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Maturity of business analytics utilization in SMEs

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Abstract

In today's highly competitive business landscape, Small and Medium-sized Enterprises (SMEs) face numerous challenges. Emerging as potential game-changers, data-driven decision making and the use of business analytics are key capacities an organization should have to be future-proof. Though many research has been done within the corporate environment, this research focusses on the relatively uncharted context of SMEs. The SME sector is an important part of the economy, containing 2,24 million companies in the Netherlands (Staat van het MKB, 2023).

This research shows how SMEs currently utilize business analytics and thereby provide an overview of different levels of maturity. Though there already exist some business analytics maturity models, most maturity models have focus on specific dimensions such as technical infrastructure, performance management, analytics strategy, data quality & use, skills & experience or analytics techniques. Main goal of this study is to provide an integrative overview of the changing nature of different dimensions of business analytics throughout the stages of maturity. This study provides valuable insights that can be guiding for both SMEs that want to start utilizing Business Intelligence & Analytics (BI&A) and researchers that are interested in business analytics in this specific context. Even though some SMEs have successfully integrated business analytics, many still lag behind due to limited resources, lack of skills and expertise or other reasons.

Keywords

Business analytics, SMEs, descriptive analytics, prescriptive analytics, predictive analytics, BI&A, analytics utilization

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1. Introduction

In this new era of big data, data-driven analytics is the way forward for major corporations in the manufacturing, information technology, marketing and logistics sectors (McAleer Et. al, 2022). Business analytics and the rise of big data don't only impact different industries, it also has an impact on different business aspects. The digital transformation age has witnessed considerable advances in data management and intelligent technologies that changed almost all business aspects such as financial, accounting, commerce, marketing, command and control (Al-Okaily et al., 2023). This is not surprising considering that substantial value and competitive advantage can be attained by businesses from making effective decisions based on data (Conboy et al., 2020; Sivarajah et al., 2017). The opportunities associated with data and analysis in different organizations have helped generate significant interest in business intelligence and analytics (BI&A), which is often referred to as the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions (Chen et al., 2012).

BI&A is in high demand due to the numerous benefits that can be generated from it such as reduction in cost, reduction in human errors, enhanced customer service, improved productivity, efficiency and effectiveness and quickening the pace of decision-making (Huang et al., 2022; Merhi, 2021). It can also help decision-makers by improving their decision-making, augmenting their creativity and boosting both their analytic and decision-making abilities (Chen and Lin, 2021). In addition, according to Al-Okaily et al. (2023), BI&A helps business organizations optimize operations, track performances, compare data with competitors, analyze consumer behavior, discover problems and predict success thus taking actions required to meet business goals.

Nevertheless, implementing BI&A is not a task that is free of risks, nor does it automatically achieve improved performance. Successful firms such as Continental Airlines (Anderson-Lehman et al., 2004) or First American Corporation (Cooper et. al, 2000) achieved up to 1000% return on investments from BI&A initiatives, while others have incurred sizable losses (Jourdan et. al, 2008). Even major corporations such as HP, Apple, Cisco, Ericsson, KFC and Boeing have failed business data analytics strategies implementation (Ramakrishnan et al., 2020). In order to ensure the success of the promising yet risky and costly technological innovation of BI&A, practitioners and researchers must comprehend the factors that drive its adoption and develop strategies to enhance its maturity.

BI&A is valuable not just for larger corporations, but also for small and medium-sized enterprises (SMEs), as it enables them to effectively monitor their business operations and optimize resource utilization (Raj, Wong, & Beaumont, 2016). Notwithstanding its importance, the literature on BI&A in SMEs is lacking (Boonsiritomachai, McGrath, & Burgess, 2016) because the majority of BI&A systems are adopted by large multinational and international enterprises; thus, research on BI&A has largely focused on them (Grabova, Darmont, Chauchat, & Zolotaryova, 2010).

According to Llave (2019), there is a notable contrast between SMEs and large enterprises, as SMEs typically possess restricted internal information technology (IT) resources and capabilities, as well as limited financial resources. Due to their limited human capital and resources for employee training, SMEs often rely on external expertise when initiating new IT projects (Levy & Powell, 2000). Thereby, Llave, Hustad & Olsen (2018) suggest that SMEs' limited financial resources have implications for BI&A investment strategies. Overall, despite the increasing prevalence of analytics in decision-making, companies are often stuck in the less mature stages of analytics adoption and are struggling to figure out how, where, and when to use these decision-making tools to achieve worthwhile outcomes (Barton & Court, 2012; Ransbotham et al., 2016; Nacarelli & Gefen, 2021).

Especially small enterprise reflects low orientation towards adoption of data analytics in business (Boonsiritomachai et.al., 2016). Surprisingly, few sectors in SME like healthcare, manufacturing, e-commerce, and retail have shown high acceptance of data analytics in business activities (Gudfinnsson, et.al., 2019; Maroufkhani, et.al., 2019). Most of the SMEs are using data analytics in report management, financial updates, supply chain function and CRM functions only (Ajibade.& Mutula, 2019). Business analytics is used only in some sectors and within some business areas. This raises the question if SMEs are either experiencing discomfort or inhibition in implementation of data analytics. Thus, there exists a huge undefined area between SMEs not utilizing business analytics as against SMEs using business analytics extensively. To identify reasons behind this gap in utilization, it is essential to gain a deeper understanding about how SMEs develop from no utilization to extensive use of business analytics, creating business value. Studying this is highly relevant for practitioners, giving them guidance in the process of maturing business analytics within their organization.

Also for researchers, studying BI&A in the context of SMEs is important because the existing literature lacks sufficient attention on how BI&A can address the specific challenges of limited internal resources and financial constraints faced by SMEs (Boonsiritomachai, McGrath, & Burgess, 2016). Still, many research gaps exist concerning the use of business analytics in SMEs. One of these gaps is the role of analytics maturity on organizational performance. And more specifically, what dimensions should mature or what type of benefits are achieved by mature use of analytics (Baijens et al., 2022). According to Vecchio et al. (2018) a maturity model is a useful for SMEs to analyze their readiness for BI&A to support organizational performance, since it can support SMEs to decide whether they should invest in data analytics depending on their business needs.

Llave (2019) conducted a literature review on the current state of BI&A research and concluded that more empirical studies on the determinants and barriers in BI&A adoption for SMEs would be valuable. Also, several studies focused on the components of BI&A (Gupta & George, 2016; Mikalef, Pappas, Krogstie, & Giannakos, 2018), but they did not address the SME context. Understanding how SMEs progress through different maturity levels of BI&A could also present opportunities for practitioners implementing BI&A in SMEs (Mikalef et al., 2017). To guide practitioners, it's essential to gain a deeper understanding of factors that promote adoption of BI&A and devise strategies to enhance its maturity (Llave, 2019).

Despite the increasing prevalence of analytics in decision-making, companies are often stuck in the less mature stages of analytics adoption and are struggling to figure out how, where, and when to use these decision-making tools to achieve worthwhile outcomes (Barton & Court, 2012; Ransbotham et al., 2016; Nacarelli & Gefen, 2021). The existing literature lacks sufficient attention to the factors driving BI&A adoption and strategies to enhance its maturity, particularly in the context of SME's. Also, main research topics established by Llave (2017) are BI&A solutions, Mobile BI&A, Cloud BI&A, BI&A application, BI&A adoption, BI&A implementation, BI&A benefits, each concerning their own issues. Therefore the objective of this study is to shed light on how BI&A maturity develops within SMEs, and, specifically the strategies and factors that enhance its utilization. This study aims to conduct an exploratory and comprehensive research to ascertain the methods by which SMEs can enhance their BI&A maturity levels and foster greater adoption within their organizational frameworks. Thereby this study aims to find out how SMEs utilize business analytics. Thus, the following research question is answered in this study:

How do SME's utilize business analytics?

Answering the business question is structured by the following sub questions:

1) How does utilization of Business Analytics develop in SMEs?
2) What are the main drivers to start utilizing Business Analytics?
3) What are the main challenges SMEs face when utilizing Business Analytics?

The term BI&A is suggested as a combined term by Chen et. al (2012) and Lim et. al (2013) for better understanding and simplification of research in the areas of Business Intelligence and Business Analytics and will therefore be used alternately. Therefore, the terms BI&A and Business Analytics (BA) will be used interchangeably in this study.

2. Literature Review

Business Analytics is an interdisciplinary field and combines machine learning, statistics, information systems, operations research, and management science (Sharda, Delen & Turban, 2017) and is usually divided into descriptive, predictive, and prescriptive analytics (Delen & Ram, 2018). With the value offered by business analytics, companies are able to discover the hidden information in the data, improve decision-making processes, and support strategic planning (Yalcin et. al, 2022). As stated by Hoffmann (2018), a BI&A maturity model is useful for SMEs to analyze their utilization of business analytics, supporting organizations to capture value from business analytics depending on the business needs. Therefore, this study will commence by providing a concise historical overview of the evolution of BI&A to facilitate a comprehensive understanding of the concept and its developmental trajectory. Subsequently, a delineation of the fundamental BI&A components and an examination of BI&A maturity will be presented to gain insights from the existing literature into the prevailing challenges and barriers encountered by organizations during the adoption and implementation of BI&A initiatives.

2.1 Business Analytics

Business Analytics (BA) is a mixture of techniques, technologies and applications used to scrutinize a corporation's data and performance to transpire data-driven decision-making analytics for the corporation's future direction and investment plans (Bayrak, 2015; Kristoffersen et al., 2021). To gain a comprehensive understanding of business analytics and BI&A, it is crucial to delve into the historical evolution of these fields.

The amount of data has grown exponentially since the advent of computers, leading to an overwhelming abundance of information that managers must navigate in order to facilitate their decision-making processes. The emergence of the internet in 1991 sparked a heightened demand for advanced analytics and technology, signaling a pivotal moment in the evolution of these fields. The internet made data available instantaneously in real-time across organizations, countries, and nations from the mid-1990s to present, driven by increased use of cloud-based systems and applications (e.g., Amazon Cloud, Microsoft SharePoint and SkyDrive/OneDrive, Google Drive, etc.) (Bumblauskas et al., 2017). However, according to Watson & Wixom (2007), use of business analytics to make business decisions already emerged in the early 1970s through the development of decision-support applications designed to aid decision-making.

The raise of the internet resulted in an increase in the amount and the availability of data across organizations and led to major investments in various transactional systems such as Manufacturing Resource Planning (MRP) and Enterprise Resource Planning (ERP) systems (Bumblauskas et al., 2017). Even though these systems are good in the collection of data, these systems are still limited as the data collected was siloed with reporting capabilities that are static and inflexible; therefore not easy to use for analytics on an ongoing basis (Nacarelli & Gefen, 2021). These advances in IT enabled businesses to develop innovative ways to collect data from both internal and external sources (Cao & Duan, 2015; Davenport, 2013), and transform these sources into actionable insights. An overview of the technological drivers, their impact on the industry and the developments supporting business analytics are shown in figure 1.

