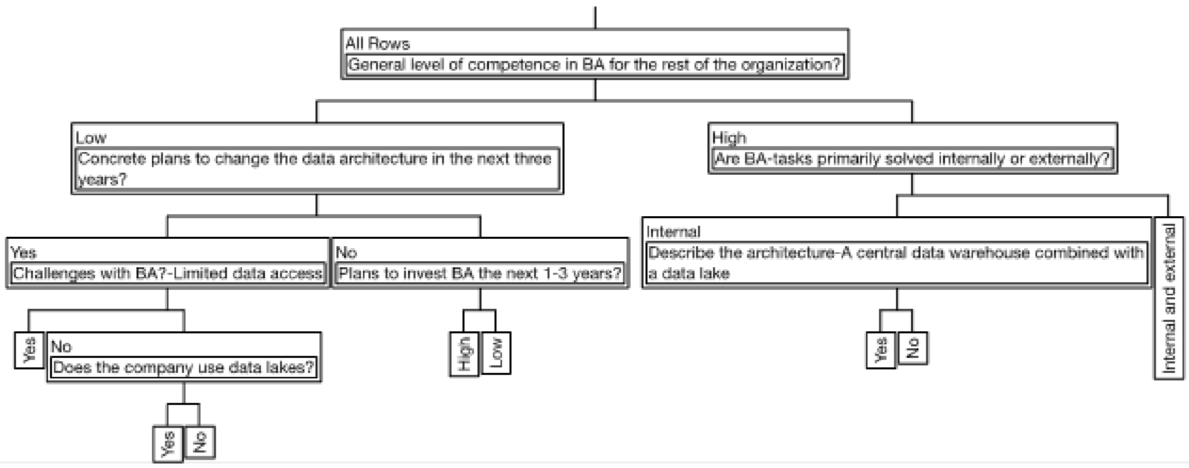


*Figure 34: Predicting strategic use of BA*

# 7. General Discussion

## 7. 1 Assessing Analytics Maturity

This section provides a summary of the findings from the studies, with relation to the challenges presented in the framework by Davenport and Harris. Following this is a general assessment of the maturity level of Norwegian organizations.

Study 2 revealed that organizations often struggle to set objectives and use cases for BA. This supports the notion of the theoretical foundation on the topic presented in Chapter 2.2.1, as elaborated in the discussion part of Chapter 4. Comparing the results from Study 2 with the results from Study 3, we find additional similarities that corroborates this. Among the related results, this study found that only 26% of the respondents have a defined strategy for BA or have it incorporated in the overall business strategy. Furthermore, only 23% claims that BA is used proactively to achieve a set of firm objectives.

Regarding the process, it is important to ensure a coordinated effort moving all the pieces in the right direction, as highlighted by Davenport and Harris as well as other researchers (see Chapter 2). An important part of this is to avoid silos, a severe obstacle in moving forward. As Study 3 showed, this is a significant challenge for Norwegian companies, with 43% reporting it as a problem. TDWI's maturity model points to pockets of enthusiasts as a common reason for this, and this is echoed in Study 2. Here, we found that while enthusiasts often have big ambitions and ideas, this frequently leads to silos using different systems and approaches resulting in shadow systems.

The informants in Study 2 argued that challenges often occur when a BA initiative is rooted in the IT side, rather than the business side. From Study 3, we see that initiatives tend to stem from IT, at 60%, rather than business and operational functions within an organization. IT is closest to the technology and the opportunities it provides, but also further away from the needs that the organization have. Our informants said that a business translator role, serving as a bridge between the two departments, could be a solution to this challenge. This is supported by the research provided in Chapter 2.

Both Study 2 and 3 revealed that lack of competence among workers is a challenge for Norwegian organizations. From Study 2, our informants pinpoint that neglecting upskilling is one of the most frequent reasons for why initiatives fail. In Study 3, the respondents reported low competence among workers, as well as low prioritization of training. The existing theory and research presented in chapter 2 also highlights the importance of competence and training. Furthermore, our second partitioning analysis in Study 3 showed that a high competence level in the organization is the best predictor for organizations with high interaction between BA and the strategic plan. This repeated finding indicates that organizations must put more emphasis on training in their project plans.

On the topic of sponsorship and executive support, the research presented in Chapter 2 showed that this is of upmost importance for succeeding with BA initiatives. This was echoed in Study 2, but our informants also noted that leaders in Norway are mature and interested in whatever help they can get to make the business better. Similarly, Study 1 showed that Norwegian organizations often holds high leadership capabilities. In Study 3, the response was also that sponsorship is rarely a challenge, and that BA competence among leaders is high. In summary, our studies found that this factor was not a significant obstacle for Norwegian organizations when it comes to BA maturity.

Cultural challenges were harder to assess than the other challenges, as found in Study 3. From Study 2, the informants highlighted the importance of open communication between IT and business functions within an organization. This supported the research presented in chapter 2. However, this is not an exclusive factor, as this is strongly interrelated with the other categories as well. Better communication could be solved by the introduction of a business translator role. Arguably, greater competence about BA would also raise the data culture in an organization, and vice versa. Culture could in many ways interrelate with all the other categories, and therefore support the claim of Anderson (2015) in Chapter 2, stating that culture permeates everything.

The last topic to discuss is technology. From Study 2, the informants claimed that the challenge related to this topic is that it steals focus from the other categories. The opportunities that technology offers cannot be utilized if the organizational factors are not in place. When it comes to technology, the TDWI maturity model is more detailed than Davenport and Harris'. For instance, while the latter does not mention data governance until stage 5, TDWI brings this already at stage 2. Regarding this, analysis 3 showed that data governance in Norwegian organizations obtains decent levels. An interesting find in the partitioning analysis in Study 3 was that the respondents with poor data quality are more active users of BA than companies where poor data quality is not considered a BA obstacle. This could also be linked to a cultural aspect, as discussed in Study 2, where organizations that do well tend to know that they can do even better.

Given the summary of the challenges provided in this section, a general assessment of the maturity level can be made. Our studies find that Norwegian organizations obtain high scores in factors related to *sponsorship* and *technology*. Organizations face more challenges when setting the *objective*, but are often able to get by through experimentation and starting at customer facing functions. Therefore, we argue that there is a decent level regarding this. *Culture*-related factors are also decent, but difficult to assess. As one of the dragging factors, *skills* among workers generally have a lot of potential, but it requires greater focus on upskilling. Lastly, our studies show that there are major challenges related to *process*, as silo formations is rapid, and there is a lack of bridge between IT and business functions.

It is not easy to pinpoint the findings in this thesis to the defined stages in Davenport and Harris' maturity model. One reasons is because the framework was developed for the use of specific organizations, and not in a general matter as this thesis aims to. Looking back at the framework presented in Figure 5, we can say that on the topic of sponsorship, our findings supports that the general level among Norwegian organizations is at Stage 4, analytical companies. Furthermore, we find objective, process and culture to be best described in Stage 3, analytical aspirations. However, we find that there are more challenges related to process than objective. Culture is as mentioned, difficult to assess on a general level. On the matter of skills, we find it best described under Stage 2, localized analytics. Last is technology, which we will refrain from assessing. The reason for this is that the content of this category is rapidly changing, but we also find it to be the easiest to obtain. The organizational and human aspects of analytics maturity are more or less constant, while the authors of the framework revise the content of technology as modern technology develops. The findings presented in this thesis indicates that organizations can easily obtain the highest level within technology, but that it will not matter unless the other categories are equally fulfilled.

## 7.2. Size and Industry Differences

With the general assessment at hand, it is time to elucidate further by looking at the relative differences found in Norwegian organizations. Through Study 1, we found interesting patterns in industry and enterprise sizes. Five clusters were formed, with varying amounts of members. While this analysis used data on digitalization rather than analytics, we showed that there is a close connection between the clusters and their scores on analytical variables in the dataset. This is hardly surprising, as they seem very closely connected. For this discussion, we have thus assumed that the results from Study 1 can be interpreted as is, also for the realm of BA.

