Master Thesis

Influencing factors of Data-Driven Decision-making adoption in the Netherlands

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Abstract

Nowadays, with Internet of Things and the exponentially increasing available data, new opportunities have emerged for organisations to base their decision-making on facts and data. Therefore, this study aimed to deepen further knowledge of the influencing factors of Data-Driven Decision-making adoption by fast-growing organisations in the Netherlands. The results of this research support the view that the factors organisation size, rate of high educated employees, executive commitment to data, and interdepartmental dynamics have a significant positive impact on the adoption of Data-Driven Decision-making of organisations. However, it seems that organisational structure, investment amount in IT, the market type and the competitive intensity in the market in which organisations are operating do not have a significant effect on the adoption of Data-Driven Decision-making in this sample. Additionally, this study provided an overview on what the organisations in this sample consider as barriers when trying to adopt Data-Driven Decision-making. Adopting new technologies often accelerates the demand for skilled and educated workers. This could also be seen in this sample as the vast majority of the respondents considered the lack of skills and workers as the biggest barrier to adopting Data-Driven Decision-making. Furthermore, this study was able to provide evidence for the mentioned factors to have a positive effect on the adoption of Data-Driven Decision-making.

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List of abbreviations

Abbreviations	*Definition*
IoT	Internet of Things
DDD	Data-Driven Decision-making
BI&A	Business Intelligence & Analytics
ADV	Advanced Data Visualisation
MPP	Massive Parallel Processing

1. Introduction

1.1 Background

In the recent years, there have been significant changes in data storage and processing technologies (Brynjolfsson & McElheran, 2016, p. 1). New opportunities have emerged to collect and leverage data, which has led many managers to change how they make decision relying less on intuition and more on data (Brynjolfsson & McElheran, 2016, p. 1). Brynjolfsson, Hitt, and Kim (2011, p. 1) state that managerial decisions in more and more companies rely less on a leader's "gut instinct" and instead data-based analytics. At the same time with the data revolution, firms are gathering extremely detailed data from consumers, suppliers, alliance partners, and competitors (Brynjolfsson et al., 2011, p. 1). Sleep, Hulland, and Gooner (2019, p. 1) also state that managers have access to a greater volume and variety of data than ever before, from customer transactions, social media interactions, online activities, wireless sensors, and mobile phones. These data sources are all driving the need for more proactive and real time analysis and decision making (Henke et al., 2016).

With the Internet of Things expanding and the evolution of Big Data, the data available is growing exponentially. This growth in the availability of data with vast volume, variety and velocity has resulted in a big data revolution that has the potential to improve the decision-making performance of organisations with associated competitive advantage (Chen, Chiang, & Storey, 2012). In 2005, the term Big Data was coined for the first time. This term referred to a large set of data that is almost impossible to manage and process using traditional business intelligence tools (Halevi & Moed, 2012). Big Data has expanded beyond the ability of commonly used software tools and storage systems to capture, store, manage and as well as process the data within a tolerable time frame (Elgendy & Elragal, 2016). For that reason, data analytics is being increasingly leveraged by many organisations to deal with the vast amounts of data they collect and to realise their growing needs for better and faster decision (Loebbecke & Picot, 2015). Data analytics is a combination of processes and tools, including those based on predictive analytics, statistics, data mining, artificial intelligence, and natural language processing (Russom, 2011). Data analytics is often applied to large datasets for gaining invaluable insights to improve the decision-making of organisations (Ertemel, 2015). According to Elgendy and Elragal (2016), data analytics can significantly improve decision making, minimize risks, and uncover valuable insights from the data that would otherwise remain hidden.

However, even though data analytics offers benefits in terms of decision-making to improve performance, there are certain challenges which organisations are facing when adopting Data-Driven Decision making (DDD). Successfully adopting DDD will depend on various organisational and technological factors (Brynjolfsson & McElheran, 2016; Sleep et al., 2019). Organisations need the right organisational structure, management, tools, staff and skills to successfully change to being data-driven (Brynjolfsson & McElheran, 2016; Sleep et al., 2019). Additionally, Russom (2011) states that big data presents technical challenges due to its volume, variety and velocity and that volume alone is a showstopper for some organisations. However, even though big data comes with challenges, the vast majority of organisations still consider big data an opportunity which can be used for business advantage (Russom, 2011). Another challenge with adopting DDD is shortage of skills. According to a recent survey of KPMG by (Wesselman & Koot, 2019), big data and analytics is the number one place of need in terms of skills shortages. This shortage in analytics skills is having a significant impact on all organisations, with two-thirds of IT leaders saying it is preventing them from keeping up with the pace of change (Wesselman & Koot, 2019).

1.2 Goal and Research question

Data-Driven Decision-making (DDD) has been an important and thoroughly covered topic in research throughout the years. The qualitative study of Sleep et al. (2019) has studied factors that influence the adoption of DDD by marketeers. The quantitative study of Brynjolfsson and McElheran (2016) has also studied the influencing factors DDD adoption, but this research is purely focused on US manufacturing organisations. According to the study of Damanpour and Schneider (2006), growth is considered a prominent factor influencing technology adoption and process innovation. Additionally, there is little to no prior research regarding the influencing factors of DDD adoption by organisations in the Netherlands. This thesis will build further on these studies by conducting a quantitative research on the adoption of Data-Driven Decision-making within fast-growing organisations in the Netherlands. As mentioned earlier, growth is considered a prominent factor influencing technology adoption, and that data analytics offers benefits in terms of decision-making to improve performance. This thesis will provide insight on which factors had a positive influence on the adoption of Data-Driven Decision-making within growing organisations who have succeeded in improving their performance. Therefore, the goal of this thesis is to research to what factors are positively influencing the adoption of DDD in growing organisations from various industries in the Netherlands. Additionally, this thesis will also study which challenges and barriers these organisations face when adopting DDD. Hence, the following research question is formulated:

"What are the influencing factors of Data-Driven Decision-making adoption for organisations in the Netherlands?"

In order to reach the goal of this thesis, a literature research will be conducted to provide information about which has already been studied related to the research question. This will be done by studying scientific articles that have been written over the years. When possible, the most recent papers have been studied for the literature review. This is done because the technologies regarding data analytics and Data-Driven Decision-making have been developing rapidly in the recent years (Brynjolfsson & McElheran, 2016). Additionally, papers which specifically focus on Data-Driven Decision-making and the adoption of it have been studied, because it is assumed that these papers will provide more insight than papers focused on technology adoption factors in general. Thereafter, surveys are conducted among organisations in the Netherlands from various industries.