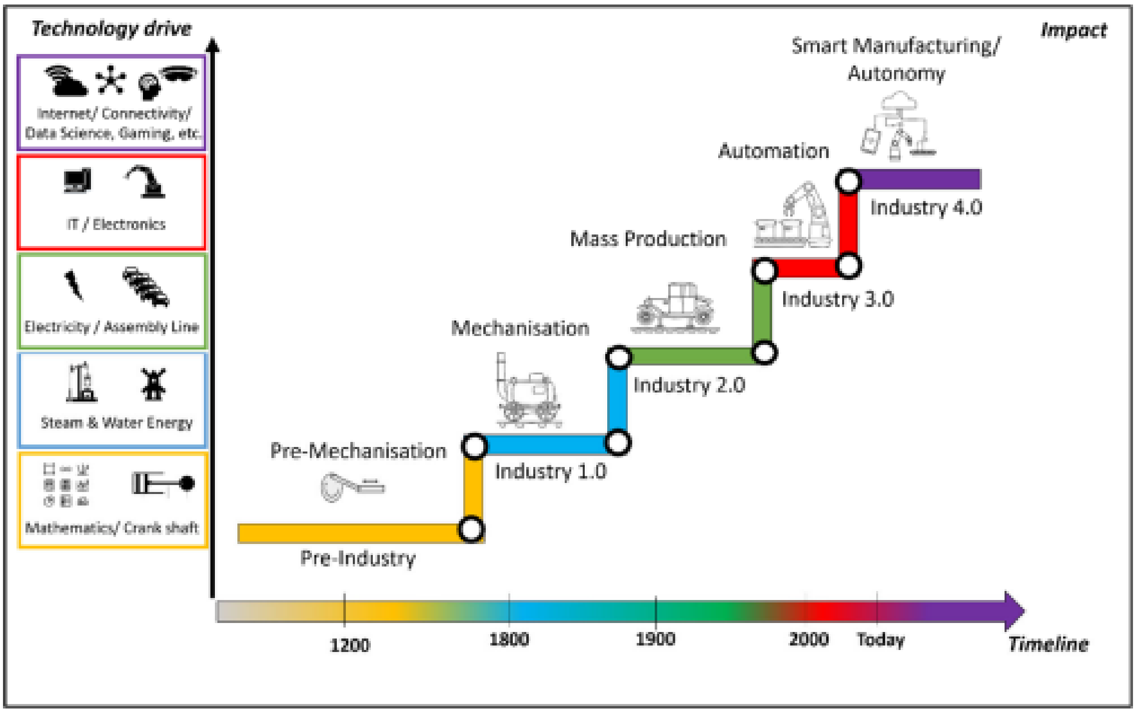

Figure 1: Key technological drives behind the industrial revolutions (Sufian et al., 2021).

The progression from industry 3.0 to industry 4.0 was not only driven by advancements in IT, IoT, and data science but also played a crucial role in establishing a robust data collection infrastructure from diverse sources (Sufian et al., 2021). Not only were managers provided with faster quality data, they also adopted advanced analytics to improve business performance (Pröllochsa & Feuerriegel, 2020).

Processing big data for business analytics is difficult and requires new and advanced technologies (Cao & Duan, 2015; Chen et al., 2012; Pröllochsa & Feuerriegel, 2020). The volume of disconnected data in various formats has made it challenging for analytical talent and existing tools that can transform data into information that managers can easily understand, interact with, trust, and ultimately adopt to make better decisions (Nacarilla & Gefen, 2021). Therefore the growing need for advanced technology and skilled business analysis professionals to collect and transform data into more sophisticated analytics is inevitable (Nacarilla & Gefen, 2021).

2.2 Conceptualization of Business Analytics

Although the use of analytics yields many successes in organizations (Conboy et al., 2020), it is important to know that analytics as a decision-making tool is not monolithic. In fact, the literature suggests there are several levels of analytics that can be adopted. To understand business analytics utilization in SMEs, we use research by Delen (2014) who suggested a gradual approach to conceptualize the depth of analytics usage in organization into three levels, namely, descriptive, predictive, and prescriptive, based on the type of data and purpose of use of analytics in decision-making. These three levels of analytics are hierarchical in terms of the level of analytics maturity of the organization starting with descriptive analytics, then moving up into predictive analytics, and finally reaching prescriptive analytics (Delen, 2014). Delen & Ram (2018) further describe the components of business analytics as shown in Figure 2. Analytical models of BA applications, as shown in Figure 2, are interconnected with each other with a certain level of overlap, and follow one another in a progressive manner (Aydiner et. al, 2019).

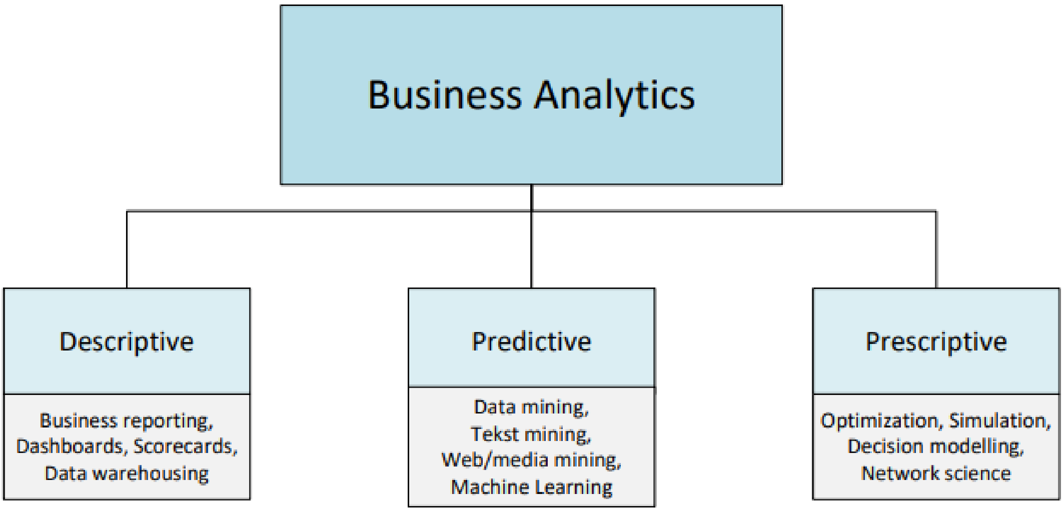

Figure 2: Main BI&A components (Delen and Ram, 2018)

2.3 Descriptive analytics

Descriptive analytics responds to the question of what happened. It is the most prevalent kind of analytics utilized by businesses and is typically identified by descriptive statistics, Key Performance Indicators (KPIs), dashboards, or other types of visualizations (Appelbaum et al., 2017). Delen and Ram (2018) describe business reporting, dashboards, scorecards and data warehousing as main components of descriptive analytics. Descriptive analytics are utilized in numerous facets of a business by companies in order to assess the quality of their operations and determine whether or not they are on track to achieve their organizational objectives and used in various ways, particularly in reports, visualizations and dashboards (De Jesus & Buenas, 2023).

Business dashboards enables a tool to monitor and analyze the business's performance and overall health while introducing fields for development and growth opportunities (Chan, 2019). The business dashboard is an information management tool for analyzing data and determining potential problems, and identifying actions that can be taken to resolve them over a wide range of subjects, whereas reports focus on a specific subject (Abellan, 2020). Reports also are a great tool for evaluating the performance of a firm and making decisions that are based on accurate and up-to-date information, comprising a numerous of separate reports that cover various areas of a business (De Jesus & Buenas, 2023). Visualization of data through the use of charts, graphs and maps, which can indicate trends in data as well as dips and spikes in a fashion that is obvious and easily accessible to the audience, is an excellent choice for providing a suitable outlet for presenting descriptive analysis (Davenport, 2014).

2.4 Predictive analytics

The majorities of enterprises employ mainly descriptive analytics and are just starting to utilize predictive analytics (Appelbaum et al., 2017). Predictive analytics (PA) is a branch of analytics that uses input data, statistical combinations and Machine Learning statistics on predicting the probability of a particular event happening, forecast future trends or outcomes utilizing on-hand data with the final objective of improving the performance of the corporation (Kumar and Garg, 2018; Davenport et al., 2020; Espadinha-Cruz et al., 2021; Izagirre et al., 2021). PA methodology allows corporations to be proactive, future-orientated, forecast outputs and behaviors based on data and not by assumptions without any supporting data or information. PA makes predictions about future events which are currently unknown, applying mathematical formulas to data and decisions for a given situation or problem that should be discovered (Mishra, 2011). Predictive analytics is more and more frequently used in business to predict customer churn or customer attrition (Renjith, 2015).

According to Brynjolfsson et. al (2021), PA is increasingly understood to be a set of techniques – from data mining to statistical modeling, including, in some firms, machine learning and AI – used to analyze historical and current data in order to make predictions about future or unknown events. Implementation of predictive analytics comes after descriptive analytics and focuses on the prediction of the future using some statistical models and data mining tools and applications (Delen, 2015) Research on this area is based on historical events and data, providing the best estimation of what will happen in the future. "This analytics is concerned with forecasting and statistical modelling to determine the future possibilities based on supervised, unsupervised, and semi-supervised learning model" (Sivarajah et al. 2017).

As shown in figure 2, also data mining is an important component of predictive analytics. Some techniques such as K Nearest Neighbors, Self-Organizing Maps approach, Logistics Regression models, Random Forests algorithm, and so on, are used for data mining (Abdel-Basset et al., 2020). The text mining component is identical to data mining, but data mining algorithms are developed to cope with structured data; text mining can process unstructured or semi-structured data sets such as emails, HTML files, and full text documents (Vijayarani et al., 2015). Also Machine Learning models are a component of predictive analysis. It involves some steps, which are: historical data selection step; data preprocessing step; model selection, model training and model validation step; and model maintenance (Alcalá, 2015). Prediction models are created based on a set of features in a supervised or unsupervised manner (Chug & Dall, 2013). Moving forward, PA will be integrated into business applications and will no longer be a premium domain of mathematicians and statisticians (Dagnino, 2021; Saxena et al., 2021).

2.5 Prescriptive analytics

In addition to predictive analytics, prescriptive analytics also suggests actionable instructions to benefit users from its predictions (Javaid et al., 2021; Lo et al., 2021). Prescriptive analytics use mathematically or computationally techniques to obtain an outcome that will give the optimum result in a given scenario to improve performance (Arismendy et al., 2021; Lana et al., 2021). Next, prescriptive analytics also examines opportunities within a decision, correlation in within decisions, influences that affect these decisions with the end goal of producing the finest solution in real-time (Arismendy et al., 2021). Prescriptive analytics has been used to enhance planning-based sports by reducing human expert cognitive biases that can induce injury while training (Houtmeyers et al., 2021). Likewise, in stock market prediction, prescriptive analytics was used to study the flow pattern of stocks, which could help stockbrokers effectively invest in the stock platform with minimal risk (Meenakshi et al., 2021).