There are some observations to be made. First, note that size does seem to matter. Cluster 2, digital leaders, has more than 50% large industries. The same trend can be seen in the second most digitalized cluster of responding conservatives, where 76% of the companies are either large or medium. This is in line with our findings in Study 2, which emphasizes that BA investments do not give a linear yield. In fact, we were even told that one manager had a rule of thumb that BA projects should equal around one thousandth of revenue, underlining that projects under 500 000 NOK rarely pay off. This was supported by other informants, sharing that scope matters and many companies lack sufficient understanding of what they are getting into. While proof of analytics project's sizes and success rates are absent, studies suggest that company size and analytics investments have a positive relationship (Liberatore, Pollack-Johnson, & Clain, 2017). The fact that BA projects tend to demand heavy investments and organizational change to their potential seem to influence the SMB segment. As a lot of them lack the necessary infrastructure and systems to get started, the bill keeps growing and this uncertainty does not help. Perhaps this is why informant 5 underlined the need to impress immature ventures from the get-go as they tend to be somewhat impatient with results. The nature of BA often makes this a difficult proposition, as it is intrinsically hard to put a price on insight.

Enterprise sizes are one thing, but patterns in industries can also be expected. The leading industries in our studies seem information heavy. Reviewing our cluster results, we see that one industry has all its representatives among the digital leaders, namely information and communication. This is as expected given that the companies involved typically provide consultants, IT services, software, and similar services. Professional and technical activities also have two representatives in this same cluster. Other heavily knowledge-based industries also score high, like hospitality, finance and insurance, and administrative and support service. Others are a bit more surprising, such as construction, education and property services. They do remarkably well in several categories, and it is not easy to pinpoint why. Broadening our view to include cluster 1 of *Responding Conservatives*, the industry variation increases significantly. This is not particularly surprising, as most of our informants found it difficult to differentiate between industry analytics level – single companies tend to stand out more. While one industry has all its enterprise sizes gathered in one cluster, namely Water, drainage in cluster 4, all the others vary. Based on our analysis, we can thus assume that revenue is a better indicator of analytics maturity than industry.

## 7.3. Beating the benchmark

In Study 2, our informants suggested how the challenges raised in this thesis could be solved. The challenges relate to the different maturity models presented throughout the thesis, with special emphasis on Davenport and Harris'. A recurring aspect among these models is that each stage permeates the entire organization. In order to master each step of the maturity model, minor upheaval changes must be conducted. In Davenport and Harris' framework there are three categories, namely organization, human and technology, with the two prior containing further sub-categories. In total, each step of the maturity ladder requires the organization to make changes in six categories.

Similar maturity models were also been discussed in Study 2 where Informant 5 presented a framework that he has relied on during his career as a consultant within the field, namely PTO. Albeit the categories differ somewhat from the models in Chapter 2, the notion of climbing the ladder only through fulfillment of each category is repeated. Informant 3 illustrated this by pointing out that projects where the objective only was to implement a technical solution, always failed, because there was no change in work practice. This is similar to Eliyahu M. Goldratt's Theory of Constraints; a company can deploy amazing technology, but because they have not changed the way they work, they have not actually diminished a limitation (Goldratt, 1984). Informant 5 suggested DevOps as one of three roles needed to succeed with analytics initiatives. The other two being a representative for the business function, and one from IT. This thesis has not explored the concepts of DevOps in business analytics, but the two other roles illustrate a recurrent attitude showed throughout Study 2, that the integration of technical resources and business needs is essential for any successful business analytics project, and thus also for reaching new stages in terms of maturity.

In Study 3, and discussed previously in this chapter, we find that competence among employees is relatively low compared to the other categories in the maturity model. Interestingly, the results in this study also showed that organizations do not properly facilitate for training of its employees. This is further echoed in Study 2, where several of the informants experienced organizations to downprioritize training. Furthermore, the survey for Study 1 reported a mediocre mean score of 4.28 of 7 on the question of structured training in digital capability, of which analytics is a particularly complex part. The solution to the challenge thus looks obvious, albeit this thesis does not explore what sort of training will be most successful. Organizations need to put more resources into training of its employees, to make them more data literate and better equipped to use new technical tools and solutions. By putting data and analytics on the agenda, organizations might also enhance its data culture, as the people start to talk about possibilities and get new perspectives. This was also noted in Study 2.

There is an alternative to developing in-house capabilities, namely outsourcing. In Study 3, 30% of the companies report that they regularly get outside assistance when working with BA. However, given the sample of this survey, the real number can be expected to be much higher. While outsourcing is helpful, it is doubtful whether it represents an adequate alternative to in-house capabilities. Our informants from Study 2 maintained that while consultants represent certain capabilities that may be hard to develop, such as up-to date knowledge and technical skills, it is important to grow competence for actually operating BA tools. This may depend on the company size. Companies of a certain size and shape that can benefit from many different aspects of BA have more to gain from in-house capabilities than for instance SMB with only a few customers. For the latter, it might be more beneficial to focus on core competency and outsource all else, including BA.

Once the data culture is enhanced, there is also a possibility that a rise in enthusiasts will occur. As found in Study 3, the enthusiast brings most initiatives to the table, but as found in Study 2, these initiatives are rarely realized and implemented. Although our studies show that lack of sponsorship is the greatest challenge for these initiatives, our research shows that Norwegian organizations obtain high scores in this category. However, the importance of the enthusiasts cannot be neglected, and organizations looking to reach new stages of maturity must take full utilization of the enthusiasts. Furthermore, to find a proper management method of these initiatives is important to block silos from occurring. If not done properly, organizations enhancing its data culture and skills, could be at a higher risk of reducing its organizational capabilities in the model. This further shows the importance of including all perspectives in the maturity model when trying to beat the current stage.

## 7.4. Data Democratization and its Challenges

With the increase in data volume and increasingly sophisticated software, data democratization has become a growing concept. Data democratization is the concept of opening enterprise data to as many employees as possible, often in raw form, within the limits of legality and security (Awasthi & George, 2020). Little research has been done on the effects of data democratization, but it is generally presented as a positive contribution to any company. This was a theme of Study 2, which identified silos as a major obstacle for BA. From Study 1, we also found that the question of structured sharing of experiences across businesses had a mediocre average score of 4.06 out of 7. One of the consequences is the loss of synergy effects. For instance, if a project is successfully implemented in one department, it might spread both ideas and processes to other parts of the organization, without starting from scratch. However, Study 3 found that information flow through access and overview of data had a negative effect on the actual BA impact. This may suggest that data democratization itself is problematic without certain prerequisites. One such is BA skills. After all, if you have no idea how to use the data available, it may end up being nothing but a time thief. If an employee assumes to have the knowledge, but really does not, it can prove even worse. Misinterpretation and poor analysis of data are a huge risk for organizations, and purely human aspects like the Dunning-Kruger effect are contributing factors. That is not to say that information derived from data, for instance through visualizations, share the same faith.

Information flow is also tightly connected to data governance, and data integrity may be affected. Thus, it is crucial that organizations have a strong comprehension of what users can do what with data. While this is somewhat related to security and data leaks, a main focus should be on editing data. Informant 2 told us that the main problem with data access is not stealing, as it all makes little sense out of context. Rather, their issues relate to users editing data, sometimes without knowledge, rendering it useless, or worse, incorrect. Data democratization could also be hyped by the suppliers. As it typically increases the complexity and demand from software systems, so does the income for the suppliers and consultants providing solutions.

Too much focus on data accessibility may also result in too many people involved in decision making, "too many cooks". Increased bureaucracy and stagnation in such scenarios might slow down company responses, which can have negative effects. The center of attention should be on defining a team related to whatever BA task at hand. Ensuring that the right people have access to data is much more important than striving for enterprise-wide democratization. Thus, creating cross-functional BA teams can be a great facilitator for BA results, while perhaps limiting data accessibility.

