# BECOMING A DATA-DRIVEN ORGANISATION

*Research in Progress*

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## Abstract

*Organisations seeking competitive advantage in the age of big data often adopt the strategy of becoming data-driven. The paper describes research in progress with an organisation pursuing this strategy. Initial results from literature study and preliminary interviews are outlined, including a two layer factor model and prototype maturity model. The next research steps are also explained.*

*Keywords: Analytics, Data-Driven Organisations, Business Intelligence.*

## 1 Introduction

Nowadays many organisations turn to analytics in order to stay competitive. Analytics can be categorised into: i) descriptive analytics, ii) predictive analytics, and iii) prescriptive analytics (Davenport, 2013; Turban et al., 2015). Descriptive analytics help organisations to analyse what has happened in the past. A data warehouse is a typical example of a descriptive approach to collecting and analysing past events. Predictive analytics help organisations discover previously unknown patterns in their data, with the aid of data mining tools. Prescriptive analytics help organisations to automate decisions, and thereby capitalise on previously discovered business insights. Organisations turn to advanced analytics (predictive and prescriptive) with the hope that they will be able to discover and capitalise on new business insights. The move towards advanced analytics requires skills that are usually not available within the organisation. Hence, beginners in advanced analytics either hire a data scientist, or turn to a consultancy firm for help.

Once an organisation has completed its first pilot(s) in advanced analytics, and intends to scale up the usage of advanced analytics across the entire organisation, they cannot continue to focus on the same factors. If they do, the limited benefits are likely be contained in silos within the organisation. Our experience (Rose, Berndtsson, Mathiason, & Larsson, 2017) is that the first pilots(s) in advance analytics, tend to have mostly a technical focus, where the main aim is to demonstrate that advanced analytics can generate new business insights through a 1-2 month project. These pilots seldom have a focus on how employees will use advanced analytics in their daily work, or how analytic competence should be organised. In the literature, there are several examples of resistance to introducing advanced analytics from middle management and other employees (Davenport & Kirby, 2015; Mazzei, McShea, & Oakley, 2016). For example, the pilot may have challenged the skills and jobs of the middle management, or they have not been involved them at all. Hence, there is no buy in for middle management to support the scale-up of advanced analytics. In summary, an organisation that wants to scale up its usage of advanced analytics can run into a number of pitfalls and unexpected implications if they have too narrow view of what factors that should be considered during the scale-up project.

Its often claimed that an organisation-wide data-driven culture musts to be established in order to exploit the full potential of advanced analytics (Anderson, 2015; Franks, 2014). A data-driven culture is characterized by a decision process that emphasise testing and experimentation, where data outweighs opinions, and where failure is accepted – as long as something is learnt from it. Organisations adopting a data-driven approach have opportunities to improve their business, and outperform other organisations (van den Driest, Sthanunathan, & Weed, 2016; Watson, 2016). In a survey done by LaValle, Lesser, Shockley, Hopkins, and Kruschwitz (2011), top-performing organisations used analytics five times more than lower performers. A data-driven culture will help organisations to have a holistic perspective on their intentions to scale up the usage of advanced analytics. This is also in line with a recent recommendation from Anand and Barsoux (2017), that executive teams should first "figure out *what* to change" before planning *how* to change.

In this paper, we report on research in progress regarding what enabling factors organisations should consider and how they can measure their progress, when they intend to scale up its usage of advanced analytics and move towards becoming a data-driven organisation. Our lessons learnt on how to start with advanced analytics are reported in (Rose et al., 2017).

The remainder of this paper is structured as follow. Section 2 describes the research approach taken. Section 3 describes enabling factors that organisations should consider. Section 4 describes a suggestion how to measure progress in analytical capability. Finally, Section 5 describes the plan ahead.