Prescriptive analytics goes beyond descriptive and predictive by suggesting one or more solutions and demonstrating each possible result (Appelbaum et al., 2017). We can use the definition of Yalcin et al. (2021) which states that optimization, simulation, decision modeling and network science are investigated under prescriptive analytics. Prescriptive analytics combines the outputs of predictive analytics and uses artificial intelligence, optimization algorithms, and expert systems in a stochastic environment to enable adaptive, automated, constrained, time-bound, and optimal decisions (Lepenioti et al., 2020).

2.6 Business problems and Analytics Techniques

The sophistication of the analytic methods applied at an organization is one of the factors that determines the level of analytics maturity of the organization (Kopsco & Pachamanova, 2017). In order to understand how SMEs utilize business analytics, it is essential to gain insight into the specific business problems that can be addressed through various analytics techniques. Often, quantitative curricula lack guidance on how to assess the business value derived from using models (Kopsco & Pachamanova, 2017). Hence, obtaining an overview of the current utilization of different analytics techniques for generating business value becomes crucial when examining how SMEs employ business analytics. A comprehensive literature study has been conducted by Kopsco & Pachamanova (2017) to summarize various business analytics techniques and their contributions to generating business value. Table 1 provides an overview of these techniques and their respective impacts on creating value within organizations.

Business problem	Analytical technique
Observe trends and relationships; formulate hypotheses	Data visualization
Decide if a new situation is “better” than the current situation	Hypothesis testing
Determine the impact of various factors on an output variable of interest	Linear regression, logistic regression, classification and regression trees
Identify groups of observations that are similar in terms of specified characteristics	Cluster analysis
Identify transactions that tend to occur together	Association rules (Market basket analysis)
Assign a score (likelihood, ranking) to an observation (customer, loan, transaction, etc.)	Logistic regression, classification and regression trees
Classify an observation (customer, loan, transaction, etc.) into a category	Logistic regression, classification and regression trees, Naïve Bayes, k Nearest Neighbors, Support Vector Machines (SVM), Neural networks)
Analyze data over time; forecast	Time series analysis
Analyze text data (customer call transcripts, social media posts, etc); perform sentiment analysis	Text analytics, Natural Language Processing (NLP)
Find an optimal mix of products given limited resources; find an optimal route / schedule / price	Optimization

Table 1 – Business problems and their analytics techniques (Kopsco & Pachamanova, 2018)

2.7 BI&A maturity models

In addition to comprehending various techniques and their business value, it is crucial to grasp the primary dimensions of BI&A maturity. This understanding enables the assessment of BI&A utilization and maturity levels within SMEs. By considering these dimensions, one can gain insights into the current state of BI&A utilization and advancement in SMEs.

A maturity model is a useful tool for SMEs to analyze their readiness for data analytics. It can support SMEs to decide whether and how they should invest in data analytics depending on their business needs (Hoffman, 2018). According to Becker et. al (2009, p. 219), a BI&A Maturity Model “consists of a sequence of maturity levels for a class of objects and thus represents an anticipated, desired, or typical evolution path of these objects shaped as discrete stages”. The following BIA maturity model characteristics as described by Raber et. al (2012) are used to measure an organization’s BI&A efforts:

- Object of Maturity Assessment: Key areas that present the BI&A environment.
- Dimension: Uniquely defined capabilities of each object of maturity assessment.
- Assessment: Conducted using either a quantitative or a qualitative approach.

The object of maturity assessment in this study are the SMEs, which are considered as key areas that present the BI&A environment. By considering SMEs as the objective of analysis, the study aims to determine whether there are notable variations between different SMEs in utilization or if there is a comparable way in which maturity develops within different SMEs.

To assess BI&A utilization in SMEs, also different dimensions of BI&A maturity should be determined. In their work, Cosic, Shanks, and Maynard (2012) aim to develop a business analytics capability maturity model, which can be used to assess the utilization of BI&A. They define business analytics capabilities spread out over four capability areas: governance, culture, technology and people. Though this framework mainly provides a framework for quantitative studies, such as surveys, this framework isn't suitable for this explorative study. However, Muller & Hart (2016) analyzed the maturity dimensions used in 15 different BI&A maturity models to generate a set of 11 dimensions used to analyze BI&A maturity. The 15 existing models analyzed by Muller & Hart all have their own criteria and focus of measurement, however none of the existing models covers all dimensions of business analytics. For example, Sen et al. (2012) focus on data warehousing maturity only. The BIDM model developed by Spruit (2010), only looks at the dimensions of architecture, data quality and performance management. This study takes an integrative approach, considering various dimensions used in existing models to provide a complete picture of BI&A maturity in the unexplored context of SMEs.

According to Muller & Hart (2016) development of business analytics throughout the years ensured that some underexposed dimensions such as skills and knowledge and performance gained a more important role in business analytics maturity. Kopsco & Pachamanova (2017) emphasize the importance of analytics techniques for business value of BI&A, and therefore utilization of specific analytics techniques will be included in this study. These dimensions are useful to structure the assessment of BI&A utilization in SMEs. In table 2 different dimensions of BI&A are described generally as stated in the literature. This study aims to gain a deeper understanding of what low and high maturity on those different dimensions means within the context of SMEs, resulting in a complete picture of the development of maturity dimensions.

Dimension	**Description or example**
BI&A applications and tools	e.g. OLAP; reporting; data mining
BI&A architecture	Structure of integration, sources, platforms
BI&A change management	Ability to manage changes
Data quality and use	Data quality, usage and management
Performance management	KPIs and metrics used to manage organization
Skills and experience	BI&A competence and skill sets
IT infrastructure	Cloud computing, networks, servers, storage
Promoting BI&A culture	BI&A awareness and top management support
Business and IT alignment	Business and IT not in silos, enterprise BI&A
BI&A strategy	Managing overall BI&A strategy
Analytics techniques	Data visualization, Cluster analysis, Support Vector Machine, Logistic regression, etc.

Table 2 – Maturity dimensions of BI&A (Muller & Hart, 2016)

3. Method

3.1 Research Design

There will be conducted semi-structured interviews, since some structure is important to be able to compare different interviews. However, being able to go in-depth can be a major advantage of semi-structured interviews compared to structured interviews. Therefore, semi-structured interviews are considered the most suitable for addressing the research objectives. The different dimensions of maturity/utilization are used to structure the interviews. In those interviews, participants will elaborate on the development of business analytics for all the different dimensions. This creates a complete picture of the development of those dimensions from SMEs starting with BI&A until a higher level of maturity is reached. Thereby, to gain a deeper understanding of BI&A maturity within SMEs, it is also important to understand what drives organizations to implement business analytics and what the main challenges are, considering the maturity of analytics within the company. Structuring the interview based on the dimensions from literature will help to collect the complete picture, without focusing on specific dimensions too much.

This study used purposive sampling since the SMEs for this study should be involved in business analytics in some extent and should be as least as mature as predictive analytics. The purposive sampling technique is a type of non-probability sampling that is most effective when one needs to study a certain cultural domain with knowledgeable experts within (Tongco, 2007). It's important to emphasize that directors or BI&A experts are interviewed form the company. If an SME is not using BI&A at all, there is no reason to gather information about evolvement of BI&A utilization and how progress through different levels is made.

3.2 Participant selection

The participants will be recruited from personal networks. Besides personal network, a request will be placed on LinkedIn to recruit participants. Finally, snowball sampling will be used. This is a recruitment method that employs research into participants' social networks to access specific populations (Browne, 2005). In this case, it means asking expert participants for other companies or experts that could be interesting for this study given the research goals.

3.3 Data Collection

The interviews used samples from both personal network and snowball sampling, which were conducted until saturation was reached. This means that no new data emerged from the interviews. In total, the number of interviewed participants is 9. Participant companies were active in different industries such as construction, accountancy, consulting, e-commerce and insurance. All companies had between 5 and 350 employees, existing between 4 and 20 years. Most important for eligibility of participants was that participants are able to assess and overview the impact, application, maturity and adoption of BI&A over different functional areas within the SME. Thereby, the participant should be able to give in-depth information about the tools and techniques used for business analytics. Interviews were mainly conducted via MS Teams. Before the interviews, participants were asked for permission to record and transcribe the interviews. To ensure privacy, names of both companies and persons were anonymized in the interviews. Within 5 weeks after the study the interviews were deleted.

Interview questions are based on the research questions, and the existing literature about business analytics. The interview guide can be seen in appendix A.

3.4 Data analysis

After the interviews were conducted, the interviews were transcribed. After transcribing all the interviews, the coding process was started using in-vivo codes. Deductive coding was used to take advantage of the structure provided by existing literature in a new context. The data was sorted using those codes. However, codes that were relevant but didn't fit in a specific category were at first stored separately to analyze separately. Based on the content of those quotes, two new codes emerged; drivers and challenges.

Different maturity levels were analyzed by looking at the sequential development of various dimensions. By analyzing data from different participants, a pattern in development of business analytics has been identified. Different levels of maturity were separated based on the value added by business analytics to the business, according to the participants.

4. Results

In the discussion section, utilization of business analytics will be discussed through analyzing the data from the interviews which have been coded deductively. However, for some relevant quotes from the interview no label was suitable. Therefore the labels BI&A drivers, BI&A challenges were added as extra labels, since a significant amount of quotes relevant to this study were found in this explorative research that best match those labels, besides the dimensions deducted from the literature. Thereby, to understand utilization of business analytics, it might be important to understand what drives the utilization of business analytics and what are challenges when the maturity of utilization is growing. Important to note is that the nature of this study is explorative, aiming to lay the groundwork for future studies and inspire other researchers to build upon this findings. Thereby, not much existing literature is existent within the context of SMEs. Within this study, many similarities were found in BI&A maturity development between the different participants. Also within different dimensions, evolvement of maturity was uniform. In this result section, the different dimensions of BI&A are discussed. For every dimension is explained how, based on different quotes, maturity and utilization developed over time in SMEs.

4.1 BI&A application & tools

When utilizing business analytics, it is important to find the right applications and tools to use. In this study, we found that Excel is used as an application many times for business analytics in companies that are immature in business analytics.

" Many SMEs have a dashboard or report in Excel, still struggling to automate reports or build reports with insights on key questions."

Even though these Excel reports gave some sorts of insight, manually updating and building reports wasn't considered efficient and sensitive to errors. Therefore, SMEs adapt modern BI&A tools like PowerBI, Tableau, or Qlik. These tools don't only allow more esthetic visualization, it also enables organizations to automate reporting and access advanced analytics.