1.3 Theoretical contribution

This thesis contributes to the emerging research on DDD and helps identify the relationship between organisation characteristics and DDD adoption. In terms of theoretical contribution, this thesis contributes to the paper of Brynjolfsson and McElheran (2016) and Sleep et al. (2019) regarding the influencing factors of DDD adoption for growing organisations in the Netherlands. The paper of Sleep et al. (2019) in particular is a qualitative study in which influencing factors have been studied. This thesis will add to the literature by conducting a quantitative research by studying the impact of these influencing factors on fast-growing organisations in the Netherlands, and whether there are noticeable differences.

The papers of Mohamed and Al-Jaroodi (2014) and Russom (2011) present the technological challenges regarding the adoption of DDD. This research will contribute to these papers by identifying what growing organisations in the Netherlands consider as challenges when adopting DDD. Lastly, according to a recent survey of KPMG by Wesselman and Koot

(2019), big data and data analytics is the number one place of need in terms of skills shortages. Therefore, this research will help to get a better understanding between the relationships of DDD adoption and the availability/shortage of skills in growing organisations in the Netherlands.

1.4 Practical contribution

In terms of practical contribution, this research will be explanatory and aims to give managers of organisations, employees, marketeers, or other researchers knowledge about the adoption of DDD and the challenges which organisations are facing when implementing DDD. The need of having this knowledge was addressed by Brynjolfsson and McElheran (2016), who provided the first systematic empirical study of the adoption of DDD and the factors influencing its adoption. However, the study of Brynjolfsson and McElheran (2016) only focused on US manufacturing firms, while this thesis will focus on organisations in the Netherlands from various industries. Furthermore, Brynjolfsson and McElheran (2016) and Sleep et al. (2019) state that DDD is of great significance in this era of data overflow and can provide unforeseen insights and benefits to decision makers in various areas. However, organisations need to focus on doing something that creates value with the data that comes available. Collecting data and making data-based decisions should not be a goal itself. Therefore, this thesis will help practitioners to get a better understanding of organisational and technological factors that positively influence DDD adoption and pitfalls that can hold organisations back from adopting DDD.

2. Literature review

This chapter introduces a variety of literature related to big data analytics and the decision-making process of an organisation. First, big data will be described in order to understand the concept of big data in general. Second, data analytics will be studied to describe its methods and the possibilities that come with it. Thereafter, Data-Driven Decision-making with data analytics will be described. Then the literature regarding the adoption of Data-Driven Decision-making will be studied. Lastly, conclusions will be drawn about the literature and further research based on the literature findings will be implied.

2.1 Data & Big Data characteristics

The rapidly increasing quantity and variety of data from customers and stakeholders is called "Big Data" by managers to describe this phenomenon (Sleep et al., 2019, p. 1). Big Data is viewed by many as critical to providing a better understanding of customers and markets and also as the basis for DDD (Elgendy & Elragal, 2016, p. 2; Provost & Fawcett, 2013, p. 1; Sleep et al., 2019, p. 1). Brynjolfsson et al. (2011, p. 5) also state that the increasing interest in big data largely emphasizes the benefits of incorporating DDD, referring to the business practices surrounding the collection and analysis of external and internal data. Therefore, literature regarding big data is studied to have a clear understanding about the concept. While big data is fairly known today, as a concept, it has uncertain origins. Big data definitions have also evolved rapidly, which has raised more confusion. An online survey of SAP among global executives showed how executives differed in their understanding of big data, where some definitions focused on what it is, while others tried to answer what it does (Gandomi & Haider, 2015). However, the size of big data was the characteristic that was common between all of the executives. Many scholar and practitioners of big data define big data in terms of three V's: Volume, Velocity and Variety (Chen et al., 2012, p. 19). The three V's have emerged as a common framework to describe big data (Chen et al., 2012, p. 19). Another example of the definition of big data is as following:

"Big data is a term for massive data sets having large, more varied and complex structure with the difficulties of storing, analysing and visualizing for further processes or results." (Sagiroglu & Sinanc, 2013, p. 1)

Additionally, Fan, Lau, and Zhao (2015, p. 1) define Big Data as:

"*The amount of data just beyond technology's capability to store, manage and process efficiently.*"

Looking further into the matter of the three V's of big data, volume is the first one that is mentioned by many studies. Volume refers to the magnitude of big data, hence the term "Big" data. However, definitions of volume are relative and vary by factors, such as time of data. What is seen as big data today may not meet the requirements in future because storage capacities will increase, allowing even bigger data sets to be captured. Variety is the second V, and it refers to the different types of data within the big data concept. The last and third V is velocity, which refers to the rate at which data are created and changed, and the speed at which it should be analysed and acted upon. Even though the three V's have emerged as a common framework to describe big data, many studies have attributed other qualities to big data. However, these new attributes differ too much per study. That is why this literature will only focus on Volume, Variety and Velocity. To have a clearer understanding about big data in terms of the three V's, the definitions of the V's and their sub-dimensions have been stated from various studies in table 1.

Table 1. Three V's of big data

Term	***Definition***
Volume	• *"Data volume is the primary attribute of big data. Big data can be quantified by size in TBs or PBs, as well as even the number of records, transactions, tables, or files."(Elgendy & Elragal, 2014, p. 3; Russom, 2011, p. 6)* • *"Consisting of enormous quantities of data" (Kitchin & McArdle, 2016, p. 1)* • *"Volume or the size of data now is larger than terabytes and petabytes. The grand scale and rise of data outstrip traditional store and analysis techniques" (Sagiroglu & Sinanc, 2013, p. 2)*
Variety	• *"Variety is the fact that data are generated from a large variety of sources and formats, and contain multidimensional data fields including structured and unstructured data."* (Russom, 2011, p. 7). • *"Data being structured, semi-structured, and unstructured"* (Kitchin & McArdle, 2016, p. 1) • *"Variety refers to the structural heterogeneity in a dataset" (Gandomi & Haider, 2015, p. 2)*
Velocity	• *"Velocity refers to the rate at which data are created and changed, and the speed at which it should be analysed and acted upon"* (Gandomi & Haider, 2015, p. 2) • *"The frequency of data generation or the frequency of data delivery"* (Russom, 2011, p. 7) • *"Data which is created in real-time"* (Kitchin & McArdle, 2016, p. 1)