# 2 Research approach

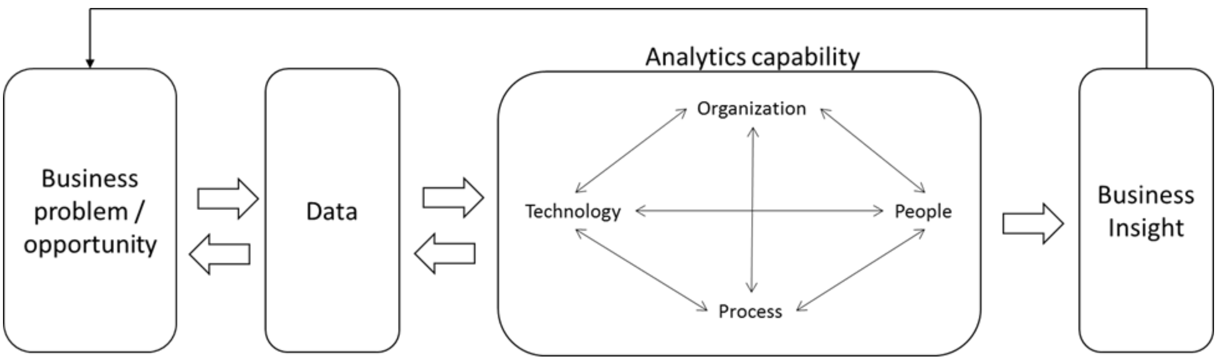


*Figure 1. Research framework adapted from (Vidgen, Shaw, & Grant, 2017).*

We adapt the diamond framework of Vidgen et al. (2017) to study challenges in becoming a data-driven organisation. We add a *business problem / opportunity* component before the data component, since data is analysed in response to a specific business problem or business opportunity. A change was made from *value creation* to *business insight*, since, since there is no guarantee that an analysis will lead to business value. However, it will normally lead to a business insight, regardless of whether the insight creates business value. The revealed business insight can in turn lead to a new business problem or business opportunity.

The research formulates the following research questions:

- **What enabling factors should organisations consider?** Two independent systematic literature reviews were set up in order to find enabling factors organisations should consider for establishing a data-driven culture. Each literate review had its own starting point: i) factors that are relevant for organisations that had just started its journey towards becoming a data-driven organisation, and ii) factors that are relevant for organisations that are more mature in their data-driven culture. To verify the findings from the literature reviews, complementary interviews were held with consultants working with advanced analytics. Finally, the findings from the two literature reviews were merged into a single set of factors.
- **How to measure progress in analytics capability?** We used the research framework (Figure 1) as a starting point, and investigated whether existing maturity models within the Business Intelligence literature could be used to measure progress in moving towards a data-driven culture. The outcome of this objective is a prototype maturity model for assessing progress in analytics capabil-

ity that can support the adapted research framework in Figure 1. The maturity model will be refined in future iterations of our research.

We had access to an international organisation that worked in the ferry business with approximately 5500 employees. The organisation had completed two pilot projects with advanced analytics, and also launched a vision to become data-driven. They helped with initial validation of the prototype maturity model. We interviewed the following people at the main office, to get a multifaceted view on the organisation's starting point:

- A digital transformation officer, who was responsible for crafting and driving the vision,
- A project manager at the IT-unit, who had a local overview picture of the current situation of implementing the vision,
- A CRM and loyalty manager for global marketing, who represented an end user within the organization, and
- A solutions architect from the IT-unit, who was in charge of the data warehouse.

# 3 Enabling factors for data-driven culture

The two literature reviews and complementary interviews with consultants, resulted in a joint map of enabling factors for implementing a data-driven culture, as described in Figure 2. The five most important factors are: management, data, tools, organisation, and decision process. For each factor, we describe three areas that need to be considered.