"PowerBI, Qlick and Tableau are the most used tools within SMEs."

When selecting suppliers for business analytics applications, a large network of expert consultants and online access to forums and help were considered important factors for supplier selection. However, not only business analytics applications were used to facilitate the utilization of BI&A. Also process digitization was considered important, since it enabled SMEs to gather data about operational processes and other business aspects.

"We used a special software to digitize processes, being able to track the performance of those processes."

When looking at the insights and the application of those insights that derived from business analytics, these were mostly used to facilitate meetings. Examples of applications are customer segmentation to facilitate marketing activities, describing industry trends, statistical analytics like AB testing, risk analysis, automated financial reporting and capacity planning visualization to support the planning department.

“Reports are used to facilitate meetings”
“BI&A is used to increase sales and do risk analysis”
“BI&A helps us to get a better definition of our customer”
“text mining is used to analyze e-mails to track customer satisfaction”

The main disadvantage of utilizing business analytics tools in SMEs is the increased dependency of external suppliers in terms of knowledge, but also in terms of making changes to reports or visualizations created. Compared to ad-hoc reporting in Excel, making adjustments in reports is more time consuming and therefore is considered a disadvantage of automated reporting in SMEs. However, SMEs are moving towards self-service BI to tackle this problem. Meaning that the data department creates a dataset and a data model on which employees can do their own analytics. Data from interviews showed that some organizations are implementing self-service BI already, but this requires additional skills from employees.

“We use tooling that enable all employees to create their own insights.”

4.2 BI&A architecture

SMEs starting with business analytics don’t have a BI&A architecture at all. Mostly reporting is gathered from automated reports within their ERP or CRM systems, which don’t have a sufficient fit with the organizational goals. Thereby, many employees are using their own Excel files for reporting, leading to multiple sources of truth and therefore discussion.

“If you build multiple reports on multiple systems or excel files, there are multiple sources of truth, therefore we need a central database.”

Due to multiple sources of truth, standardized system reports and lack of historical data in organizational systems, SMEs that want to improve their business analytics start building a BI&A architecture. This architecture helps to generate value from business analytics.

“Building the database structure was a huge milestone to be able to generate value from analytics.”
“Right now most SMEs use separate tools, but SaaS companies are moving towards an integrated approach for the whole analytics process.”

SMEs that are immature with business analytics tend to build the visualization layer immediately on their systems. The first main step in the process of building the BI&A architecture, is moving from directly withdrawing data from the systems for reporting, to a more integrated approach; storing data at a central point and build a standard data model to report on. Therefore, the extracting, transforming and loading of the data can be done from a central place leading to a higher control on data quality and a single version of truth organization wide. Thereby, some organizational IT systems don’t store historical data and therefore lose descriptive value of data over time. Another huge advantage is the possibility to combine data from different silo's. Multiple SMEs reported on a major growth in value captured from business analytics due to combining data from different sources and systems.

"Both the complexity and the value is in coupling different datasets."
"Data warehouse enables us to connect data from different data silo's."
"We use external API's to enrichen our data warehouse."
"We started building a data-warehouse to be able to get access to historical data."

One major risk in this process mentioned, is that knowledge about the database structure and architecture isn't described and stored at one person within the organization. Leading to a higher dependency of a single person within the organization. However this can be avoided by describing the database structure.

"A major risk is that the database structure and architecture of the data warehouse is stored at one person, which makes it hard to transfer."

The most common way to structure the BI&A architecture is connecting all enterprise systems to a data lake and/or a data warehouse using APIs. The data lake is mostly used for data science application, where unstructured data is used for the models. Data warehouses are mostly used for descriptive analytics but can also be used for predictive and prescriptive analytics. What most SMEs found important was building a cloud data warehouse for scalability, being able to connect data from different sources and systems both now and in the future.

"We build a cloud data warehouse to be able to connect data from different sources and systems."
"To capture value from predictive analytics one has to integrate multiple data sources and clean that data."
"The visualization layer is built on the warehouse, mostly using PowerBI."

Some SMEs struggled to find out what data to include and what data to exclude from the warehouse. Mostly the first step is extracting and cleaning the data from internal systems and digitized processes, which delivers significant descriptive value. The descriptive analytics give essential information about quality of the data model. However, when capturing predictive and prescriptive value, mostly open data from external sources have to be included in the warehouse to build predictive models.

"We combine internal data with open data to generate insights."

4.3 BI&A change management

Even though the applications, tools and the architecture are important dimensions of business analytics from a technological perspective, utilization of BI&A is highly dependent on the people who use it. Change management refers to the change due to BI&A initiatives and how to manage this change. One key issue that came forward in this study is the visibility of BI&A within the organization. Business analytics, and the way it can create value within an organization, is relatively new for many employees in SMEs. To adapt to the change due to business analytics, it's important to create basic products to show employees the value of

BI&A and the possibilities. This helps them to come up with initiatives themselves, ensuring the utilization of business knowledge within the organization when implementing BI&A. Thereby, constant awareness of the impact an existence of business analytics with visibility throughout the offices is a very important part of managing the change.

“Key issue is creating visibility for BI&A within the organisation.”
“By creating basic analytics products, employees create a better understanding of the possibilities of business analytics.”
“The most important example of business analytics adoption is being able to show the pro's for departments and individuals.”
“We made sure that dashboards are visually present in every room using TV screens, so everyone stays aware of the existance.”

Also, it’s considered important that business analytics isn’t implemented as a disruptive change, but case by case so people can get used to the data-driven way of working. Thereby, it’s important to start with a proof of concept that delivers value, so BI&A can get a higher level of support within the organization. Therefore, it’s not only important to create insights that are reliable but also important that needs and wishes are translated properly from a business perspective to a technical solution.

“We implemented business analytics case by case, to make sure the change is not so disruptive.”
“When we start working with data, we work to a proof of concept that delivers value. This helps with support for BI&A.”

Besides the fit of the technical solution with the business, it’s important to create awareness and training within the organization. Especially employees who need extra training should be facilitated in data trainings to reduce the level of resistance. Thereby, when business analytics become more mature within the organization, analytics should be decentralized within the organization, meaning that different departments aren’t dependent on the analytics department for questions, but also have some knowledge within the department stored at employees that aren’t from the analytics team. This is in line with the finding of growing importance of self-service analytics within SMEs.

“To create awareness, we trained 6 employees to be ambassador and be able to answer questions on organisational level.”
“There is difference in ability of employees to adapt to a data driven way of working, when this is hard, the level of resistance tends to be higher.”
“We want everybody in the organization to work data-driven.”

4.4 Data quality and use

As stated before, reliability of insights is key for the change management process of BI&A. Therefore, it’s interesting to study the dimension of data quality and use in SMEs. When organizations start using business analytics, mostly descriptive analytics is the first stage of analytics. Huge advantage of this analytics type is that it gives information about the data quality. Users know the business context and therefore can immediately spot differences between shown insights and reality.

"Descriptive analytics tells you if your data quality is high or low."

Where descriptive analytics helps to spot issues with data quality, it's interesting to know what causes data quality issues and how to overcome those issues. Mostly, SMEs with a low level of maturity rely on manual processes for data extraction. This leads to a higher chance of errors in data and therefore is a risk for data quality. Thereby, immature organizations also mostly only use internal data (from their internal systems) for analytics purposes.

"All data visualization, of which parts were indispensable for the organization, was sensitive to errors due to data extraction with exports by hand. "
"We mostly use internal data."
"Automation of data imports helped us to be less vulnerable to losing data and errors in data."

A solution for the errors due to manual extraction is in line with a growing maturity of BI&A architecture; the use of a central data warehouse. When data can be imported automatically, the extraction process has to be optimized once and eliminates the errors made by humans. However, mostly automatic extraction of data is done on a larger scale, leading to a higher level of detail in data and therefore more data issues. However, to advance business analytics maturity, more data and higher quality data is essential.

"When data is exported automatically, it's usually done on bigger scale which gives a higher level of detail and therefore more issues are spotted."
"The more you go to predictive or prescriptive, the more data you need."
"The more complex the context of your problem, the harder it is to find connections and the more data you need for predictive analytics."

Besides the quality of data, also the use of data changes with the maturity of business analytics within the organization. When an organization becomes more mature, and has a higher level of analytics skills and literacy within the organization, it becomes more important to facilitate with verified datasets as an business analytics team. Where data quality management and data analytics and visualization is mostly done by the same person in premature stages, with a growing maturity the extraction and cleaning of data into a verified dataset becomes a specific role apart from the analytics and visualization.

"We have publiced verified datasets, so employees can build their own analytics."

For data quality, in larger corporations mostly data governance is used to ensure security, data quality and give responsibility to certain persons. What's done mainly different within SMEs is that governance is limited and very informal within SMEs. This is mostly due to the scale and relative impact of business analytics compared to larger corporates.

"Data governance is usually limited in SME's and very informal."
"Data responsibility is usually not given to someone specific within the organization."

4.5 Performance management

Most of business analytics is used in operations by impact analyses. For example the impact of changing internal processes on customers, but also testing the impact of certain changes in price, capacity or demand. Main goal of those insights is to make work more easy for employees, and make processes more efficient. However, another effect is reached within the organization due to the performance management dimension of business analytics: responsibilities are very clear for every team and persons within the organization.

"We were able to analyse the impact of change of internal processes on customers."
"We use data to test assumptions on how we can best do business."
"We are able to predict customer demand and adjust our internal operations according. We do this because we want to act proactive instead of reactive."
"Analytics reports can help creating clarity in personal responsibility if used well. To manage this, it's important to make sure the right people with certain roles get access to the right dashboards to be able to track progress."

Business analytics enables the organization to create actionable insights for employees, facilitating their work and enabling employees to work more effective and efficiently. In order to create this value, it's important to create a right fit between the role of an individual, the team goals, the organizational goals and the insights from analytics. Standard dashboards from ERP systems tend to lack context, and therefore mostly aren't suited for performance management. For example: when the sales department sells 100 packages of toilet paper but the impact of the corona-crisis run for toilet paper isn't included in the context, the sales department would seem to perform high due to lack of context. Even though they might be underperforming.

"Standard dashboards in ERP systems lack context, reaching 500 more sales this month compared to the last month doesn't mean anything if Christmas has an effect on sales. "
"Insights should be actionable in order to create value."

Lastly, an important way SMEs use performance management are the translation of strategic goals or pillars to operations to actionable insights. Key Performance Indicators are used to measure and monitor progress on strategic goals. This helps everyone in the organization to spot if they are still on track in reaching the strategic goals, but also to change timely when necessary to reach strategic goals.

"We monitor on our strategic goals to check our progress."
"We can deploy strategic goals to departments and persons, so everyone knows what they are responsible for."
"We translate strategic goals to KPI's to measure progress."

4.6 Skills and experience

"It is important to know what roles and competencies are important for developing business analytics in your organization."