However, even though big data analytics offers many benefits, it does come with certain challenges. According to Mohamed and Al-Jaroodi (2014, p. 1), the sheer size of such data halts new technological challenges in terms of storage capacity and management, organisation, processing and analysis. L'heureux, Grolinger, Elyamany, and Capretz (2017, p. 4) add to this by stating that volume is one of the main challenges encountered in computations with big data. Consequently, as the volume of the data becomes larger, even insignificant operations can become costly (L'heureux et al., 2017, p. 4). Additionally, Russom (2011, p. 12) also states that big data presents technical challenges due to its volume, variety and velocity and that volume alone is a showstopper for some organisations. However, even though big data comes with challenges, the vast majority of organisations still consider big data an opportunity which can be used for business advantage (Russom, 2011, p. 12). Another challenge with big data is shortage of skills. According to a recent survey of KPMG by (Wesselman & Koot, 2019, p. 14), big data and analytics is the number one place of need in terms of skills shortages. This shortage in analytics skills is having a significant impact on all organisations, with two-thirds of IT leaders saying it is preventing them from keeping up with the pace of change (Wesselman & Koot, 2019, p. 19). Because big data is often the basis for

DDD, looking ahead of this research, these challenges of big data may also reflect on the adoption of DDD within organisations in the Netherlands.

2.2 Data analytics

Data in itself without extracting insight from it is worthless. The potential of data lies in its ability to drive decision making. In order to realise decision making based on data, organisations need efficient processes to turn high volumes of rapid and diverse data into meaningful insight (Gandomi & Haider, 2015, p. 4). This is where data analytics come into play. According to Labrinidis and Jagadish (2012, p. 1), the overall process of extracting insights from big data can be broken down into five stages, which can be seen in figure 1. The five stages consist of two main sub-processes: data management and data analytics. Data management refers to the processes and supporting technologies to obtain and store data and to prepare and retrieve it for analysis. Analytics refers to the techniques which are used to analyse and obtain intelligence from big data. Thus, data analytics can be seen as a part of the overall process of extracting insight from big data (Gandomi & Haider, 2015, p. 4; Labrinidis & Jagadish, 2012, p. 1).

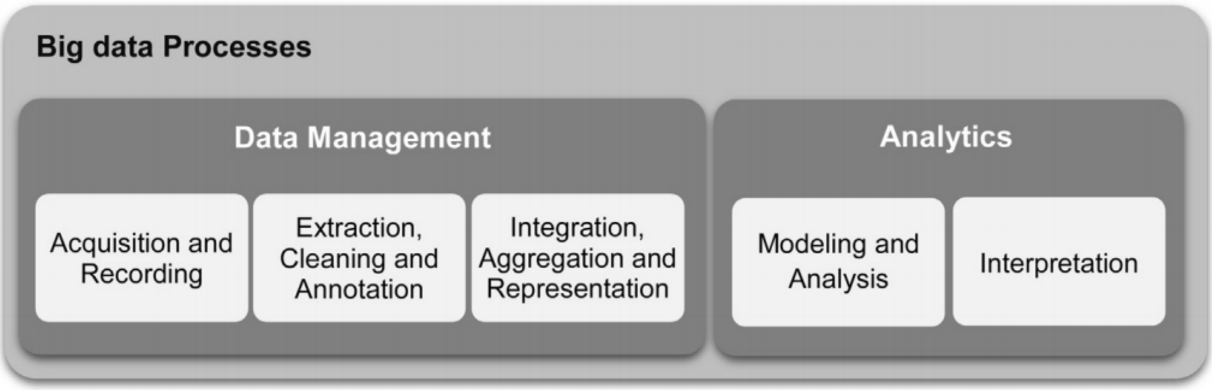

Figure 1. Processes for extracting insights from big data (Labrinidis & Jagadish, 2012).

Data management is the first thing organisations have to deal with when working with big data. The management part is where and how this data will be stored once it is acquired (Gandomi & Haider, 2015, p. 4). The first step in Data Management is data acquisition. There are data sources which can produce immense amounts of raw data, such as sensor networks. However, most of this data is of no use, and it can be filtered and compressed by orders of magnitude (Labrinidis & Jagadish, 2012, p. 1). The challenge in this process is to define filters in such a way that they do not discard useful information. An example of this is retaining certain information which is taken from new reports. The challenges with this method are the options to retain only the news reports that mention the name of a company of interest, to retain the full report, or just a snippet around the mentioned name (Labrinidis & Jagadish, 2012, p. 1). The second big challenge is being able to generate the right metadata automatically to describe what data is recorded and how it is recorded and measured. In order to conduct a downstream analysis, the generated metadata is crucial, because the source of each news report may need to be known if duplicates have to be examined (Labrinidis & Jagadish, 2012, p. 1). Usually, the information which is collected will not be in a format which can be analysed immediately. The second step of the data management process is the extraction process. This process pulls out the required information from the sources and expresses it in a structured form which is suitable for analysis (Labrinidis & Jagadish, 2012, p.

1). A news report for example will get reduced to a concrete structure, such as a set of tuples or even a single class label, to facilitate analysis. However, the information which is extracted from big data may not always be correct. News reports for example can be inaccurate. Thus, the data management process ensures that the data is cleaned, transformed, and catalogued in order to make it available for data analytics. The data which is collected is stored by using Extract, Transform, Load (ETL) tools. These tools extract the data from outside sources, transform the data to fit operational needs, and then load the data into the database or data warehouse (Elgendy & Elragal, 2014, p. 4). The databases that are used for large datasets are Massive Parallel Processing (MPP) databases. MPP databases are optimised for analytical workloads, such as aggregating and processing large datasets, and they allow complex analytical queries to be processed much more quickly and efficiently (Bani & Girsang, 2018, p. 2). Additionally, Elgendy and Elragal (2014, p. 4) also mention the use of Non-relational databases, such as Not Only SQL (NoSQL), which are developed for storing and managing unstructured or non-relational data. NoSQL databases are used for massive scaling, data model flexibility, and simplified application development and deployment. Opposing to traditional databases, NoSQL databases separate data management and data storage. NoSQL databases focus mainly on the high-performance scalable data storage, and they make it possible to write in the application layer for data management tasks instead of writing in databases using specific languages designed for a certain database (Elgendy & Elragal, 2014, p. 4).