## 7.5. Industry implications

Study 1 identified five clusters of industries, assessing their digital maturity and market orientation. While this analysis used data on digitalization rather than analytics, we showed that there is a fairly close connection between the clusters and their scores on analytical variables in the dataset. This is hardly surprising, as they seem very closely connected. For this discussion, we have assumed that the results from Study 1 can be interpreted as is, also for the realm of analytics. The discussion in Study 1 identified some findings, but with the additional insights from Studies 2 and 3 a few new points are worth considering.

While all companies have some use for analytics, there is no doubt that both its usefulness and scope vary greatly. This can be due to several aspects. For instance, our interviews revealed that SMBs often have fewer and bigger clients. This can explain why they are typically absent from the more advanced clusters, as the value from digitalization tend to significantly drop in such cases. After all, most of the analytics tools and techniques are useless without significant data volumes. Another important factor is industries supply and value chains. While the interviewees maintained that such differences are hard to spot, banking and finance was mentioned by several. This absence of industry superiority is echoed in our own findings in Study 1, with no industries seeming to be dominating the others. Still, Study 1 found that knowledge heavy industries tend to have high digitalization maturity, with banking and finance being a great example. Looking at their value chain, it is almost entirely driven by information; from marketing through advertising and branding, to product sales with funding, investments and services, and transactions with payments. Almost all of this is driven by technology and human capital, as opposed to other factors of production. Cluster 5, on the other hand, is quite different with 50% being from *Agriculture and* *forestry*. These firms rely heavily on other production factors like land and labor. Other such sectors, like I*ndustry* and *Water and Drainage,* are typically found in rather low scoring clusters.

Another interesting difference could be found between B2B and B2C firms. Our data provides limited insight in this, as both kind of companies exist in all industries and this was not part of any questionnaire. However, there are studies implying a divide. For instance, Circle Research found that 73% of B2B marketers report their companies had inadequate data analytics, specifically in predictive analytics (Circle Research, 2016). While this is tightly linked to marketing, it provides indications of the general analytics level. As seen in Study 3, almost 65% from the sample had automated measures aimed at customers in different situations. Customer insight is also the second most used area for predictive analytics. To the extent that B2B companies are lagging behind, they can gain significant advantages by integrating standard analyses like churn prediction and customer segmentation.

### 7.6. Recommendations by Industry Cluster

With the different components of digital and analytical maturity thoroughly reviewed, it is worth taking another look at the five clusters from study 1 and how they can improve their maturity level. These specific recommendations may not only apply to the included industries, but also other companies in the same situation.

*Responding Conservatives (*Segment 1): This segment has a balanced understanding of challenges and opportunities. They have also enabled some measures to cope with it and are doing fairly well. To improve, they should focus on creating an organization-wide strategic approach to analytics, management measures, and review their current data governance programs.

*Digital leaders* (Segment 2): Of all the segments, this has come the furthest in digital mastery. In essence, they should continue the current path by continuously exploring new areas of use for analytics, improving data governance and maintaining a holistic organizational approach. It is important to stay alert to keep analytics as a differentiator.

*Bystanders* (Segment 3): While leadership capabilities are poor, the biggest challenges for these companies are their digital capabilities. Identifying small and simple projects solving concrete business cases is a good start to understand some of the possibilities that lie in analytics. Involving executives early and encouraging departments to identify such cases would help further.

*Relaxed conservatives* (Segment 4): Similar to segment 3, the *relaxed conservatives* should focus on exploring different user cases and possible implementations. However, they can aim at more than isolated business cases. They should focus on preventing silos and performing regular analyses, for instance customer related.

Freeloaders (Segment 5): While this segment's digital capability is not the worst, there seems to be a lot of untapped potential. By focusing on executive involvement and management, they can increase their understanding and strategic approach to analytics projects. Combined with increased competency, this will provide crucial support for future use. Their working processes support an innovative culture, and this must be facilitated to support further progress in analytics and digitalization.

# 8. Conclusions

Through three studies, this thesis has explored the state of digitalization and BA among Norwegian companies. While there are differences in maturity, these seem to be more company- and size-specific than industry-specific. However, we believe that maturity assessments provide a limited picture of a complex phenomenon. The reality of BA is that it is incredibly hard to master at many different levels, which makes enterprise-wide change a difficult proposal with plenty of hurdles. However, some aspects and considerations that stand out. As shown in our proposed framework, it all starts with executive support. If this is absent, BA-related projects and decisions derived from analytics will be difficult to implement. Rooting BA in strategy is the next obvious step, where companies define where and how to use BA.

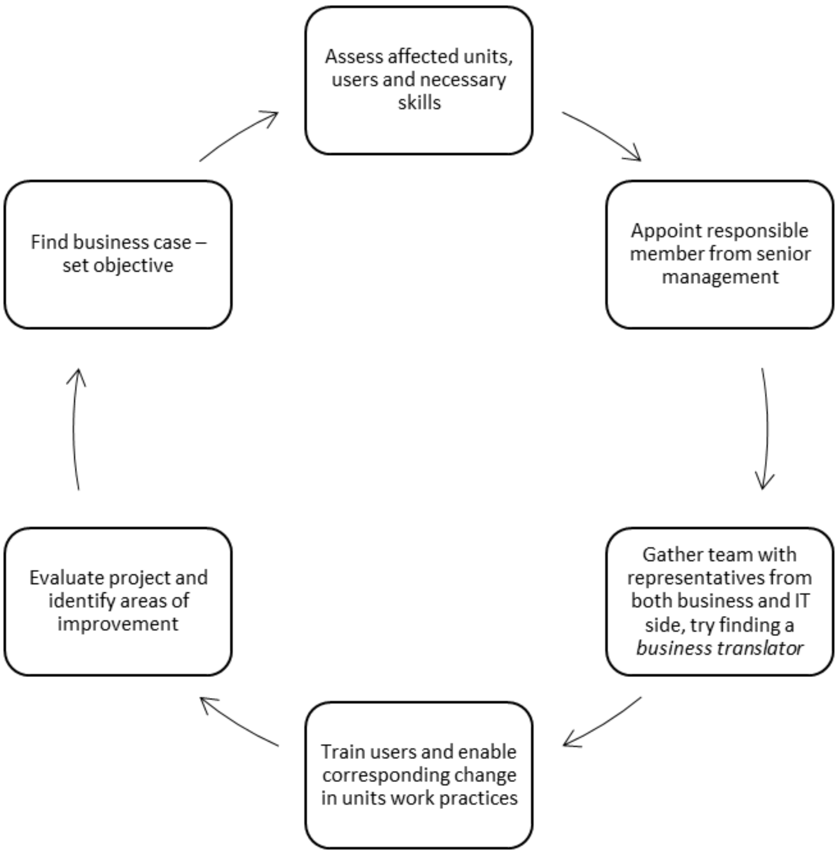


*Figure 35: BA project circle*

Too often, these initiatives come from IT departments. This provides several issues going forward, and companies should prioritize projects rooted in the business side. However, lack of BA skills is often a challenge. Thus, it is crucial to ensure that users and business resources have a certain level of knowledge, and combine this with data scientists and the like.

Again, the importance of business cases and senior management sponsor is underlined. Adding to previously discussed elements, we strongly recommend that companies train business translators for their BA teams. These individuals have the task of bridging the gap between technical and business members, and are increasingly important. Based on our interviews such individuals are few and far between, but their contributions greatly ease any BA project. While there are other aspects that are necessary to support analytics, for instance technical ones, Study 2 and 3 found that the most challenging ones relate to the factors presented above.