Skills and experience are an important dimension of business analytics, since the combination of business acumen and technical expertise are enabling the implementation of BI&A within SMEs. Within a business analytics team, different specialist roles are needed to reach a higher level of maturity within the organization. Main roles of a BI&A team are a data engineer building ETL pipelines and connecting multiple data sources, a data analyst creating dashboards and insights, a data manager who supports the whole business analytics process, a data scientist who can do advanced analytics and maybe an analytics translator who can translate business needs to technical solutions.

"The main roles in our data team are data analyst, data engineer and data manager."
"The data analyst creates dashboards and insights."
"The data engineer creates and manages the data-infrastructure."
"The data manager ensures collecting, organizing and visualizing data to support efficient decision making."
"The art of data science is being able to spot predictive value in datasets."
"Data quality and analytics translation are key parts of making descriptive analytics work, and therefore captering value from descriptive analytics"

However, SMEs tend to be highly dependent on external parties. All different types of specialist skills are too expensive and a bit of an overkill given the size of the organization. Therefore a main difference in terms of skills compared to corporates is the importance of managing external relationships with suppliers and consultants since they have the knowledge and are critical to the success of business analytics. Especially in the premature stage of business analytics, a generalist being able to fulfill multiple roles within the organization is highly valued. However, mostly in the starting phase of business analytics there is no fulltime employee working on business analytics. Mostly it's a side-job of an employee starting to build some visualizations on existing systems. When further developing business analytics, a generalist profile being aware of possible challenges and risks is needed to build relationships with external suppliers and consultants. Given the relative size and importance of business analytics the department can be built with the different roles mentioned above. Compared to larger corporations, the growth of the business analytics department is mostly more incremental given relatively limited resources.

"Be aware of the possible challenges and risks, and therefore get help from professionals that have the knowledge."
"Many SMEs don't have the skills and experience in-house to capture value from BI&A."
"To be able to use business analytics, one should be able to manage external relationships with suppliers and consultants since they are critical to the success."
"Smaller organizations need more generalists to add value, larger organizations can attract more specialist in depth skills."
"SMEs are mostly dependent on external expertise since they don't have all expertise in house."

4.7 IT infrastructure

Since SMEs tend to have more traditional IT infrastructure, this dimension of business analytics is mostly limiting the utilization of business analytics. Especially for older and organizations in a more traditional sector, ERP and CRM systems can complicate the implementation of BI&A due to the complexity of extracting data from the systems. Some SMEs even need to implement a new ERP that's suitable in order to capture value from BI&A. Thereby, modularity of the IT infrastructure can be a driving force for business analytics. Since organizations change, and therefore their processes, flexibility is offered using a modular architecture. When new processes can be digitized quickly, the data from those processes can be used for analytical purposes. Due to the size and impact of the implementation of a new ERP, this can be a restraining force for SMEs in adapting business analytics.

"Older and more traditional organizations tend to have a ERP and a CRM system that complicate the implementation of business analytics."
"The ERP we have doesn't log historical data, which loses the possibility to create insights.
"We have a modular architecture, which means we are able to connect new functionalities easily."
"Because of an old traditional system, the change for the organization was very big."

4.8 Promoting BI&A culture

A data-driven culture is essential for BI&A adoption. As discussed in the change management section, resistance to change and lack of awareness can hinder business analytics initiatives. What thrives business analytics adoption is support from top-level. Firstly, from a financial perspective, to utilize business analytics there has to be a willingness to invest from a top-management perspective. Secondly, to connect business strategy with business analytics initiatives, top-management support is needed since they mostly formulate strategy.

"It helped that the CEO has a high willingness to invest in business analytics and data."
"Awareness of business analytics is maintained by giving analytics a seat at the table with managing directors."

Besides top-management support, the extend to which there is a bureaucratic culture is important for the speed of BI&A adoption. SMEs tend to have a lower level of bureaucracy and should therefore be quicker in implementing a BI&A promoting culture. However, data can be felt as a threat for employees since their performance is visible within the organization. Therefore, clear communication is essential to create a promoting BI&A culture. Key goal of a BI&A promoting culture, is placing data central in approaching business problems throughout the whole company.

"We don't have a bureaucratic culture, so we could implement business analytics relatively quick."
"What we see in developing a data driven culture, is that data becomes more central in approaching problems."
"When SMEs start with business analytics, it can feel threatening for employees due to transparency about their personal and team performance within the organization. "

4.9 Business and IT alignment

Another dimension crucial for maximizing value of business analytics is business and IT alignment. Data from this study showed that SMEs have two core areas that connect business and IT. Firstly, they use business strategy as input for creating insights in business analytics. Using business strategy as key framework to structure reports and insights, helps to align business and IT.

“Strategically we have 5 result area's that give direction to our BI&A practice: quality, customer satisfaction, costs, safety, fun.”

The main risk in utilizing business analytics is that developers of BI&A products lack business sense, and therefore BI&A does not create value due to a lack of alignment of products with business goals. Using strategic result areas, defined by the business and cascaded to department level, team level and personal level, helps not just to show everyone their impact on company goals. It also gives IT a proper guide on what insights the business expects them to facilitate.

“In my experience, technical oriented data engineers lack business sense, which is a risk for implementing business analytics.”

However, besides strategic alignment there is also alignment with operational activities. When business analytics should be used within an organization, it’s important that products are adjusted to the needs of end-users. Crucial is building a feedback-loop, enabling end users to share their knowledge about business context. Therefore, especially in SMEs that don’t have fulltime employees working in their data-department, it’s important to make someone responsible for aligning business and IT. At best, someone at board level who has a deep knowledge of the business context to drive alignment from business strategy. Thereby, some employees should get a key role in giving feedback on dashboards, reports and other data-products to make sure products are aligned with end-users in business operations. When business and IT are not aligned, end-users won’t be satisfied with insights and business analytics won’t create value.

“There are two types of uses for business analytics; monitoring operational activities and increasing efficiency, and monitoring long term strategic goals.”
“For implementation of business analytics it's important to ask user feedback”
“You can determine what to include in your data lake or data warehouse using business knowledge and data models.”

Even though business and IT alignment is used as a dimension in literature, the results of this study did put some question marks to IT as a dimension of business analytics. Even though IT is seen as an enabler of BI&A due to the data that’s extracted from systems, most SMEs unfairly see IT and business analytics as the same thing. As stated by experts in interviews, the main difference between business analytics and IT is that IT is merely focused on the basis structure of business processes to enhance productivity through support, where BI&A is purely focused on increasing business performance through insights. Though there is a grey area between those two functional areas, it might be interesting to see how those two fields will relate to each other in the future. Looking at the changes in organizational structure of the SMEs in this study, distinguishing BI&A from the IT department , the separation between these area's will become more clear in the future.

"IT is more focused on the basis structure of business processes, BI&A is focussed on increasing business performance."

4.10 BI&A Strategy

SMEs are increasingly recognizing the strategic value of BI&A in gaining a competitive advantage, and therefore business analytics is getting growing attention as a strategic theme within SMEs. As dimension of business analytics, BI&A strategy focuses on the systematic approach that an organization takes to leverage business analytics and take informed decisions, drive business performance and gain competitive advantage. What stands out is that many SMEs know that data and business analytics are important themes in the future, but they don't fully understand how to create value using BI&A and bring business analytics to the next stage in the organization.

"We believe that if you're not data-driven at a certain point, you will lose to competitors on the long term."
"The main purpose was to be proactive as a company instead of reactive."

Therefore, most SMEs are searching for a framework that can help them build BI&A capacities in a structured way. Some of the respondents in this study used organizational strategy as leading input for their analytics departments. What stood out is that organizational strategy gave direction to end-products and insights needed from a business perspective, but did sometimes lack the guidance for technical skills and infrastructure needed to bring BI&A to a higher level. It's mainly those area's that are new for SMEs and where skills and experience are needed to formulate and implement strategy.

"Organizational strategy is leading for us as analytics department."
"Sometimes business analytics is linked to organizational strategy, but it depends on size if there is a formulated strategy in SMEs."

Thereby, not all SMEs tend to have an organizational strategy. Mostly it is dependent on size if SMEs have a formulated strategy. Smaller organizations, or organizations without an organizational strategy tend to look at implementation of BI&A from a more pragmatic and operational perspective. A list with feedback from different users is drawn and minimum viable products are launched. An advantage of this method is that value is captured relatively quickly compared to projects where primary investments are in BI&A architecture and tools. However, most organizations indicated that they expect scalability issues on the long term due to this method.

"What stood out in the results of this research, was that some organizations used feedback from employees to draw a list with requirements to create a dashboard."

Key goals of a BI&A strategy found in this research are making better decisions, create grip on the business, create value with actionable insights, creating a competitive long-term advantage and make working more easy by facilitating in tooling and insights.

"The key value in bi&A is making better decisions."
"Mostly is the goal from a bi&a perspective to create grip on the business."
"Goals and insights need to be actionable in order to create value."
"Data is a competitive adventage on the long term."
"Our main business analytics strategy is to become a data driven organisation, in which everyone has access to data analytics and is therefore better in doing what he or she is supposed to do. "
"We want to give every department the space to do what they are good at, by facilitating the conditions such as tooling and insights."

4.11 Analytics techniques

Automated insights is a technique used for standard reports. These insights are mostly presented using data visualization techniques. Kopsco & Pachamanova (2017) formulated visualization as a technique to observe trends and relationships. Within SMEs this analytics technique is used the most, due to the low barriers to use. Data can be extracted directly from existing systems and little data transformation has to be done to generate insights. However, this is also a pitfall since some experts reported on underestimating the importance of the right visualization.

"Creating dashboards and reports is relatively easy to do, if one employee understands the visualization tool it's a small step to create impactful insights."
"Data visualization is an art, you need to tell a story without overwhelming the user with information."
"Mostly business analytics is presenting insights automatically."

Besides visualization, self-service BI is a technique that starts to grow within SMEs. To further drive this development, data literacy has to be increased within SMEs since currently there is a lack of data literate employees which are necessary for self-service analytics.

"We expect self-service BI to grow in the future, since we expect data-literacy to grow."

Finally, more advanced techniques are used by exception in SMEs. Techniques like clustering for segmentation of customers, predictive models to foresee changes in customer demand, benchmarking to compare performance to industry averages and machine learning models like correlation, random forest and XG boost (decision tree).

"Clustering is used as a technique, mostly for segmenting customers."
"We expect self-service BI to grow in the future, since we expect data-literacy to grow."
"We are using benchmarks to compare our performance to industry averages."
"Analytics techniques we use are correlation, random forest model, XG boost.

4.12 BI&A drivers

To understand how SMEs utilize business analytics, it's also important to understand what drives them to use BI&A. The first major driver for business analytics is the enabling technology and tooling, which is usable at lower cost due to cloud technology and SaaS analytics platforms. Due to the relatively low costs compared to the potential impact to the business, it helped SMEs to start utilizing business analytics.