After the data management process, the analytics process comes into play. According to Elgendy and Elragal (2014, p. 5), there are four critical requirements for big data analytics. The first one is fast data loading, which is reducing data loading time. This is necessary, because the network traffic interferes with the query executions during data loading. The second requirement is fast query processing, which is necessary for requirements such as heavy workloads and real-time requests, because many queries are response-time critical (Elgendy & Elragal, 2014, p. 5). Thus, the structure of the data placement has to be capable of retaining high query processing speeds as the amounts of queries significantly increase. The third requirement is the efficient use of storage space for big data processing. The rapid growth in user activities demand a well-managed data storage, a scalable storage capacity and computing power in order to address issues on how to store the data so that space utilisation can be effectively applied (Elgendy & Elragal, 2014, p. 5). The last and fourth requirement that is mentioned by Elgendy and Elragal (2014, p. 5) is the strong adaptivity to highly dynamic workload patterns. This is necessary because big data sets are analysed by different applications and users for different purposes and in different ways. Thus, the underlying system should be highly adaptive to unexpected dynamics in data processing and analytics, and not restricted to a certain workload pattern. Furthermore, Labrinidis and Jagadish (2012, p. 1) mention that big data analytics is considerably more challenging than simply locating, identifying, understanding and citing data, because these processes need to happen in a completely automated manner in order for the large-scale data analytics to be effective. In order for this to be effective, the difference in data structure and semantics must be able to be expressed in forms that are computer understandable and then robotically resolvable. There remains an important question of suitable database design, even for more simple analysis that depend on only one data set, because there will be many alternative ways to store the same information. Some data base designs will have certain advantages over others for certain purposes and certain drawbacks for other purposes (Labrinidis & Jagadish, 2012, p. 1). However, at the end of the data analytics it all comes down to interpreting the results, because having the ability to analyse big data is of limited value if users cannot understand the analysis. Ultimately, a decision maker has to interpret the results of the big data analytics which involves examining all the assumptions that are made and retracing the analysis (Labrinidis & Jagadish, 2012, p. 1). There are many obstacles which are mentioned above for possible errors during the analytics process. The decision-maker can base their interpretation on wrong data if errors are made during this process, which is why it is crucial that the data analytics process must be without any errors (Labrinidis & Jagadish, 2012, p. 1). For all of these reasons, the results that are generated by the computer must provide supplementary information for the user by explaining how each result is derived and based upon precisely what inputs (Labrinidis & Jagadish, 2012, p. 1). Advanced Data Visualisation (ADV) is a technique which helps to present the results of data analytics so that people can consume it effectively, in order for analysts to be able to properly analyse data in way to lead to concrete actions (Elgendy & Elragal, 2014, p. 7). ADV refers to the technique which goes typically beyond the traditional data management, that uses the examination of data to discover deeper insights, make predictions, or generate recommendations (Elgendy & Elragal, 2014, p. 7). ADV combines data analysis methods with interactive visualisation to enable comprehensive data exploration. ADV does this by displaying data through interactive data visualisation with multiple dimensions, views, animations, and auto focus. This technique works particularly well in situations where analysts have little knowledge about the data. The demand for ADV has risen increasingly for many application domains, because of more and more data of high volume and complexity. The visualisation of ADV takes advantage of human perceptual and reasoning abilities, which enables people to thoroughly analyse data at both the overview and detailed levels (Elgendy & Elragal, 2014, p. 8). The intuitive representation and interaction of ADV is needed for the size and complexity of big data to facilitate the perception and reason of the analysts. ADV can enable faster analysis, better decision-making, and more effective presentation and comprehension of results by providing interactive statistical graphics (Elgendy & Elragal, 2014, p. 8). Furthermore, the reason why ADV is a natural fit for big data is, because it can scale its visualisations to represents thousands or millions of data points, unlike standard pie, bar, and line charts. Additionally, ADV can handle diverse data types, as well as present analytic data structures that are not easily flattened onto a computer screen, such as hierarchies and neural nets (Elgendy & Elragal, 2014, p. 8). Lastly, most ADV tools and functions can support interfaces to all the leading data sources, which can enable analysts to explore data widely across a variety of sources in search of the right analytics dataset (Elgendy & Elragal, 2014, p. 8).

However, regarding the future of big data analytics, the possibilities are endless. New possibilities are arising with evolution of technology and knowledge about data analytics. The future of BI&A, presumably to be addressed to as BI&A 4.0, is expected to be focused on the industrial environment along with the revolution of industry 4.0. Sharma and Pandey (2019, p. 1) state that the accelerating pace in change of information and communication technology has brought a phenomenal change in the industrial environment. With the evolution of the Internet of Things, massive amount of data has been generated and its optimal utilisation has contributed to shaping up the fourth industrial revolution. As a step towards the development of smart and sustainable industry, big data analytics is playing a critical role (Sharma & Pandey, 2019, p. 1). The overview of the BI&A eras along with their applications and emerging research areas can be seen in figure 2.