This study is the first of its kind in Norway, and we sincerely hope it lays the groundwork and inspires others in the future. Our goal was to explore the general analytics maturity level of Norwegian companies, in addition to the challenges they face. Through three diverse studies, we have proposed a framework for how companies can use and create value from analytics. However, this thesis has several limitations. The sample size and skewedness of Study 3 greatly restricts its generalizability. Furthermore, it is important to underline that a complex field such as analytics does not have the luxury of providing one-stop solutions. Rather, companies face different challenges and possibilities, and must be carefully analyzed. Thus, our findings cannot be blindly applied for any company, but we believe that they provide a solid fundament.

As the relevance and impact of BA shows no sign to slow down, there are numerous aspects to explore further. While there are plenty of case studies, we hope future students will share our goal of illuminating the bigger picture. Looking into the analytics maturity and BA challenges in some industries in depth is one alternative, as well as other segments such as SMB. Another is to compare larger sets of industries, identifying patterns and differences. An additionally interesting study would be a gap analysis of the market needs as assumed by consultancy firms and other suppliers, and the actual needs of Norwegian companies. Furthermore, the role of data democratization is important. As shown in Study 3, there is no straight correlation between increased data access and the impact of BA. Exploring how this should be managed optimally will hopefully provide answers to an unresolved issue. Lastly, a study of the roles and composition of BA groups can expand the concept of business translator and importance of cross-functional teams.

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# Appendices

## Appendix 1: Distribution of Organizations across Industries (Study 1)

| Industry | N | Industry | N |
|---|---|---|---|
| Large, Property services | 1 | Medium, Property services | 11 |
| Medium, Agriculture, forestry | 1 | Medium, Water, drainage | 12 |
| Small, Health and welfare services | 1 | Small, Transportation and storage | 13 |
| Large, Culture, entertainment | 2 | Large, Education | 15 |
| Medium, Culture, entertainment | 2 | Small, Administrative and support service | 15 |
| Small, Hospitality | 2 | Large, Transportation and storage | 17 |
| Medium, Education | 3 | Small, Construction | 19 |
| Medium, Other services | 3 | Large, Mining | 21 |
| Small, Finance and insurance | 3 | Medium, Retail | 22 |
| Small, Public administration | 3 | Small, Industry | 23 |
| Small, Water, drainage | 3 | Small, Energy | 24 |
| Medium, Public administration | 4 | Large, Public administration | 25 |
| Large, Hospitality | 5 | Small, Other services | 25 |
| Large, Water, drainage | 5 | Small, Retail | 25 |
| Medium, Hospitality | 5 | Large, Energy | 27 |
| Small, Agriculture, forestry | 5 | Large, Finance and insurance | 30 |
| Small, Culture, entertainment | 5 | Large, Construction | 31 |
| Large, Agriculture, forestry | 6 | Medium, Construction | 31 |
| Medium, Mining | 6 | Medium, Information and communication | 35 |
| Small, Education | 6 | Medium, Industry | 41 |
| Medium, Finance and insurance | 7 | Large, Professional and technical activities | 45 |
| Small, Mining | 7 | Small, Information and communication | 48 |
| Large, Health and welfare services | 8 | Medium, Professional and technical activities | 53 |
| Medium, Administrative and support service | 8 | Large, Information and communication | 54 |
| Large, Administrative and support service | 9 | Medium, Energy | 56 |
| Large, Other services | 9 | Small, Property services | 57 |
| Large, Retail | 9 | Large, Industry | 75 |

| | | | |
|---|---|---|---|
| Medium, Transportation and storage | 9 | Small, Professional and technical activities | 151 |
| Medium, Health and welfare services | 10 | | |

## Appendix 2: Discriminant Function Coefficients (Study 1)

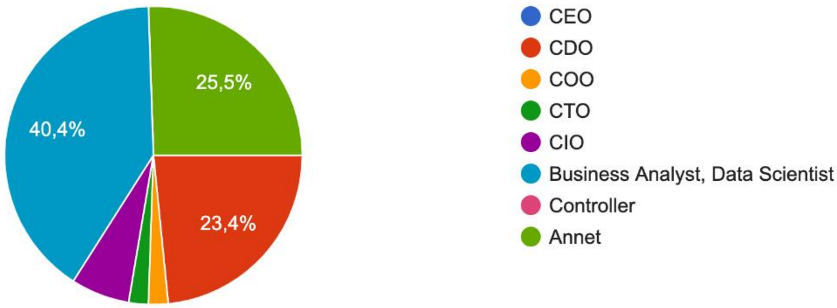
| Independent variable $X_i$ | Discriminant coefficients $W_{ij}$ | | | |
|---|---|---|---|---|
| | Unstandardized | | | |
| | Function 1 | Function 2 | Function 3 | Function 4 |
| Recognition of digital opportunities | 6.69 | -4.17 | -1.89 | 4.27 |
| Consistent strategy formation | 4.00 | 3.49 | 7.00 | 5.97 |
| Implementation capabilities | 3.30 | -4.57 | 3.37 | -6.29 |
| Culture of innovation and work processes | 1.85 | 10.04 | -2.06 | 4.36 |
| Customer centricity | 4.08 | -0.43 | -5.70 | 6.74 |
| Product development | 5.31 | 0.27 | -0.66 | -8.30 |
| | Standardized | | | |
| | Function 1 | Function 2 | Function 3 | Function 4 |
| Recognition of digital opportunities | 0.64 | -0.4 | -0.18 | 0.4 |
| Consistent strategy formation | 0.39 | 0.34 | 0.69 | 0.58 |
| Implementation capabilities | 0.34 | -0.47 | 0.35 | -0.65 |
| Culture of innovation and work processes | 0.18 | 0.98 | -0.20 | 0.42 |
| Customer centricity | 0.40 | -0.04 | -0.56 | 0.66 |
| Product development | 0.53 | -0.03 | -0.07 | -0.83 |
| Eigenvalue | 7.62 | 1.24 | 0.31 | 0.03 |
| Percent variance | 83.00 | 13.50 | 3.00 | 0.50 |
| Canonical correlation | 0.94 | 0.74 | 0.48 | 0.18 |
| $F$ | 10.63 | 4.36 | 1.98 | 0.53 |
| $df$ | (165. 17) | (132. 91) | 98 | 50 |
| $p$ | 0.0001 | 0.0001 | 0.0568 | 0.6613 |

## Appendix 3: Interview Guide (Study 2)

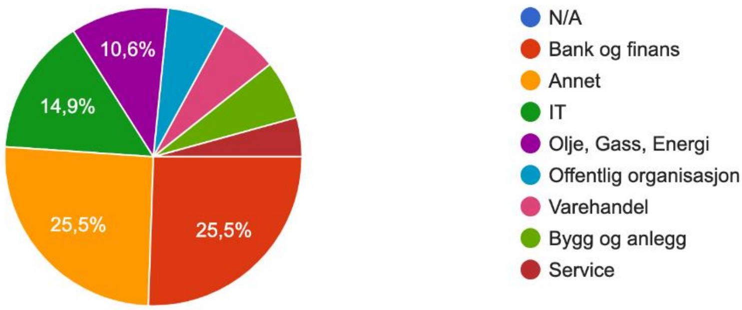
1. How do you work with companies in identifying what data sources to use?
2. In what ways do you ensure the data quality? Is there a standard approach to this?
3. What root causes for poor data quality have you experienced?
4. Are Norwegian companies ready for data lakes and to what extent is it used today?
5. What role does future scaling/potential play for companies?
6. To what degree do companies have in-house capabilities to handle BA?
7. To what extent do companies have a strategic idea on what analysis they want/need?
8. Do you feel that the companies have the necessary commitment going in to BA, especially on the executive side?
9. In what ways have your customers benefitted from data analytics?
10. What are the biggest challenges Norwegian companies face from BA?