"Cloud technology is an important driver of business analytics."
"PowerBI is usable at low cost, and therefore interesting to use within our company."

Besides enabling technology, one interviewee also reported that one employee was hired with business analytics skills and became a thriving force in implementing business analytics. The main reason overall, was that SMEs encountered a specific problem they had to deal with, and found that business analytics can be a solution. One interviewee reported problems with adjusting production planning to customer demand, and therefore started utilizing business analytics to predict customer demand and visualize machine capacity, employee capacity and material capacity over time to optimize production planning. Therefore, the main driver for business analytics are specific problems encountered within an SME.

"The major problem we had was being unable to adjust production planning to customer demand."

Also, efficiency problems were reported as an important driver of BI&A. Mostly, processes couldn't be optimized since SMEs experienced a lack of insight in processes for which business analytics could be a solution. Thereby, when organizations grew in size, the need for control grew. The need to track strategic performance and check if the organization is still on track reaching business goals is considered an important driver.

"Business analytics is mostly used to help companies work more efficiently"
"Both efficiency problems and technical opportunities push the development of business analytics"
"To have control over my growing organization, I need want to monitor if we are on schedule reaching our business goals and adjust when necessary."

4.13 BI&A challenges

Within this study, the interviewees reported on different challenges when utilizing business analytics. Even though this dimension isn't reported in the literature, the dimension is added due to its practical relevance and its relevance for future research. The first main challenge for utilizing BI&A in SMEs are limited resources. Firstly, limited financial resources make it hard to implement business analytics due to the relatively low scale of SMEs. The limited resources combined with seeing business analytics as a cost center, makes it hard to advocate for structural investments in BI&A. This again emphasizes the importance of top management support. Besides the financial challenges, also political challenges to prioritize analytics projects can be challenging.

"Data is mostly seen as part of IT, and therefore as a cost center. In bad times, the first department to cut costs."
"First the challenge is political, determining what data projects to prioritize and how much to invest in bi&a, then the challenge is technical, delivering a data solution."

Secondly, technical challenges are mostly centered around skills available in the organization within SME's. Where corporates can use a team consisting multiple experts, SMEs mostly depend on one generalist. Sometimes this generalist is an employee who's doing business analytics as a part-time role beside another function, coordinating external suppliers and consultants. Some aspects of the process of implementing business analytics require specialist knowledge and are therefore challenging for SMEs.

"Currently it's hard for us to find out how we combine external data with ERP data and our digital quality system."
"Data and digital literacy among employees, political and cultural challenges, legacy systems that don't suit analytics."
"Biggest challenge is focus, if you want to do new things to quickly it's a risk that you lose the robustness of your data infrastructure."

Thirdly, literacy among employees and cultural change is a challenge many SMEs encounter. Employees have some level of resistance to change since working with new tools requires additional skills. This doesn't only include the use of standard insights from the ERP system in stead of the insights created by business analytics department. It also includes right use of the systems to collect the data needed for BI&A. Finally, the mindset of approaching problems with a data-driven mindset is challenging. Especially when moving from ad-hoc reporting to automatic reporting, employees lose the ability to do ad-hoc analytics the way they used to. Therefore they start working around the existing infrastructure.

"Adoption of analytics tools was hard, since employees still used the ERP system to gain insights, and not the dashboards created for them."
"Unability to change and adapt quickly to changing context adds some complexity to automated reports."
"A serious challenge for a data driven culture is that anyone should know how to work with data."
"Sometimes analysts forget to add an important dimension, and therefore you get real different conclusions and insights"

Finally, data quality is a huge challenge for business analytics in SMEs. The combination of building the ETL pipeline, creating a data model that is well defined and understood throughout the organization and making sure systems are used properly to ensure quality data. This barrier can also be seen as an opportunity. What stood out is that combining data from multiple systems in a central data warehouse not only lead to higher data quality, it also created value for the organization due to new insights that could be generated from combined data sources.

"Biggest challenge for business analytics are data quality and implementing the solution which means including users and their demands in using the systems."
"Garbage in is garbare out."

5. Analysis

In the result section each of the different dimensions were analyzed. Analyzing the different dimensions gave an overview of the development of maturity within different dimensions. However, to create an overview of business analytics maturity and utilization within SMEs, it's important to show how the development of maturity within different dimensions can be translated into an overview of maturity stages. This provides integrated insights into the way different dimensions are developing relative to each other. By dividing the development of BI&A in maturity stages, it becomes clear what steps are generally taken to become more mature or improve utilization of business analytics in SMEs. Different maturity levels were analyzed by looking at the sequential development of various dimensions. By analyzing data from different participants, a pattern in development of business analytics has been identified. Different levels of maturity were separated based on the value added by business analytics to the business, according to the participants.

5.1 Business Analytics Maturity/Utilization in SMEs- Overview

Utilization level: Novel / Beginner

Dimension	**Characteristic**
Application & Tools	Excel
Architecture	-
Change management	Creating awareness of potential of BI&A
Data quality and use	Low data quality, multiple versions of truth
Performance management	-
Skills and experience needed	Analytics translator for translating business needs to a roadmap and minimum viable products
IT infrastructure	Use of traditional systems
Promoting BI&A culture	Presence of top management support
Business and IT alignment	Business requirements used for operational systems, not for business analytics
BI&A Strategy	Short term operational wins for BI&A are formulated
Analytics techniques	Decentralized reports
Drivers	-
Challenges	Lack of efficiency and oversight, processes not digital

Table 3 – Utilization of SMEs novel to business analytics

Utilization level: Developing

Dimension	**Characteristic**
Application & Tools	PowerBI, Tableau, Qlick (Visualisation tools)
Architecture	Data is extracted directly from systems
Change management	Value is created with minimum viable products
Data quality and use	Low quality, but better insights in data quality due to use of applications
Performance management	Performance management available for some organizational functions
Skills and experience needed	Data analist for creating visualisations and exctraction of data from systems
IT infrastructure	Extract data from ERP/CRM systems
Promoting BI&A culture	Involve users in product development
Business and IT alignment	Business requirements are used to prioritize first business analytics initiatives
BI&A Strategy	Business analytics roadmap is formulated, focusing on architecture
Analytics techniques	Automated reports
Drivers	More efficient reporting and fact-based decision making for specific cases
Challenges	Lack of context definitions, data in silo's with low quality

Table 4 – Utilization of SMEs in early development stages of business analytics

Utilization level: Competent

Dimension	**Characteristic**
Application & Tools	Data Lake / Data warehouse
Architecture	Data silo's are combined, data stored central
Change management	Data literacy increased with training
Data quality and use	Central data model used to report on
Performance management	Contribution to organizational strategy is monitored for teams and individuals
Skills and experience needed	Data engineer, building the data warehouse
IT infrastructure	Processes are partly digitized
Promoting BI&A culture	Clear communication about the advantages of business analytics
Business and IT alignment	Use most important operational bottlenecks as input for BI&A initiatives
BI&A Strategy	Formulate business analytics roadmap based on organizational strategy and operational bottlenecks
Analytics techniques	Visualisation
Drivers	Integrating insights from different systems
Challenges	Technically challenging to connect data from different systems

Table 5 – Utilization of SMEs that are competent in the field of business analytics

Utilization level: Advanced

Dimension	**Characteristic**
Application & Tools	Self-service analytics environment
Architecture	Create a role structure to enhance self-service analytics
Change management	Promote a fact-based approach to problems
Data quality and use	Descriptive models give an indication of data quality
Performance management	Individuals can do suggestions to improve performance based on analysis
Skills and experience needed	Data management skills needed for creating self-service analytics datasets
IT infrastructure	Most processes digitized
Promoting BI&A culture	Facilitate individuals to increase data literacy
Business and IT alignment	Business is actively sharing data needs to data engineer / data manager
BI&A Strategy	Formulate business needs for predictive and prescriptive analytics
Analytics techniques	Self-service BI
Drivers	Maximum use of business and context knowledge throughout the organization for analysis
Challenges	Data literacy and cultural change

Table 6 – Utilization of SMEs that are advanced in the field of business analytics

Utilization level: Expert

Dimension	**Characteristic**
Application & Tools	Python, R
Architecture	API's with external databases to enrich data warehouse
Change management	Make sure data-science solutions are placed in the right context
Data quality and use	Need to integrate external data sources
Performance management	Predicting future performance
Skills and experience needed	Data scientist
IT infrastructure	-
Promoting BI&A culture	Place data central in approaching business problems
Business and IT alignment	Dependent on business to constantly adjust context for analytics initiatives
BI&A Strategy	-
Analytics techniques	Predictive and prescriptive analytics
Drivers	Optimization of efficiëncy and proactive capacities
Challenges	Many skills needed at high costs

Table 7 – Utilization of SMEs that are expert in the field of business analytics

6. Conclusion

This study has proposed an overview of utilization of business analytics in SMEs, using the different dimensions of business analytics proposed by the existing literature. Where immature organizations mostly use Excel, Saas analytics platforms are used widespread in SMEs that are more mature in analytics. Tools seen the most are PowerBI, Qlick and Tableau. Especially widespread availability of external resources in terms of consultancy and online forums were important in tool selection. The tools were mostly used to facilitate meetings due to automated reporting. However, more mature SMEs moved to self-serving analytics where everyone could do their own analysis on a central data model. The extraction of data to a central data warehouse seemed an important milestone within SMEs for the utilization of business analytics, since it enabled them to create a single version of truth and a substantial basis for the use of BI&A. Also combining multiple internal and external data sources within the central database turned out to be a large step in the utilization of BI&A. Quality of the data is key to create reliable insights and maintain support within the organization. Even though its importance, data governance is mostly limited and very informal within SMEs.

Regarding the change management process, business analytics can be utilized as long as employees are still on board. This requires visibility of BI&A initiatives, involving employees in the process and ensuring there is enough training to ensure data literacy among employees. Resistance to change is important to manage, especially when employees feel that their performance is visible throughout the organization. However, the performance management aspect can also help to make clear where responsibilities are lying and show what contribution of individuals, teams or departments are to strategic goals. To properly execute performance management, it’s important to create the right context for results. In this way individuals feel their performance is tracked in an honest manner.

Not only are business analytics utilized to track strategic goals and performance, it’s also utilized to work more easy and efficiently. However, to effectively implement business analytics, multiple specialist roles are needed. Data engineer, data manager, analytics translator, data analyst, data scientist are the main roles, which are an overkill given the size of SMEs. Therefore, the main skill needed to implement business analytics is the effective coordination of external relationships with suppliers and consultants, since they can add up to the business knowledge with technological skills to build solutions. Thereby, before starting with analytics, the IT infrastructure should be assessed based on its potential complications for the implementations of business analytics. Modern systems with a modular architecture tend to be preferred over traditional systems.