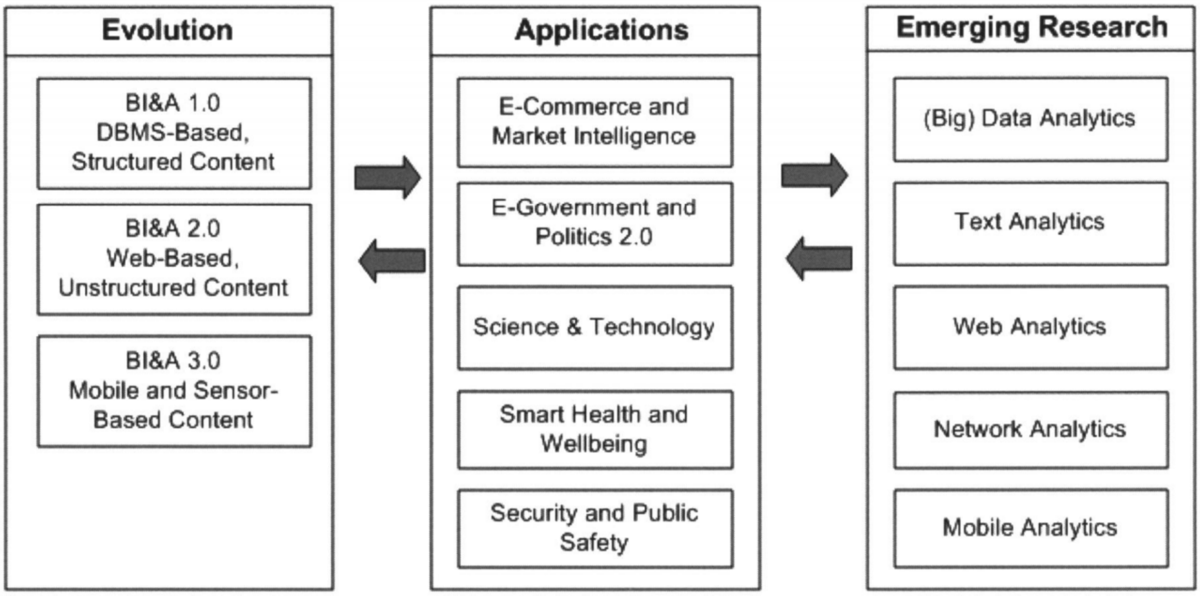

Fig 2. BI&A overview: Evolution, applications and emerging research (Chen et al., 2012, p. 3)

2.3 Data-driven Decision-making

After the collection of data from big data sources and the analytics of these data with BI, a decision has to be made to move forward as an organisation. According to Forman and Selly (2001), decision-making is the process of choosing among alternative courses of action in order to attain goals and objectives. Forman and Selly (2001) also argued that decision-making is the heart of all managerial functions, and that a rich decision-making process is the basis for the success of enterprises, because making the right decisions is crucial for gaining and maintaining a competitive advantage. There are many different decision-making models in the literature, however the most well-known process is the Decision-making process of Herbert Simon. Simon's model defines four phases of decision-making process: Intelligence, Design, Choice and Implementation phase (Simon, 1960). In the intelligence phase, decision makers examine reality and try to identify problems or opportunities correctly (Chiheb, Boumahdi, & Bouarfa, 2019, p. 2). In the design phase, the main goal is to develop and analyse different solutions to the problem or opportunity (Chiheb et al., 2019, p. 2). In the Choice phase, decisions are made by choosing one or more of the available alternatives developed in the previous phase (Chiheb et al., 2019, p. 2). In the last phase, which is the implementation phase, the chosen solution is implemented. Implementation can be either successful or not. Successful implementation results with a solution to a defined problem. On the other hand, failure results in a return to an earlier phase (Chiheb et al., 2019, p. 3).

However, decision-makers are constantly on the lookout for chances to make more informed decisions and they need to be able to understand and utilize big data in order to further enhance the traditional decision-making process into Data-Driven Decision-making (DDD) (Elgendy & Elragal, 2016, p. 2). Provost and Fawcett (2013) describe DDD as the practice of basing decisions on the analysis of data rather than purely on intuition. Furthermore, with the development of DDD, Elgendy and Elragal (2016, p. 4) have developed the B-DAD or the "Big – Data, Analytics, and Decisions" framework, which can be seen in figure 3. This framework was developed in order to map big data tools, architectures, and analytics to the different decision-making phases (Elgendy & Elragal, 2016, p. 4). In the B-DAD framework, the first phases are structured according to the Decision-making process of Simon with the four phases. The first phase in the B-DAD framework, which is the intelligence phase, is where data is collected from internal and external sources which can be used to identify problems and opportunities (Elgendy & Elragal, 2016, p. 3). In this phase, the sources of big data need to be identified, and the data needs to be gathered from different sources, processed, stored and then migrated to the end user. The first step is in the framework is identifying the big data which will be used for the analysis. In addition to relational data and common transactional or operational data, there is data from Internet of Things such as social media data, text, images and audio (Elgendy & Elragal, 2016, p. 3). Additionally, there is data which results as the output of machines and devices, such as system log files, sensor data, satellite data, and mobile or GPS data. Moreover, geospatial data has become very important for analysis, along with internet data, clickstream files and XML (Elgendy & Elragal, 2016, p. 3). Such big data needs to be treated accordingly, so after the data sources and types of data required for the analysis are defined, they need to be acquired and stored adequately. The acquired data can then be stored in any of the big data storage and management tools. These tools range from the open source mySQL or PostgresSQL, to EDWs and columnar or MPP databases, such as Cassandra, PADB, and SAND (Elgendy & Elragal, 2016, p. 3). After the big data is acquired and stored, it is then organised and, prepared and processed. This is done with high-speed network using ETL/ELT or big data processing tools. Hadoop and MapReduce, as well as in-memory management can be used for big data processing. Furthermore, the data can be checked, and computations and processing can be applied using several different languages, ranging from Pig and Hive, to R for statistical computing, to SQL, and SQL-H for directly accessing Hadoop data. These tools, along with others, can enable big data discovery and preparation for the desired analysis (Elgendy & Elragal, 2016, p. 4). The next phase is the decision phase, where possible courses of action are developed and analysed through a representative model of the problem. The framework divides this phase into three steps: model planning, data analytics and analysing. In the model planning step, a model for data analytics is selected and planned. In this step, the models and algorithms which are found to be appropriate, based on the types of data available and the analyses or output intended, are selected and planned for. The different models and analyses which can be chosen are depicted in the framework figure 3. Subsequently, in the data analytics step, the selected model is applied and in the analysing step, the output of the previous step and the results of the analytics are analysed. Accordingly, the possible courses of action to be taken are defined (Elgendy & Elragal, 2016, p. 5). These courses are then chosen in the next phase, which is the choice phase, where methods are used to evaluate the impacts of the proposed solutions, or courses of action from the design phase. In the framework of Elgendy and Elragal (2016, p. 5), this phase is divided into two steps, evaluate and decide. In the evaluate step, the proposed courses of action and their impact are evaluated and prioritised. The next step in the choice phase is to decide on the best course of action. This is where the decision actually takes place based on the results of evaluating the possible courses of action, and finally choosing the best or most appropriate one (Elgendy & Elragal, 2016, p. 5). Finally, the last phase is the implementation phase, where the proposed implementation from the previous phase is implemented and monitored. Hence, big data tools and technologies can be used in monitoring the results of the decision, as well as in providing real-time or periodical feedback on the outcomes of the implementation (Elgendy & Elragal, 2016, p. 6).