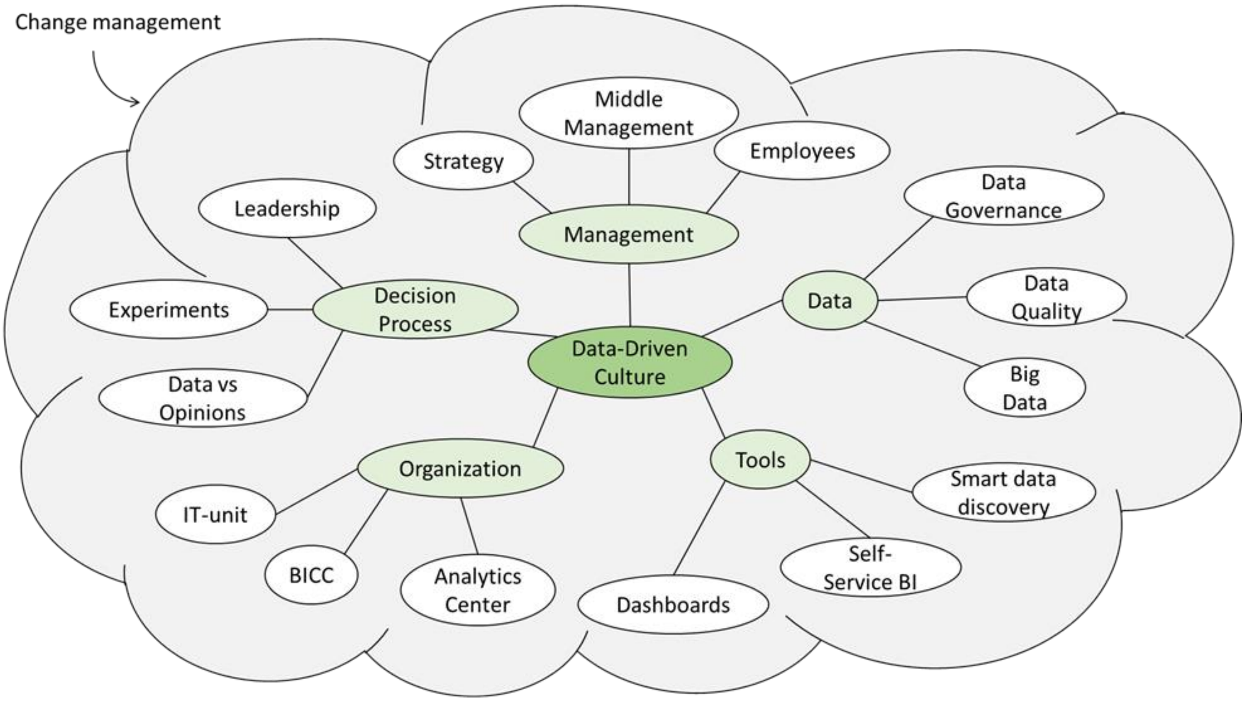


*Figure 2. Overview of enabling factors for implementing a data-driven culture.*

**Management**

Top level management is important and needs to be actively involved in developing a strategy for establishing a data-driven culture. Otherwise, the initiative will be stuck in silos within the organisation (Watson, 2016). It is not uncommon that employees feel threatened when data scientists try to help them find patterns and insights in their data. Introducing a data-driven approach to decision making can be especially challenging for middle management (Mazzei et al., 2016). One typical explanation is that the 'algorithm' produces results that challenge the skills and salaries of the employees. On the other hand, the algorithmic approach opens up doors for other employees, such as stepping up in their career, or getting involved in designing the next generation of decision support (Davenport & Kirby, 2015). It is not only resistance to advanced analytics that top management need to monitor, but also the other side of the spectrum, where employees and middle managers have too high expectations of advanced analytics. Thus, top level management has to be actively engaged in discussions of why it is important for the organisation to establish a data-driven culture.

### Data

A strong data governance (Alhassan, Sammon, & Daly, 2016) and access to data of good quality (Heinrich, Hristova, Klier, Schiller, & Szubartowicz, 2018) are mandatory for any type of analysis. If these features are not in place, then trust in business insights generated by various tools will deteriorate, and undermine the move towards a data-driven culture. There has been much research into data governance and data quality in previous decades, e.g., with the introduction of data warehouses. In our previous work on how organisations start with advanced analytics, we noticed that several organisations that had their data in good shape (due a previous data warehouse initiative), now felt that the move towards advanced analytics and data-driven culture set them back to square one. The reason is that old data is now analysed in different ways than was originally intended. Furthermore, demands to incorporate external data, raises new difficulties with data quality. Nowadays, data comes in all types of shapes, with different arrival frequencies, and massive volumes. Big Data frequently appeared in the literature reviews - however Big Data is not mandatory for all data-driven organisations, instead it is an option that is available.

### Tools

Any organisation planning widespread adoption of analytics and data-driven culture, needs to put suitable tools in the hands of their employees. As a first step, let employees use any tool they like to develop a dashboard that is related to their daily work. Self-service BI (Alpar & Schulz, 2016) implies that users can do some of their descriptive analysis on their own. This requires that users are trained in tools such as Power BI, Tableau, Watson, or Qlik Sense. Adopting self-service BI puts pressure on the IT-unit to enable easy access to data, and it also has implications for the decision process, since employees will now more frequently arrive at meetings with their own analysis. The next step on the ladder are data mining tools that allow users to do predictive analysis, e.g., Azure Machine Learning, RapidMiner, and the programming language R. Some of the features in the data mining tools are now beginning to appear in typical tools for self-service BI. As with self-service BI, it is important to train the users both in the tools, and the theory behind the various algorithms. More advanced tools, allow organisations to use (semi) automated insight discoveries or smart data discoveries. Even though the tools might be technical advanced, the purpose is that they should be user friendly, e.g., natural language interface, visualizations, recommendations. This category of tools is likely to generate business insights faster than current traditional approaches for advanced analytics. However, it is still an ongoing debate whether it is suitable for an organisation to bypass and ignore descriptive analytics, and focus on insights and recommendations from smart data discoveries.