To advocate for the necessary investments and political support, the role of top management and a promoting BI&A culture is key. Thereby, low levels of bureaucracy in SMEs tend to accelerate implementations. This is also considered a risk due to the potential lack of focus and the need for scalable and robust analytics infrastructure. When focusing on a specific BI&A project, ensure constant user feedback and visibility throughout the organization. Most business analytics projects derive from BI&A strategy, which is partly a derivative from organizational strategy and partly focused on the technical aspects as architecture, data quality, and analytics techniques.

What became clear in this study is that many SMEs don't know what steps to take in maturing their business analytics and therefore search for some sort of framework structuring their approach to utilization of business analytics. Mostly driven by enabling technologies and specific problems business analytics is implemented within SMEs. However, there are some returned and uniform challenges faced by SMEs such as data quality, lack of support and visibility, lack of integral insights, lack of skills and expertise, inability to collect the right data from internal sources due to lack of digital processes and most important; an absence of overview of different stages of utilization with its impact on different dimensions of business analytics.

The main goal of this study was exploring different BI&A dimensions to gain deeper insight in utilization of business analytics in SMEs. By studying how different SMEs utilize BI&A on different business analytics dimensions, the different stages of BI&A maturity for SMEs can be guiding for practitioners implementing BI&A. Also understanding the barriers and challenges faced when utilizing business analytics are relevant insights for practitioners. The maturity model proposed in this study can guide practitioners in the process of capturing value from BI&A.

Thereby, the overview of utilization of business analytics in SMEs can be guiding for future research. This is the first integrative maturity model, meaning that all important dimensions are considered instead of focusing on specific dimensions. This more complete and integrative maturity model can be used for studies regarding the implementation of business analytics or the adoption of business analytics in the context of SMEs. Thereby, this study focusses on the SME context which is underexposed in current research and could therefore be used as guidance for further research. Technical barriers and challenges found in this study can be guiding for further research in computer science. Organizational components of business analytics utilization can be guiding for further research in the field of organization studies or business administration. For example, new hypothesis can be formulated and tested based on this study. It might be interesting to test the relationship of BI&A maturity with financial performance, customer satisfaction or employee satisfaction. Besides validating the model and developing new hypothesis, also benchmarking of different sectors in SMEs could be interesting for further research. This can give SMEs insights in their own relative maturity position compared to the market or competitors.

This study has given a clear overview and offered a gradual approach to the utilization of business analytics within the context of SMEs. It shares different best practices, but also barriers and drivers of BI&A utilization. Thereby, given the different stages of utilization and implementation of the different companies interviewed, the study gives direction for BI&A implementation in the SME sector. The gradual approach on utilization shows the cohesion of different dimensions of BI&A and their relative importance for creating business value.

6.1 Limitations and suggestions for further research

This explorative study could be input for qualitative studies that can test the different levels of utilization proposed in the framework as result of this study. Based on a larger sample, there might be new insights regarding the utilization of business analytics. The small sample size is a limitation of this research. Interviews were mostly 1 to 1,5 hour of duration and therefore suited for explorative and in depth analysis. Thereby the data collection was done until saturation was reached. The main limitation of the sample size could therefore be the generalizability of this study. For future research, more SMEs can be interviewed to check up on the proposed framework to reach a higher generalizability.

Thereby, through purposive sampling only SMEs that were mature were interviewed in this research. To get a more complete image of challenges that withhold SMEs to start with business analytics, the sample should be more broadly and also include SME's that don't have utilized business analytics activities yet. However, this potential bias is mitigated by selecting some agencies for this study that oversee multiple SMEs and the way they utilize BI&A. For further research, also quantitative studies are suggested. For example the factors that lead to adoption or assessing the specific impact of business analytics utilization on SME performance.

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Appendices

Appendix A: Interview protocol

1. <u>Introduction</u>
- Introducing the interview, explaining the purpose of the interview and explain that the data is used for research purposes only.
2. <u>History of business analytics in the organization</u>
- How did the use of business analytics develop throughout the years in the organization?
- Did implementation require a significant amount of change in the organization and culture?
- What were pitfalls and challenges when developing maturity of business analytics?
- What are potential trade-offs or challenges that may arise when implementing BI&A?
- Is there a business analytics strategy? And is business analytics part of the organizational strategy?
- What were the main drivers of business analytics implementation (and later utilization)?
    - Affordable technologies
    - Increasing data availability
    - Competitive pressures
    - Internal/external business analytics skills
3. <u>Current use of BI&A</u>
- What business applications and tools are used?
- What analytics techniques are used?
- How is the BI&A architecture structured? i.e. How are different applications and tools integrated?
- How is data gathered and used?
- How is dealt with the governance of data?
- How are business analytics products linked to performance management?
- How are KPI's and Metrics created?
- What is the impact of business analytics on the performance of different parts of the company?
- What skills and experience are needed in the organization to maintain the current level of business analytics maturity?
- How do you ensure business and IT are not working in silo's but enterprise wide?
4. <u>Quick wins and best practices</u>
- What are examples of business analytics products that were relatively easy to implement and had a relatively high business value?
- What best practices can be shared?
- Are there specific functional area's that are considered more suitable for business analytics? I.e. easy to implement or high business value?
- If I had an SME, and I want to make a start with business analytics, what would be your advice?

- What are skills you definitely need in your organization to successfully utilize business analytics?
- What is the biggest pitfall for organizations that want to utilize business analytics?

5. <u>Future of business analytics in the organization</u>

- What is the next big step for your organization regarding business analytics?
- What barriers are you facing right now? And how are you planning to overcome them?
- What trends or developments do you see that can impact your business analytics strategy?

6. <u>Conclusion and closing</u>

- Thanking the interviewee, offer the opportunity to add additional information which isn't discussed but might be important for the study. Also ask for snowball samples.

Appendix B: Coding Scheme (236 quotes)

Deductive Code	Original Text
BI&A application & tools	When we started with business analytics, we had many different version
BI&A application & tools	At first, we used a large Excel file with many pivot tables to visualise data
BI&A architecture	We build a cloud data warehouse to be able to connect data from differe
BI&A change management	We started to build data awareness within the organisation by training 'c
BI&A strategy	We wanted to professionalize business analytics, so we started a trajecto
Analytics techniques	Creating dashboards and reports is relatively easy to do, if one employee
BI&A maturity	We started with operational reporting, how many turnover per product.
BI&A drivers	All data visualisation, of which parts were indispensible for the organizat
Data quality and use	All data visualisation, of which parts were indispensible for the organizat
BI&A architecture / application & tools	We used a cloud data warehouse to be scalable.
BI&A change management	We want everybody in the organisation to work data-driven
BI&A strategy	We want to give every department the space to do what they are good a
BI&A application & tools	We use tooling that enable all employees to create their own insights.
Roadmap	We started with building visualisations to create value for departments a
Roadmap	After creating dashboards, we build a data governance, to ensure we kno
BI&A change management	To create awareness, we trained 6 employees to be ambassador and be a
Business and IT alignment	Dashboards and insights are created based on questions from employees
Business and IT alignment	When the data department was created as a seperate department, the n
Skills and experience	The main roles in our data team are data analist, data engineer and data
Skills and experience	The data analist creates dashboards and insights.
Skills and experience	The data engineer creates and manages the data-infrastructure.
Skills and experience	The data manager ensures collecting, organising and visualising data to s
BI&A maturity	We only use descriptive modeling, in the future we want to go to predict
Data quality and use	We mostly use internal data.
BI&A change management	The most important example of business analytics adoption is being able
BI&A change management	We implemented business analytics case by case, to make sure the chang
Business and IT alignment	We changed processes based on insights generated by our data departm
Performance management	We were able to analyse the impact of change of internal processes on c
Data quality and use	Automation of data imports helped us to be less vulnerable to losing data
Skills and experience	We are lucky to have a relative young organisation with data and digital r
IT infrastructure	Older and more traditional organisations tend to have a ERP and a CRM s
BI&A architecture	Data warehouse enables us to connect data from different data silo's

IT infrastructure	We have a modular architecture, which means we are able to connect ne
BI&A change management	Being a young organisations helps us in the way that we don't have to ge
Challenges	Biggest challenge is focus, if you want to do new things to quickly it's a ris
BI&A maturity	We guard the development of maturity by using a roadmap.
BI&A strategy	We guard the development of business analytics by developing dashboar
BI&A strategy	Organisational strategy is leading for us as analytics department
Business and IT alignment	Cases from business operation are leading for our activities as analytics d
BI&A application & tools	The next analytics step we want to take is customer segmentation.
BI&A application & tools	In the future we want to use open-data sources, like KvK or other registe
BI&A maturity	The heavyness of projects moves to data engineering when we are going
Roadmap	In the premature stadium the most important role of a analytics departm be able to connect multiple data sources. When moving to more advance
Skills and experience	The most important role of a data engineer is connecting multiple data s
Performance management	We use data to test assumptions on how we can best do business.
BI&A strategy	Our main business analytics strategy is to become a data driven organisa
change management	There is difference in ability of employees to adapt to a data driven way o
BI&A strategy	Data is a competitive adventage on the long term.
BI&A application & tools	We visualise data in tableau.
BI&A application & tools	We use a cloud data platform.
BI&A architecture	We use external API's to enrichen our data warehouse.
BI&A strategy	We expect process mining to be a large component of our analytics depa
Data quality and use	We have publiced verified datasets, so employees can build their own an
Analytics techniques	We expect self-service BI to grow in the future, since we expect data-liter
Functional fields	We currently use business analytics in HR, marketing, operation, strategy
BI&A maturity	My most important advice to start with business analytics is: start small a
Skills and experience	Be aware of the possible challanges and risks, and therefore get help fron
BI&A strategy	We started with business analytics with watching: what are our needs? W
IT infrastructure	Because of an old traditional system, the change for the organisation was
Drivers	The major problem we had was being unable to adjust production planni
Data quality and use	The ERP we have doesn't log historical data, which loses the possibility to
IT infrastructure	The new ERP was the first step to start implementing business analytics.
IT infrastructure	The ERP made it possible to gain real-time access to customer demand.
architecture	We started building a data-warehouse to be able to get access to historic
Business and IT alignment	The first demand for business analytics came from the purchasing depart
Performance management	We are able to predict customer demand and adjust our internal operatio
BI&A application & tools	We choose for PowerBI since there is a large community to help with que
Skills and experience	We used help of an external party to create dashboards and create a dat
Promoting BI&A culture	It helped that the CEO has a high willingness to invest in business analytic
Promoting BI&A culture	It helped that we don't have a bureaucratic culture, so we could impleme
Skills and experience	We used expert relations to help us develop business analytics maturity w
BI&A strategy	We made a checklist with user requirements, dashboard requirements as
application / infrastructure / value creating	The first big step was matching sales and operations data.
bi&a architecture	Building the database structure was a huge milestone to be able to gener
Skills and experience	An important role is the data manager, connecting business to analytics r
Business and IT alignment	In my experience, technical oriented data engineers lack business sense,
Skills and experience	Requirements were determined by business users, execution was done b
challenges	It's hard to gain requirements from business users, when they don't know