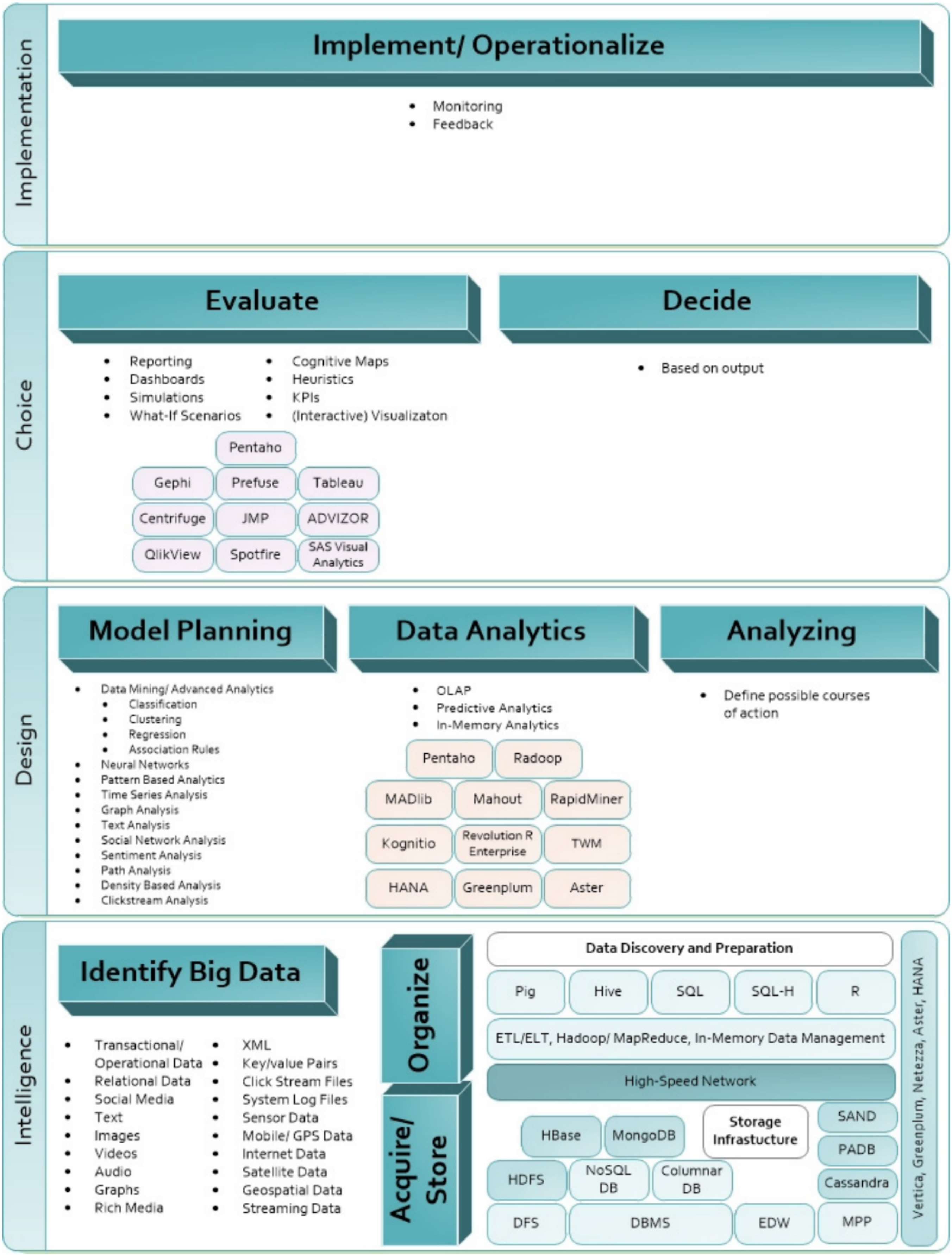

Figure 3. B-DAD Framework (Elgendy & Elragal, 2016, p. 4)

Furthermore, the study of Chiheb et al. (2019, p. 6) has shown that DDD has the potential to enhance the decision-making process by improving the quality of decisions and achieving a competitive advantage for organisations. However, Chiheb et al. (2019, p. 6) do mention that their conducted research is a theoretical model built on the results of previous studies. Chiheb et al. (2019, p. 6) also state that models such as the B-DAD model of Elgendy and Elragal (2016, p. 4) which presents the decision and their requirements in a clear, simple, unambiguous way allow the communication and collaboration between decision-makers and data analytical team. Elgendy and Elragal (2016, p. 13) add to this by stating that applying such analytics to big data, valuable information can be extracted and exploited to enhance decision making support informed decisions. Sleep et al. (2019, p. 14) also state that even though the amount of data firms may use will vary at a foundational level, data enables managers to answer business related questions that they previously were unable to answer. An earlier study of Provost and Fawcett (2013, p. 8) support this by stating that there is strong evidence that business performance can be improved substantially via DDD based on big data.

However, Elgendy and Elragal (2016, p. 13) also mention that even though it is shown that data analytics could enhance decision making and enable the extraction of unforeseen insights and knowledge, it is not an easy task. According to a report of Davenport (2013), only 25% of organisations reported that analytics has significantly improved their organisation's outcomes. The report of Colas, Finck, Buvat, Nambiar, and Singh (2014) support this by stating that only 27% of organisations that invested in data analytics reported their initiatives as successful. These reports argue that most organisations could not take full advantage of using these tools due to a variety of reasons such as having low quality data, not using appropriate data analytics tools, and the lack of available analytical skills (Ghasemaghaei, Ebrahimi, & Hassanein, 2018, p. 2). The study of Akter and Wamba (2016) also argue that while using data analytics has great potentials for improving the outcomes of organisations, the challenges in order to reap the benefits have to be addressed. Lastly, Ghasemaghaei, Hassanein, and Turel (2017) state that not all organisations investing in data analytics can improve their decision making, because different firm resources may play critical roles in successfully using these tools.

All in all, there are many different analytics tools to incorporate data from various sources for decision-making. The B-DAD framework of Elgendy and Elragal (2016, p. 4) is an example of how various data can be incorporated into a decision-making process with different analytics tools being used. In this case, the decision-making process was that of Simon (1960). However, transitioning to an organisation that is able to utilise all the tools for analytics and successfully implementing these for decision-making is a multi-year process (Brown & Gottlieb, 2016). Apart from technological challenges such as data analytics, there are also various organisational factors that come into play (Brynjolfsson & McElheran, 2016; Sleep et al., 2019). Therefore, the literature review will focus further on the factors that influence the adoption of DDD for organisations.