### Organisation

Most organisations already have an IT-unit and something similar to a Business Intelligence Competence Centre (BICC) in place. Typically, these units provide standardised reports on a monthly or quarterly basis, and any requests for ad hoc reports are added to their to-do lists. However, advanced analytics has a greater emphasis on test and learn, rather than producing standardised reports. Hence, where in the organisation should competence in advanced analytics be placed? Some organisations, treat competence in advanced analytics as a natural extension to their existing BIIS, whereas other organisations introduce a separate analytics competence centre (Schüritz, Brand, Satzger, & Bischhoffshausen, 2017). Regardless of where advanced analytics is placed within the organisation, the IT-unit need to shift its focus to enable easy access to data, for all the employees (Franks, 2014). An organisation that enables easy access to data for its employees, allows them to immediately test their ideas on quality assured data, and hopefully generate new insights. No more sending requests to the IT-unit and waiting for access.

The work by Ross, Beath, and Quaadgras (2013) suggest that continual coaching is a key to building big data capabilities. In addition, we also envision that an organisation wide analytics unit, together with analytics champions, have an important role to play in terms of educating and coaching employees to enhance their analytics maturity.

**Decision process**

Out of the five enablers, decision process, is the one that will act as signal whether the move to a data-driven culture is working in practice. If the other enablers for a data-driven culture are in place, then employees will develop a decision process where:

- a "test and learn" environment is the norm. Some experiments will go wrong, failures will appear and managers need to resist the instinct to blame and shame. Instead, focus needs to be shifted to what can be learnt from the experience,
- it does not matter who within the organisation analysed the data and put forward the insight, as long as it is correctly generated. Focus should be on improving the business. Thus, a senior manager cannot trivialize or ignore a business finding from a junior employee. If senior management take the wrong position here, employees will not dare put forward their insights.
- leaders should not have an instinct-based veto over data generated insights that have been advanced. Hence, a leader who says "my gut feeling says that we should go in this direction, despite the data", will undermine the effort to become data-driven.

In an ideal situation, the business question to be solved, dictates what data should be collected and analysed. Moreover, data scientists and business people need to work together, in an iterative manner, in order to gain new insights. For most organisations, establishing a data-driven culture is a paradigm shift in how decisions are made.

**Change management**

Change management can be described as structured tools and concepts used to achieve willingness to change in people, organizations and corporations. Implementing a data-driven culture is really about changing the culture which is challenging. According to Anand and Barsoux (2017), any organisation that embarks on a transformation quest should reflect upon what is the end. They claim that most organisation transformations can be categorised into (Anand & Barsoux, 2017): i) global presence, ii) customer focus, iii) nimbleness, iv) innovation, or v) sustainability. A transformation of an organisation to a data-driven culture can support any of these five categories. Experiences from organisations, tell us that even though all the components in Figure 2 are in place, there are no guarantees that people within an organisation will adopt a data-driven culture. Why - because people are complex creatures with different needs, urges and incitements. How people act and think is also a result of their cultural heritage and experiences, as well as the corporate culture they work within. It is important that the vison of a data-driven culture is rooted into the daily operations of employees (including management), and how the change can improve their working situation, lead to better performance, and perhaps also increase their salary. Hence, change management concerns all the previously described enablers.

# 4 Analytics capability maturity

Analytics capability (Mikalef, Pappas, Krogstie, & Giannakos, 2017) can be categorised in several ways. In addition to the diamond framework used in this paper and in (Vidgen et al., 2017), Gupta and George (2016) suggest that organisations should use a mix of tangible, human, and intangible resources for building big data analytics capability.

There are several maturity models available in the BI-literature (Gudfinnsson, Strand, & Berndtsson, 2015; Lahrmann, Marx, Winter, & Wortmann, 2011; LaValle et al., 2011). For example, LaValle et al. (2011) suggest a three stage model for assessing analytics adoption, with the categories: motive, functional proficiency, business challenges, key obstacles, data management, and analytics in action. These maturity models cannot easily be mapped into the four factors within the *analytic capability* component in Figure 1, hence a simple maturity model for measuring analytics capability within an organization was developed and tested against an external organisation.