## Appendix 4: Complete Univariate Results (Study 3)

1. Hva er din stillingstittel? Velg det som passer best:
47 svar

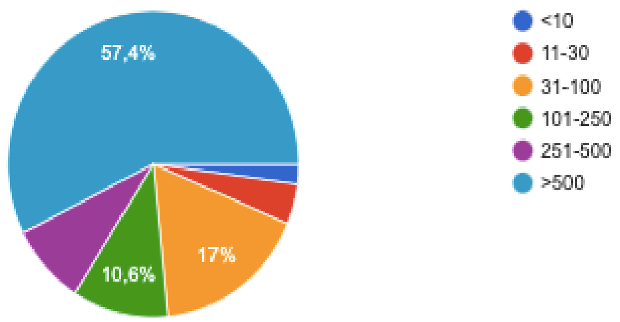



2. Hvilken bransje befinner din virksomhet seg i?
47 svar



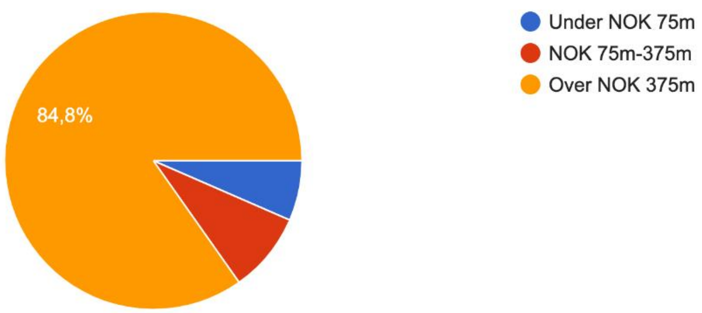
3. Hvor mange ansatte har virksomheten?

47 svar



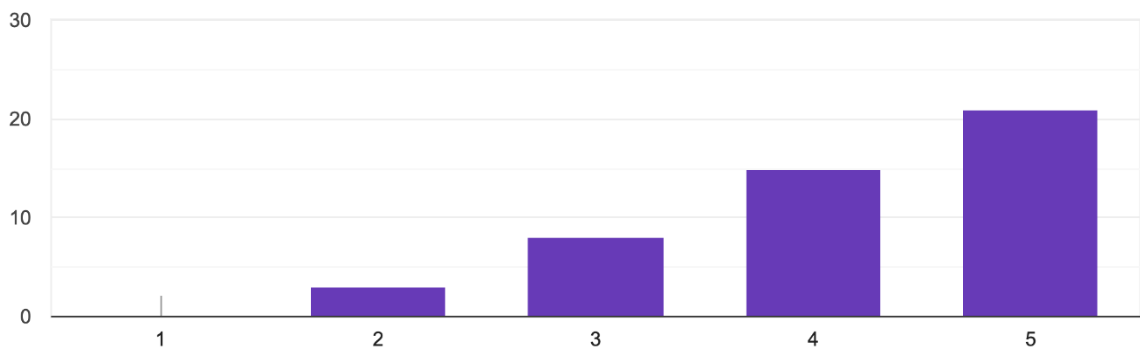

4. Hva er din virksomhets årlige omsetning?

46 svar



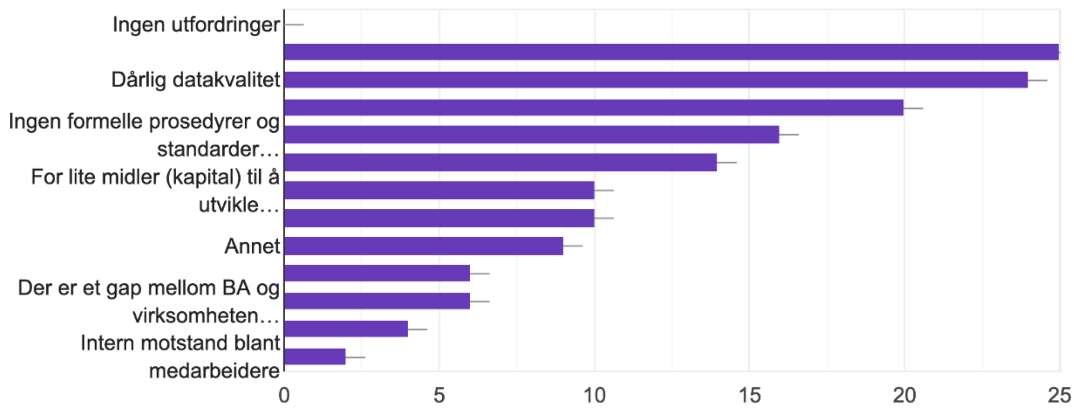

5. I hvilken grad har din virksomhet planer om å investere i BA i løpet av de kommende 1-3 år?

47 svar



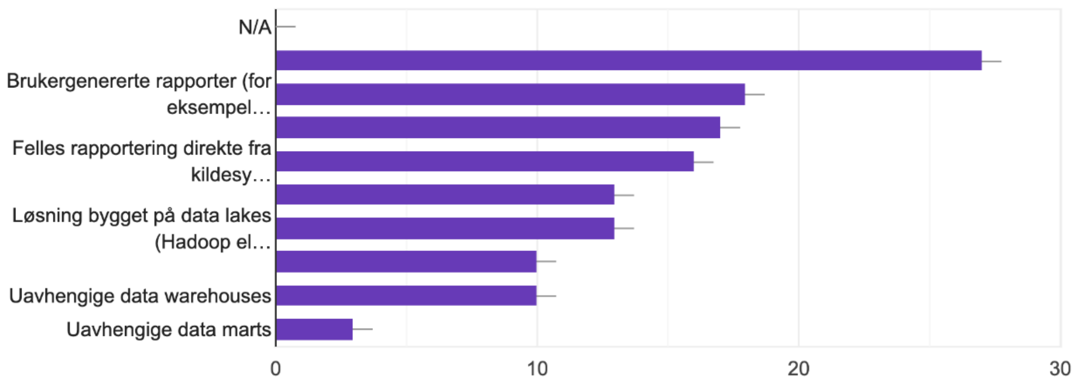
7. Hva er virksomhetens største utfordringer knyttet til BA? Sett kryss på alle alternativene som passer.