2.4 Adoption of Data-Driven Decision-making

Looking at research regarding the adoption of Data-Driven Decision-making, the study of Brynjolfsson and McElheran (2016) shows that the use of DDD in US manufacturing nearly tripled from 11 percent to 30 percent of plants between 2010 and 2015. This rapid increase is consistent with the higher productivity of DDD adopters. Yet adoption is uneven. Practitioner-oriented accounts emphasize that benefits of new data-related technologies are primarily realised through significant changes in management practices (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012, p. 8) . Some econometric evidence also links DDD with superior performance of large public firms (Brynjolfsson et al., 2011, p. 31). The study of Brynjolfsson and McElheran (2016) has also shown three key findings. Firstly, economies of scale seem to matter, because plants with higher employment and those that belong to multi-unit firms are significantly more likely to adopt DDD (Brynjolfsson & McElheran, 2016, p. 2). Complementary investments may also play an important role, higher IT investment and a greater percentage of educated workers are correlated with the adoption of DDD (Brynjolfsson & McElheran, 2016, p. 2). Thirdly, according to Brynjolfsson and McElheran (2016, p. 5) awareness of these practices and how to implement them has not reached saturation: a great number of learning modalities has a strong association with DDD adoption. Firms that learn about new practices from multiple sources are also more likely to adopt DDD. Yet, the tripling of DDD rates in five years suggests that firms are overcoming barriers to implementation rapidly (Brynjolfsson & McElheran, 2016, p. 2). The study of Brynjolfsson and McElheran (2016, p. 6) also shows that better data creates opportunities to make better decisions. New digital technologies have vastly increased the scale and scope of data available to managers (Brynjolfsson & McElheran, 2016, p. 6). Additionally, DDD is also correlated with more structured management, but the relationship is complex (Brynjolfsson & McElheran, 2016, p. 5).

Furthermore, looking at the rate of adoption according to the paper of Brynjolfsson and McElheran (2016, p. 3), it can be seen that there is indeed rapid adoption of DDD. This is shown in figure 4. The tripling of adoption rates for DDD in 2015 compared to 2010 occurs in both multi-unit firms and those that have only one plant, but single-unit establishments start and end with less than half of the adoption level of their bigger brethren (Brynjolfsson & McElheran, 2016, p. 3).

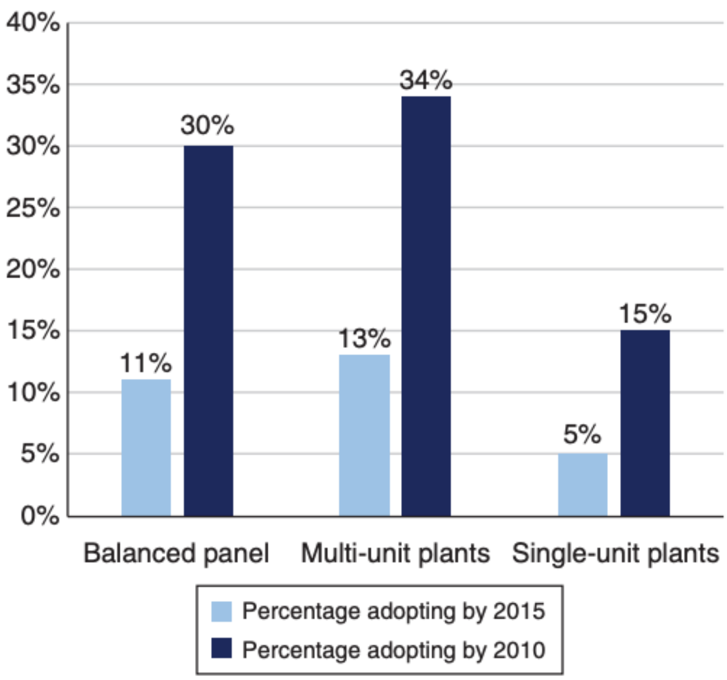

Figure 4. Adoption of Data-Driven Decision-making in US manufacturing (Brynjolfsson & McElheran, 2016, p. 3)

Furthermore, figure 5 shows how each factor contributes to the likelihood of DDD being adopted. It begins with the average rate of adoption and layers on the marginal effects based on the influential factors to show the cumulative probabilities for certain types of plants.

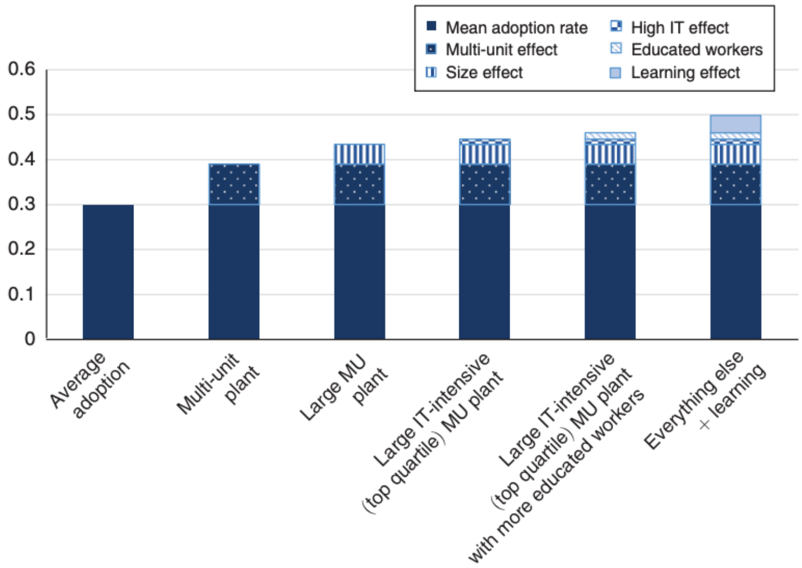

Figure 5. Probability of adopting Data-Driven Decision-making by type of plant (Brynjolfsson & McElheran, 2016, p. 6)

Moreover, Data-Driven Decision making in itself is promising when it comes to improving the performance of organisations. However, Brown and Gottlieb (2016) state that transitioning to a fully data-driven organisation is a multi-year process that requires continual support from senior executives, adequate resources, a focus on change management, and the involvement of employees in the development and implementation of DDD. Therefore, the various phases of DDD adoption have been formulated based on the stages of the Big Data Hierarchy of Sleep et al. (2019, p. 5). The DDD adoption phases can be found in table 2.