## 4.1 Level 1

Organisations at level one are rather immature in data and analytics, and have no dedicated unit for BI or analytics. The most important key performance figures about what has happened in the past, are usually distributed via spreadsheets. The data in the spreadsheets are often up for scrutiny, which in turn ignites time consuming debates about the validity of the data. Furthermore, given the embedded insecurity about data validity in spreadsheets, it is easy for decision makers higher up in the hierarchy to dismiss some spreadsheet reports as not trustworthy, and then make decisions based on their gut feeling.

## 4.2 Level 2

Organisations at level two have taken a major step in collecting and analysing historical data in a systematic manner. In order to have a sustainable systematicity in the collection and analysis of the data, a dedicated unit, e.g., BICC, is introduced. Typically a data warehouse is present, from which reports and dashboards about the past can be generated. Although, a data warehouse is seen as “the single version of the truth”, there are still some mixed feelings about analytics among the employees.

## 4.3 Level 3

Organisations at level 3 have moved into advanced analytics, and use data mining tools for discovering previously unknown business patterns. Typically, the usage of data mining tools brings along a test and learn culture, regarding how to discover new business insights. This approach is different from the culture of generating standardised and ad-hoc reports in a BICC. Hence, it is not uncommon that organisations have separate units for descriptive analytics and predictive analytics. Mixed feelings towards advanced analytics is usually present among employees, on all levels, since advanced analytics is perceived as something that challenge skills and jobs of employees. At this stage, the data in the data warehouse is trusted by most employees, and self-service tools for accessing data are used.

## 4.4 Level 4

Organisations at level 4 have established an organisation wide unit for analytics, where the unit is responsible for all types of analytics. There is an emphasis in the organisation on implementing business insights as soon as possible, preferably via (semi) automated decisions. Self-service tools for both descriptive analytics and predictive analytics are available and used.

## 4.5 Maturity level at external organisation

The external organisation had a maturity level at level two, as their starting point when they launched the vision project in 2016 to become more data-driven, see Table 1.

| | Level 1 | Level 2 | Level 3 | Level 4 |
|---|---|---|---|---|
| **Organisation** | No explicit BI or analytics unit | A dedicated BI unit is established | BI and advanced analytics are separate units | An organisation wide analytics team is established |
| **Technology** | Mostly spread-sheets | Data warehouse is in place | DW and data mining tools are being used | Insights are opera-tionalized ASAP |
| **Decision Process** | Hippo-culture | Reports and dash-boards are generated automatically and on demand | Test and learn culture | (semi) Automatized decisions |
| **People** | Little trust in data and ana-lytics | Mixed feelings about analytics | Self-Service DW<br>Mixed feelings about advanced analytics | Self-Service Analytics |
| **Analytics** | Descriptive | Descriptive | Descriptive, predictive | Descriptive, predic-tive, prescriptive |

*Table 1. Summary of analytics capability maturity at the external organisation.*

A dedicated BI-unit was established, but they worked mainly together with the finance unit and controllers on how current figures compared to budget.

A classical data warehouse with a star schema was used to collect and analyse historical data. All statistics and analytics regarding CRM was done by the aid of the IT-unit, who put requests for ad hoc statistics and analytics on their todo-list. Hence, this usually meant 4-7 weeks of waiting, before the results were delivered to the CRM staff. Furthermore, some data integration problems were present, which prevented the organisation from running global CRM analysis queries.

People within the organisation had mixed feelings about more advanced forms of analytics, and did not to 100% trust the data in the data warehouse, e.g., the CRM and loyalty manager claimed that some data that data that appeared in the generated reports were wrong. Similar lack of trust about the data was not found at the IT-unit. Instead, the solutions architect from the IT-unit highlighted that they learn about the data and discover new patterns all the time. However, when they brought the new discoveries to the attention of the business side, then it was not always well received by the business side.

# 5 The plan ahead

*In this paper, we have described our research in progress with respect to how organisations work to establish themselves as a data-driven organisation. A long term goal is to establish a road map for becoming a data-driven organisation.*

Figure 3 presents an overview of research in progress and future research.