47 svar

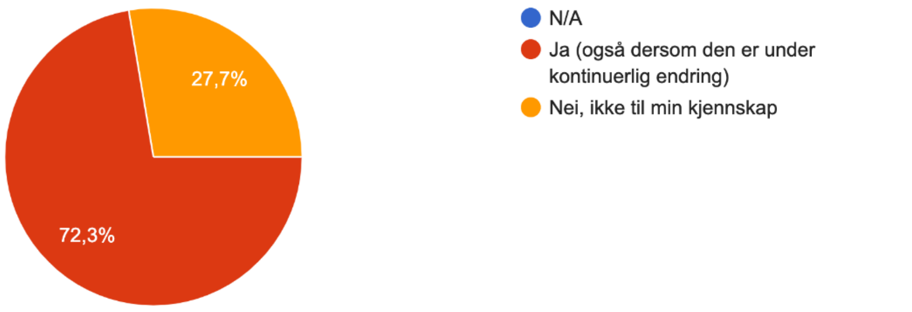



8. Hvordan kan virksomhetens data-arkitektur beskrives? Sett kryss på alle alternativene som passer.

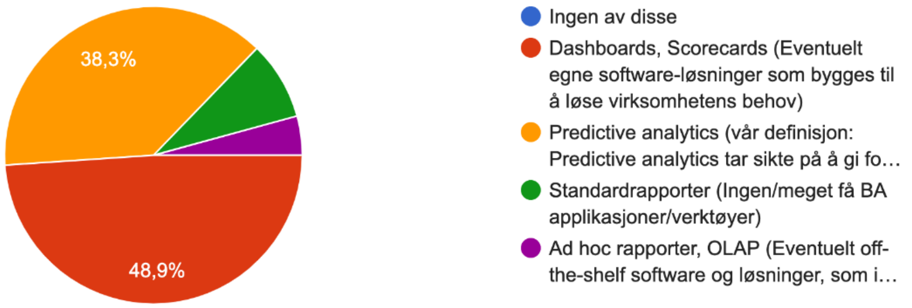
46 svar



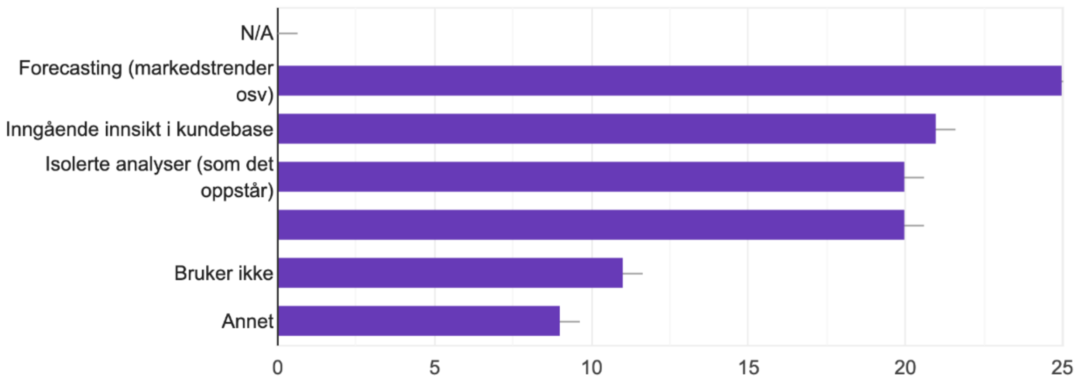
9. Har virksomheten konkrete planer om å endre denne arkitekturen de kommende tre årene?
47 svar



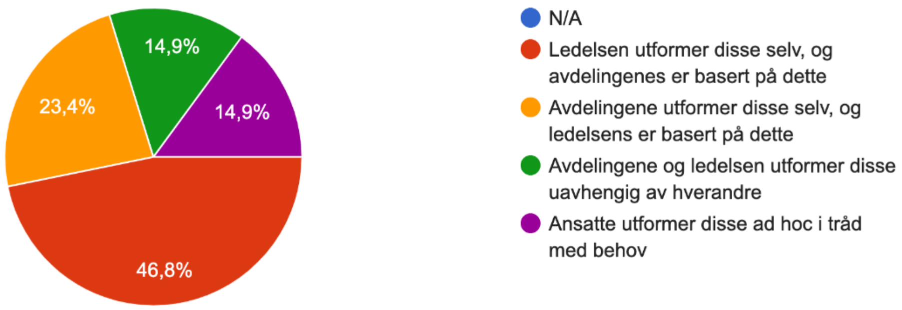

10. Hvilke applikasjoner/verktøy passer best til å beskrive hva som anvendes i virksomheten på nåværende tidspunkt?
47 svar



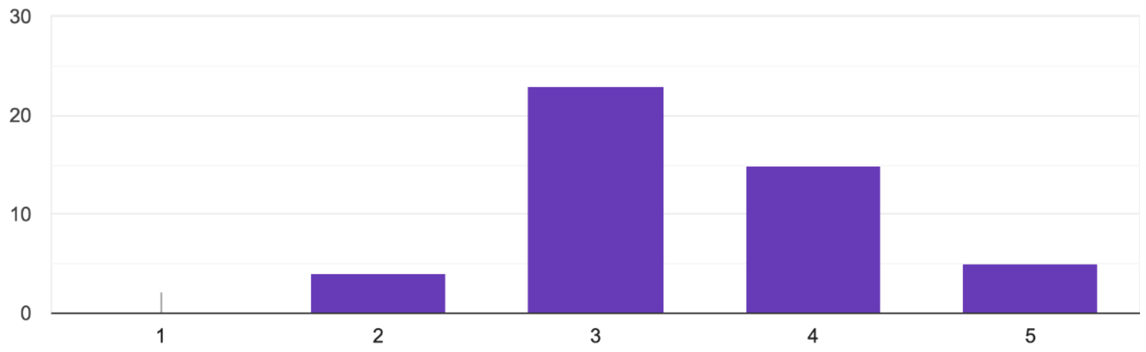

11. Dersom virksomheten bruker predictive analytics, hva slags formål har dere med bruken? Sett kryss på alle alternativene som passer.
46 svar



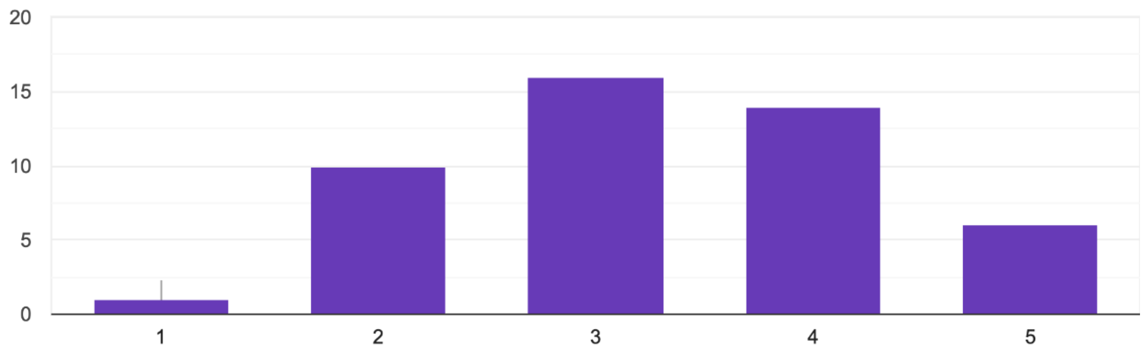
12. På hvilken måte utformer virksomheten primært måltall (KPIer) i for eksempel dashboards?
47 svar




13. Hvordan vil du vurdere virksomhetens datakvalitet?
47 svar

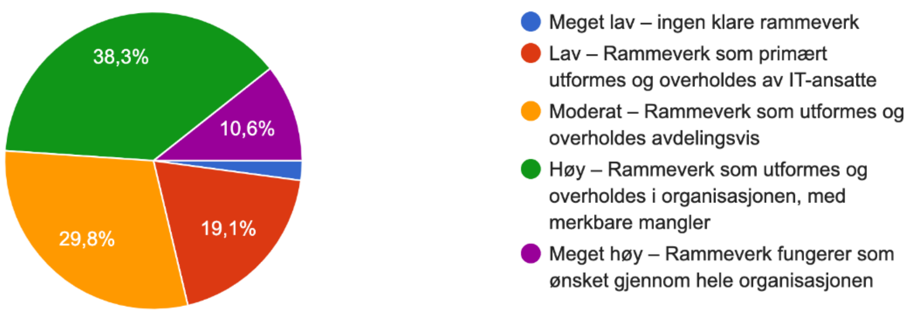



14. I hvilken grad har brukerne adgang til data de har bruk for?
47 svar

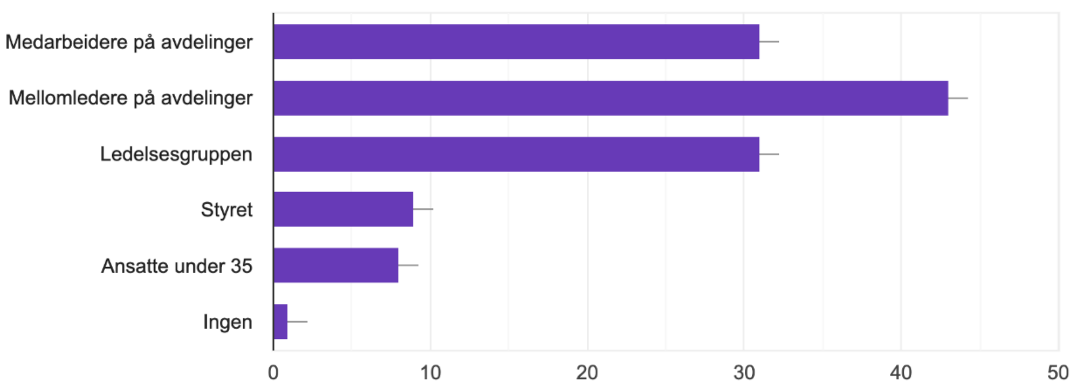


15. I hvilken grad har ansatte oversikt/mulighet til å se virksomhetens data, også utover hva de selv har adgang til? (eksempel: åpent system, men med låste filer)
47 svar