challenges	Adoption of analytics tools was hard, since employees still used the ERP s
adoption / change management	To help adoption we organised a kick off so the advantages are understa
Business and IT alignment	To ensure quality of dashboards, feedback from users is really important
BI&A strategy	We use meta data to ensure dashboards are used properly
change management / adoption	We made sure that dashboards are visually present in every room using T
Skills and experience	We need employees that are data literate, since now we started with bu
Analytics techniques	We use trends in our data to be able to predict changes in customer dem
Skills and experience	A full time employee responsible for data management is important to e
change management	The organisation should be facilitated with data continuously, in order to
Promoting BI&A culture	Awareness of business analytics is maintained by giving analytics a seat a
Performance management	We translate strategic goals to KPI's to measure progress
change management	By creating basic analytics products, employees create a better understa
Performance management	Analytics reports can help creating clarity in personal responsibility if use
strategy	Governance is important to be sure employees look at trustable insights.
architecture	A major risk is that the database structure and architecture of the data w
strategy	Business analytics is also important for us to be able to automate proces
Analytics techniques	We could use business analytics more for our finance department.
BI&A strategy	An important challenge was the structuring of such a large project as sta
Skills and experience	To be able to use business analytics, one should be able to manage exter
bi&a architecture	Both the complexity and the value is in coupling different datasets.
challenges	Employees that don't have affinity with systems and data are challenging
Skills and experience	It is important to know what roles and competency's are important for d
architecture	Currently we use analytics on different silo's within the organisation. We
Analytics techniques	We are using benchmarks to compare our performance to industry avera
Analytics techniques	We use analytics to optimize planning and efficiency based on customer
drivers	Business analytics is mostly used to help companies work more efficientl
strategy / architecture	Most companies want to stop working decentral and exporting data man
challenges	Mostly technical barriers stopped companies to use business analytics, a
BI&A application & tools	The visual aspect of the tool PowerBI makes it an attractive tool for diffe
drivers	Both efficiency problems and technical opportunities push the developm
current state	I don't think many organizations are data driven in the SME sector, even
Analytics techniques	Mostly business analytics is presenting insights automatically
Promoting BI&A culture	I don't think the culture will change due to business analytics
maturity	Business analytics allways starts with the informational demand.
drivers	Examples of informational demand are tracking strategic goals, more eff
maturity	Because an organisation starts exporting data automatically, you spot m
Analytics techniques	When data is exported, data is modelled so it's more easy to report on th
Data quality and use	When data is exported automatically, it's usually done on bigger scale wh
Skills and experience	SMEs are unaware of the costs of advanced analytics implementation an
challenges	Biggest challenge for business analytics are data quality and implementin
Business and IT alignment	For implementation of business analytics it's important to ask user feedb
change management	When insights are shown that are incorrect, it can be devestating for imp
BI&A application & tools	Within reports one should define how things are measured to understan
BI&A strategy	sometimes business analytics is linked to organizational strategy, but it d
BI&A application & tools	If not linked to organisation strategy, business analytics is mostly used fo
drivers	Cloud technology is an important driver of business analytics.
Business and IT alignment	SMEs use business analytics also for marketing purposes to share insight
application & tools	PowerBI, Qlick and Tableau are the most used tools within SMEs.

maturity	There are not many companies that are looking for predictive modeling.
Performance management	liquidity planning is between predictive and descriptive analytics. Becaus
drivers	biggest advantages for using business analytics are efficiency, accessibilit
challenges	Disadvantage are feeling for the context of some visualisations.
challenges	Automated reports give problems regarding the ad-hoc reporting in exce
challenges	Unability to change and adapt quickly to changing context adds some cor
architecture	Architecture mostly is build up out of the company systems, a data-layer
Data quality and use	Data governance is usually limited in SME's and very informal.
Data quality and use	Data responsibility is usually not given to someone specific within the org
Business and IT alignment	There are two types of uses for business analytics; monitoring operationa
Skills and experience	SMEs are mostly dependent on external expertise since they don't have a
Skills and experience	For succesfull use of business analytics, both business and technical know
BI&A strategy	business analytics are mostly used in finance, but also in operations, HR a
quick wins	Easy to implement with high business value is the automation of reports
Business and IT alignment	We use business analytics to support the choices we make in the compar
implementation	The first step in implementing business analytics was making an overview
strategy	The main purpose was to be proactive as a company in stead of reactive.
bi application & tools	We know what the trends in the industry are, now we managed to captu
application & tools	Describing trends in industry helped us to give actionable insights for peo
bi application & tools	We used a special software to digitise processes, being able to track the p
bi&a strategy	We use reports to share information with customers and partners in a m
change management	To manage the change, it's important to show the benefits in terms of ef
quick wins	Data enables us to justify certain choices based on facts, in stead of feelir
architecture	We could capture more data from systems, which right now doesn't hap
architecture	The outdated system we use is a barrier for us to develop our BI&A
bi&a strategy	We want to use our predictive capacities to no longer stand for surprises
Performance management	We monitor on our strategic goals to check our progress
change management	BI&A still doesn't get the attention and urgenci it should. In the organisat
Skills and experience	Currently it's hard for us to find out how we combine external data with
Skills and experience	Our BI&A is so premature, we don't need governance yet.
quick wins	BI&A gives us business value by being able to make fact-based decisions.
BI&A application & tools	Reports are used to facilitate meetings
Business and IT alignment	Strategically we have 5 result area's that give direction to our BI&A pract
BI&A application & tools	We monitor progress on projects in % finished.
bi&a architecture	A big next step for us is to collect data in a central place. So we can gathe
bi&a strategy	To bring business analytics to the next level, we need someone to pay fu
bi&a architecture	If you build multiple reports on multiple systems or excel files, there are
Performance management	We can deploy strategic goals to departments and persons, so everyone
Skills and experience	We need someone who can guide us through the maturity process and s
Skills and experience	For bi&a you always need a combination of business administration skills
BI&A strategy	We believe that if you're not data-driven at a certain point, you will lose
Skills and experience	You need ETL engineers to build the data pipeline
change management	When we start working with data, we work to a proof of concept that de
bi&a strategy / skills	Becoming more mature in data starts with top management, they need t
Skills and experience	Many SMEs don't have the skills and experience in-house to capture valu
BI&A application & tools	Many SMEs have a dashboard or report in Excel, still struggling to autom
challenges	Some SMEs have a BI&A team, a frequently made mistake is that they de
Performance management	Insights should be actionable in order to create value.

maturity	Data quality and analytics translation from business goals to actionable i
Skills and experience	Data quality and analytics translation are key parts of making descriptive
maturity	You can't start with predictive analytics if the basis isn't ready, and the b
maturity	With descriptive analytics you create the context, which helps you to bui
architecture	Mostly data scientist are using unstructured data from a datalake or stru
Data quality and use	descriptive analytics tells you if your data quality is high or low
change management	Key issue is creating visibility for BI&A within the organisation.
architecture	To capture value from predictive analytics one has to integrate multiple
bi&a strategy	It's important to not reason from data, but from business problems and
Performance management	mostly we translate organisational strategy to operational problems to d
Performance management + analytics maturity	Standard dashboards in ERP systems lack context, reaching 500 more sal
bi&a strategy	Goals and insights need to be actionable in order to create value
application & tools	Building something employees or a manager wants is something differen
Data quality and use	The more you go to predictive or prescriptive, the more data you need.
bi&a maturity + data quality and use	To be able to predict something, data needs to have predictive value.
Skills and experience	There is a lack of knowledge in SMEs on how to build an ETL pipeline tha
bi&a architecture	Based on the predictive value you want to capture, you can fill your data
Skills and experience	The art of data science is being able to spot predictive value in datasets.
change management	Organisation wide there has to be a change in culture to adapt bi&a
change management	Data can be felt as a threat for people, since their performance is sudde
challenges	Data is mostly seen as part of IT, and therefore as a cost center. In bad ti
challenges	First the challenge is political, determining what data projects to prioriti
Business and IT alignment	To optimise processes using data, one has to get insight in bottlenecks s
bi&a strategy	Value can be quantified by calculating cost reduction due to a specific da
strategy	To start with BI&A one should make a proof of concept or a product that
drivers	main driver of BI&A is efficiëncy
applications & tools	statistical analysis like AB testing and basket analysis is used.
BI&A application & tools	clustering is used as a technique, mostly for segmentating customers
bi&a architecture	mostly a datalake is connected to all systems with API's, and the data wa
application & tools + architecture	The visualisation layer is built on the warehouse, mostly using PowerBI.
application & tools + architecture	Right now most SMEs use seperate tools, but saas companies are moving
Data quality and use	governance is important from a security perspective.
Skills and experience	Skills needed in an organisation depends on the size of the company.
Skills and experience	Soft skills in data are needed on board level.
Skills and experience	Smaller organizations need more generalists to add value, larger organiz
Skills and experience	Visualisation of data is an important skill to start with bi&a, since it has t
bi&a strategy	IT is more focused on the basis structure of business processes, BI&A is f
implementation	A great functional area to start with is often commercial, since they have
implementation	a functional area to start with is finance, since they are used to working
bi&a strategy	Mostly is the goal from a bi&a perspective to create grip on the business
application & tools	BI&A is used to increase sales and do risk analysis
application & tools	BI&A helps us to get a better definition of our customer
architecture	We combine internal data with open data to generate insights.
Business and IT alignment	You can detemine what to include in your data lake or datawarehouse us
drivers	Behind the step of prescriptive there is a step where you can automate d
maturity	Certain parts of an organization can be further in automating stage, othe
implementation	When you want to tackle a business problem, it's important to start with

Data quality and use	You need historical data to be able to validate your predictive models.
Analytics techniques	Analytics techniques we use are correlation, random forest model, XG bo
Data quality and use + maturity	The more complex the context of your problem, the harder it is to find co
maturity	The step to prescriptive analytics is nothing more as translating your pred
change management _ culture	What we see in developing a data driven culture, is that data becomes m
challenges	A serious challenge for a data driven culture is that anyone should know
challenges	Sometimes analysts forget to add an important dimension, and therefore
strategy	when implementing bi&a, it's important to look at the expected business
maturity + strategy	when organization siz is increasing, scalability of different predictive mod
application & tools	tekst mining is used to analyse e-mails to track customer satisfaction.
strategy	generally we divide our data projects in two strategic themes; efficiency
application and tools	attribution models give insight in customer processes and help prioritize
bi&a strategy	the key value in bi&A is making better decisions
Skills and experience	Important for implementing bi&a is knowing the market that your compa