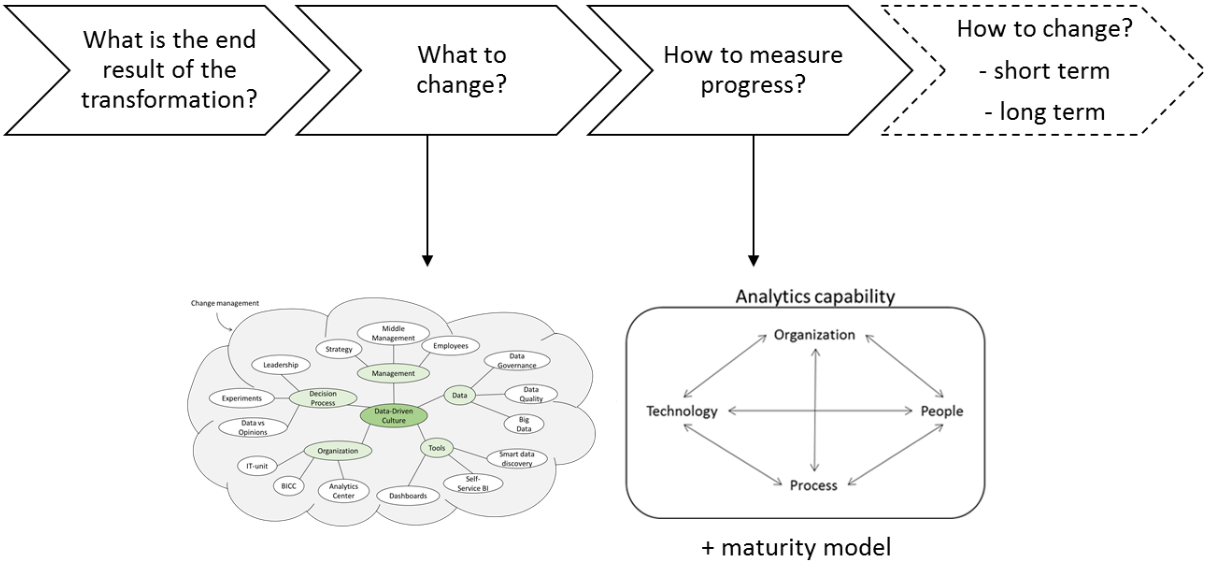


*Figure 3. Overview of research in progress and the plan ahead.*

We see potential in using findings from the area of change management, in order to identify the underpinning reasons for making the transformation to a data-driven organisation. The literature reviews have produced an initial map of factors that organisations should consider, when transforming to a data-driven organisation. An initial maturity model has been provided that can be used to measure progress in analytics capability. Both the initial map of factors and the initial maturity model will be validated with organisations that have initiated projects to become data-driven. One of these organisations, was mentioned in Section 4.

As future work, we intend to investigate how to make changes in practice, both in the short term and in the long term. Preliminary discussions with companies that are in their first year of transformation, indicate that *how to organise analytic competence*, tend to appear high up on their to-do list.

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## References

Alhassan, Ibrahim, Sammon, David, & Daly, Mary. (2016). Data governance activities: an analysis of the literature. *Journal of Decision Systems*, *25*(sup1), 64-75.

Alpar, P., & Schulz, M. (2016). Self-Service Business Intelligence. *Business & Information Systems Engineering, 58*(2), 151-155.

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

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

Davenport, T. H., & Kirby, J. (2015). Beyond Automation. *Harvard Business Review, 93*(6), 58-65.

Davenport, T. H. (2013). Analytics 3.0. *Harvard Business Review*(December).

Franks, Bill. (2014). The Analytics Culture *The Analytics Revolution*: Wiley.

Gudfinnsson, K., Strand, M., & Berndtsson, M. (2015). Analyzing Business Intelligence Maturity. *Journal of Decision Systems, 24*(1), 37-54.

Gupta, Manjul, & George, Joey F. (2016). Toward the development of a big data analytics capability. *Information & Management, 53*(8), 1049-1064.

Heinrich, Bernd, Hristova, Diana, Klier, Mathias, Schiller, Alexander, & Szubartowicz, Michael. (2018). Requirements for Data Quality Metrics. *J. Data and Information Quality, 9*(2), 1-32.

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

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

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

Mikalef, Patrick, Pappas, Ilias O., Krogstie, John, & Giannakos, Michail. (2017). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management*, 1-32.

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

Ross, J. W., Beath, C. M., & Quaadgras, A. (2013). You May Not Need Big Data After All. *Harvard Business Review*(December), 90-98.

Schüritz, R., Brand, E., Satzger, G., & Bischhoffshausen, J. (2017). *How to cultivate analytics capabilities within an organization? - Design and types of analytics competency centers*. Paper presented at the Proceedings of the 25th European Conference on Information Systems (ECIS).

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

van den Driest, F., Sthanunathan, S., & Weed, K. (2016). MARKETING Building an Insights Engine A customer-centric approach is vital for driving growth, and Unilever's insights and analytics group exemplifies the 10 necessary elements. *Harvard business review, 94*(9), 64-64.

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

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research, 261*(2), 626-639.