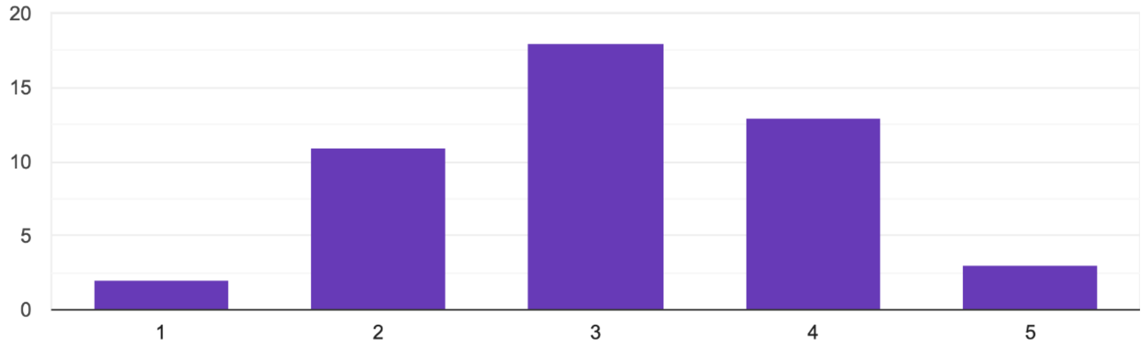

16. I hvilken grad har dere et fungerende rammeverk for dataforvaltning (data governance)?
47 svar



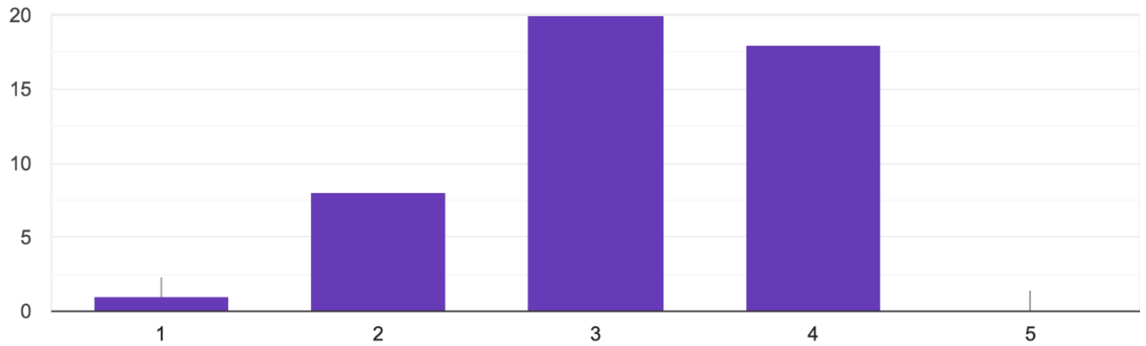

17. Hvem i virksomheten benytter aktivt/regelmessig BA rapportene til å ta beslutninger? Sett kryss på alle alternativene som passer.
47 svar



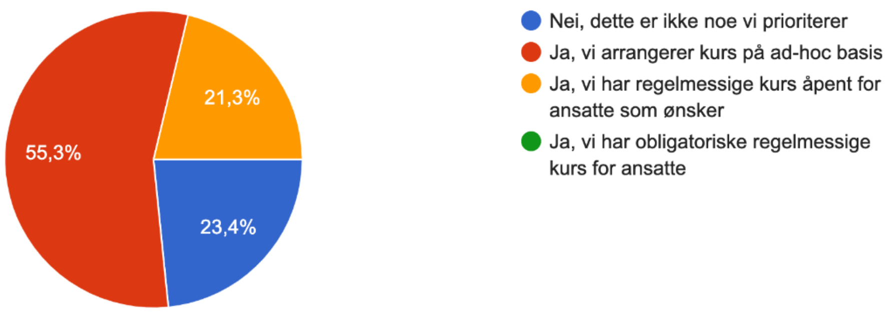
18. Hvordan vurderer du det generelle kompetansenivået innenfor BA hos ledelsen?
47 svar




19. Hvordan vurderer du det generelle kompetansenivået innenfor BA hos resten av organisasjonen?
47 svar

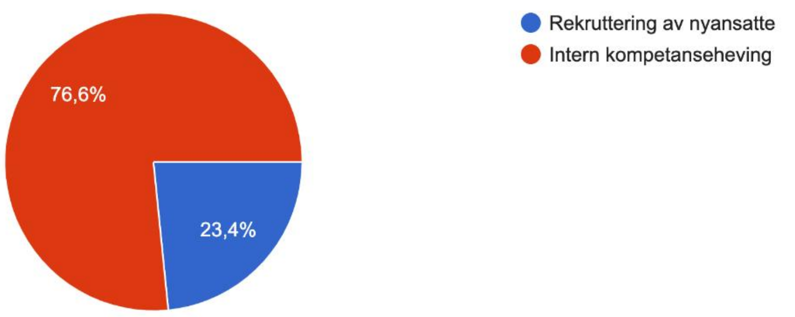



20. Har dere systematisk opplæring av ansatte innenfor BA i virksomheten?
47 svar



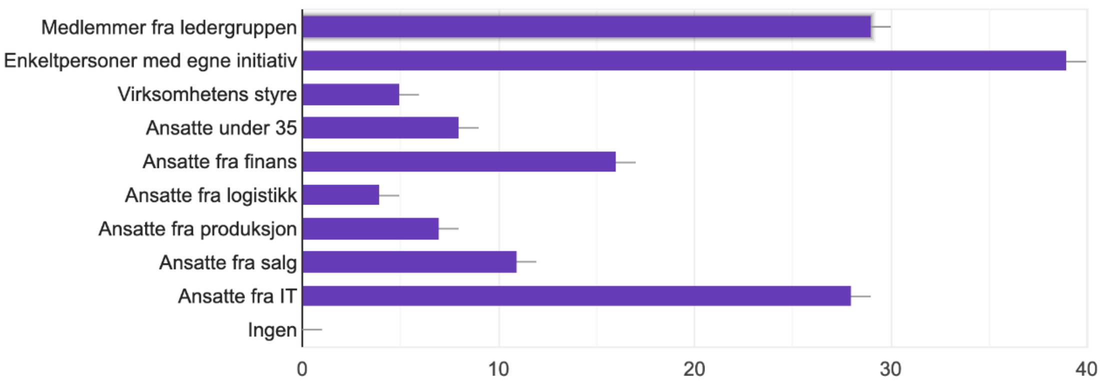
21. Hvor ligger virksomhetens hovedfokus på videre utvikling av egen BA-kompetanse?

47 svar




22. Hvem er primærdrivere/initiativtakere for videreutvikling av BA i virksomheten? Sett kryss på alle alternativene som passer.

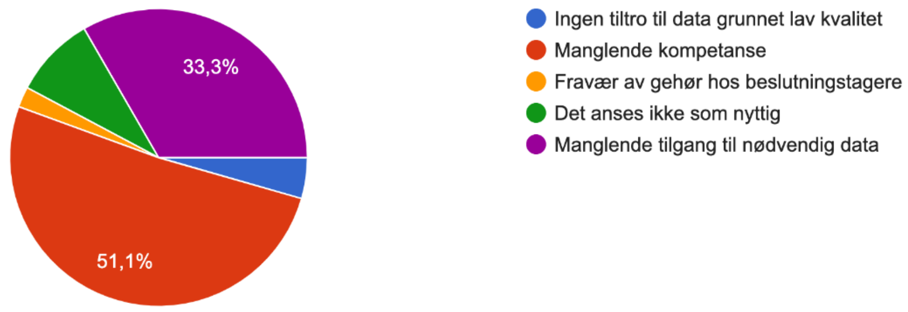
47 svar



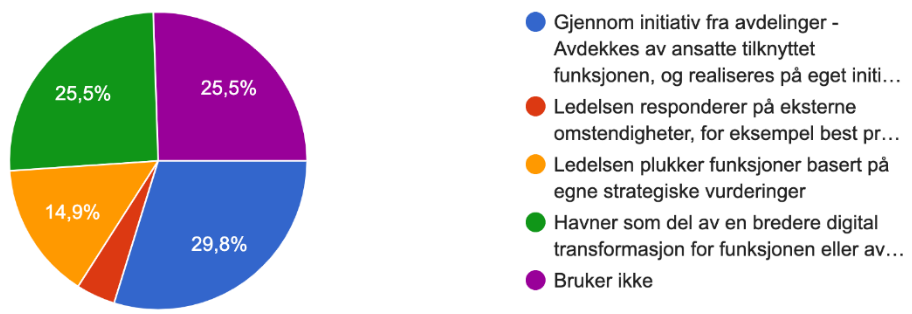

23. Hvordan støtter majoriteten av brukerne seg til data som kommer fra BA?

45 svar

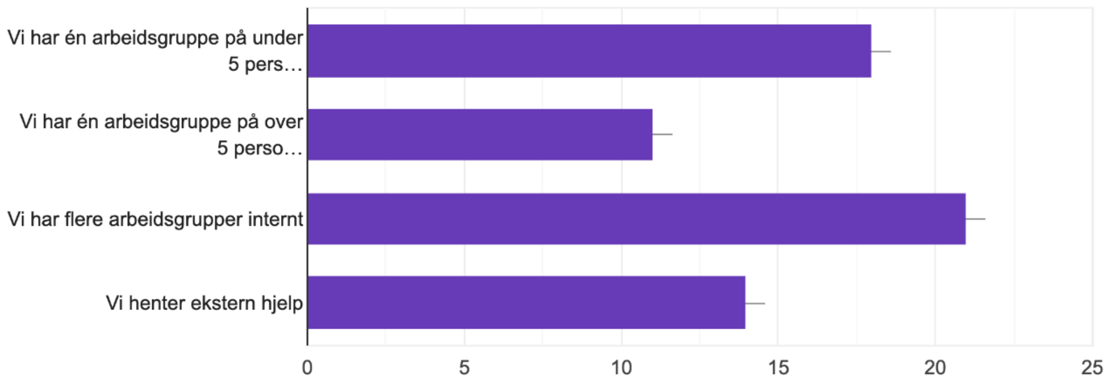
24. Hva er hovedgrunnene til at virksomhetens brukere ikke støtter seg til data? Sett kryss på alle alternativene som passer.
45 svar




25. Hvordan avdekkes og realiseres primært aktuelle funksjoner for predictive analytics?
47 svar

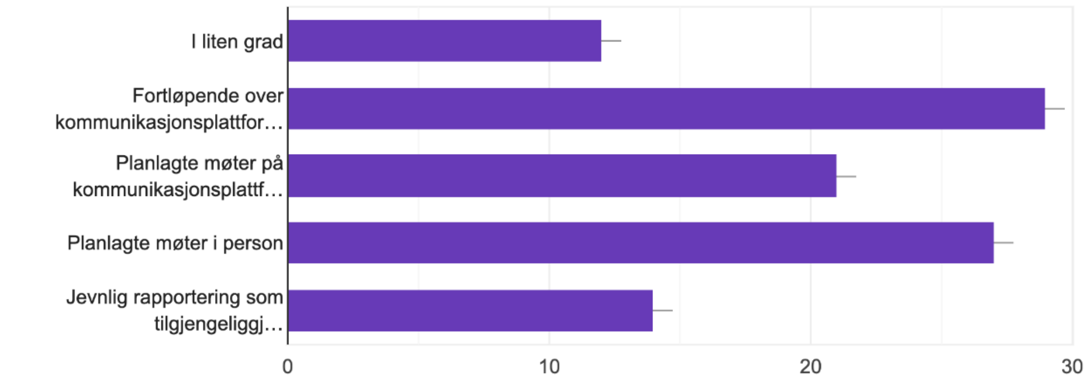



26. Har dere en gruppe/avdeling som primært utfører oppgaver knyttet til BA (Business Analysts, Data Scientists, og lignende), eller henter dere inn ... til BA? Sett kryss på alle alternativene som passer.
47 svar



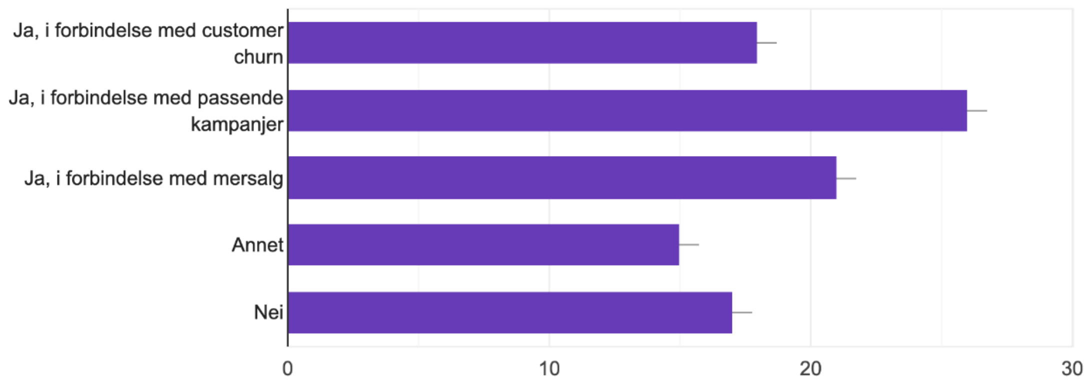
27. Hvordan jobber virksomheten med BA på tvers av avdelinger (vennligst beskriv normalsituasjonen, ikke under COVID-19). Kryss av alt som passer.

46 svar



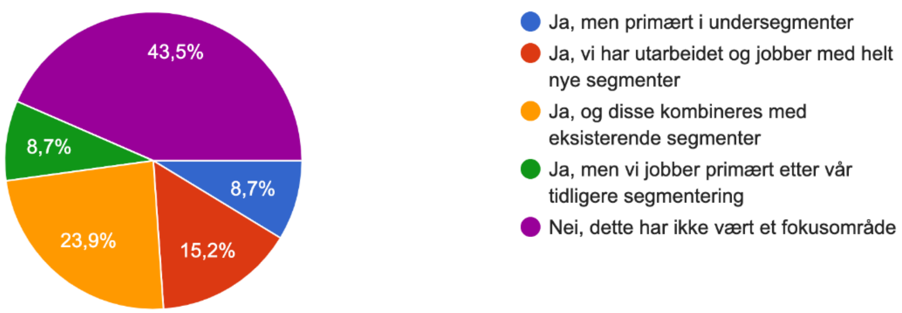

28. Har virksomheten noen automatiske CRM-tiltak basert på data, for eksempel at kunder kontaktes automatisk i en gitt situasjon? Velg alternativene som passer

47 svar




29. Har dataanalyser bidratt til nye kundesegmenteringer for virksomheten?

46 svar



30. Har predictive analytics vært en hoveddriver for endringer i virksomhetens produkt- og/eller servicetilbud de siste tre årene?
47 svar


31. Hvordan anvender virksomheten BA og med hvilke formål? Kryss av det som passer.
47 svar


32. I hvilken grad er det samspill mellom BA og virksomhetens strategiske plan?
45 svar

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