Table 2. DDD adoption phases (Sleep et al., 2019)

DDD adoption phases	***Definition***
Phase 1	The organisation has limited or no access to data. The data which is available is either unorganised, unprocessed or barely being utilised, providing little to no value without context and interpretation. The managers are making business decisions based on experience and intuition rather than data and facts.
Phase 2	The organisation is starting to make use of data by making standardised reports. Only structured data is being used and correlations are being made based on the structured data that they have from a limited variety of data sources. The organisation does not have the analytic capabilities to turn complex and unstructured data into insights. Managers are passive in their requests for data and are not heavily involved in the data collection process.
Phase 3	The organisation is using variety of data sources from structured to unstructured data. Decision making goes from static reporting to addressing specific management and business issues using data analytics as a tool. Managers become active participants in requesting and managing available data and drive need for information. There is an improving communication with the different functions within the organisation, such as management and data sourcing. Decision making is based on the combination of data analytics and human decision making.
Phase 4	The organisation has adopted DDD completely and are not only addressing current business issues, but also proactively determining future business strategy based on predictive analytics. With DDD the organisation is able to balance both short run and long run interests, and as a result, both current and future business needs. The management is committed to being data-driven and is reinforcing the benefits of DDD. There is strong communication and partnership between data sourcing and other departments within the organisation. This ensures that there is ability to pull and analyse information throughout the organisation with incorporated unstructured data and access to real time data.

However, there are some influencing factors regarding the adoption of DDD by organisations according to the studies of Brynjolfsson and McElheran (2016) and Sleep et al. (2019). Even though both studies have researched the factors regarding the adoption of DDD, the study of Brynjolfsson and McElheran (2016) focuses more on the increased rate of adoption, while the study of Sleep et al. (2019) focuses more on the maturity stages of DDD.

The study of Sleep et al. (2019, p. 7) shows that there are external and internal drivers for organisations when adopting DDD. The external drivers that Sleep et al. (2019, p. 7) mention are market characteristics and competitive intensity. The internal drivers that Sleep et al. (2019, p. 8) mention are executive commitment to data, interdepartmental dynamics, organisational structure and firm complexity. These drivers influencing the adoption of DDD for organisations can be found in table 3. The combination of external and internal drivers determines the stage of DDD adopted by an organisation (Sleep et al., 2019, p. 9). Sleep et al. (2019, p. 5) has formulated stages in big data hierarchy in terms of capabilities required. The hierarchy builds from left to right and bottom to top in terms of capabilities needed at each stage. Each stage is a distinct phase that incorporates the capabilities from the previous phase. This big data hierarchy can be found in figure 6. However, organisations that want to move to a higher stage in the big data hierarchy because they see it as a promising new innovation or an opportunity to close a performance gap relative to the competition may need to incorporate structural, technological, or organisational changes (Sleep et al., 2019, p. 9). The ability to implement these changes and advance to a higher stage of the Big Data Hierarchy relies on what is referred to as transition capabilities by Sleep et al. (2019, p. 10). Transition capabilities are a combination of internal capabilities which are described in table 4.

However, there are factors which can negatively impact the adoption of DDD. An early research of Joshi (1991) has shown that insufficient change management, conflict of interests among user groups, user acceptance, and changes to work environment can all have a negative effect on the implementation of new technologies. The research of Sleep et al. (2019, p. 14) has also shown that the shift to a data-driven culture is a slow process that can lead to implementation difficulties. Additionally, Sleep et al. (2019, p. 14) state that there may be resistance to change because new responsibilities or processes can impact the status quo. Lastly, according to Court (2015), a factor which can lead to less future funding on the adoption of DDD can be caused by managers not seeing an immediate return on their investment or employees who do not understand the impact of analytics on decision making.

Table 3. The external and internal drivers of DDD adoption (Sleep et al., 2019)

External drivers	
Market characteristics	*"Whereas large amounts of data drive the need for Big Data analytics and skills, the business environment influences the amounts and type of data available. Business-to-consumer (B2C) firms have larger transaction volumes and less direct customer interaction, increasing the availability and use of data. Business-to-business firms (B2B), on the other hand, use less data because they rely on relationship selling for high revenue, low volume transactions and, thus, have greater knowledge of clients."* (Sleep et al., 2019, p. 7)
Competitive intensity	*"The level of competition facing the firm also has a large impact on data adoption. For organizations in a relatively stable, comfortable business environment, data can play a much less significant role than for organizations in a dynamic, competitive environment. When the level of competition is higher, firms are more open to innovation. As a result, marketers are more willing to adopt data-driven strategies to better understand customers and competitors."* (Sleep et al., 2019, p. 7)
Internal drivers	
Executive commitment to data	*"Executive Commitment to Data Executive commitment significantly impacts the firm's adoption of Big Data use in decision making. When data are a fundamental part of the decision-making process, that commitment is largely driven by the CEO and senior executives. Leaders play a critical role in communicating and reinforcing the benefits of technological changes, affecting how others think about the technology. As a result, using data in decision making becomes ingrained in the culture of the organization as dictated by senior management."* (Sleep et al., 2019, p. 8)
Interdepartmental Dynamics	*"Another distinction between stages in the Big Data Hierarchy is how marketing interacts with other functions within the firm to collect, store, and manage available data. Those firms at the higher stages of the hierarchy view integration between marketing and data functions, such as information technology (IT), business intelligence (BI), and finance, as a critical component for providing strategic insights and improving firm performance."* (Sleep et al., 2019, p. 8).
Organisational structure	*"A significant factor influencing interdepartmental dynamics is how the firm is organized to meet business objectives. Product centric organizations, organized by specific product types, place a higher focus on product innovation and the market as a whole versus understanding each customer. As a result, these organizations are more likely to use Historical or Inquiry data analysis because the siloed nature of each product line hinders sharing across business units."* (Sleep et al., 2019, p. 8)

Low — **Stages of the Big Data Hierarchy** — High

Levels of the Wisdom Hierarchy (Low → High)

	Highest Paid Person's Opinion (HIPPO) Decision Making	**Historical Decision Making**	**Inquiry Decision Making**	**Predictive Decision Making**
Wisdom				- Data-driven decision making - Combination of management and data supported marketing decisions
Knowledge			- Managers drive need for information - Relationship between marketing and data sourcing organization - Segmentation capabilities	- Predictive analytics - Partnership between marketing and data sourcing organization - Complete customer view
Information		- Standardized reports support decision making (dashboards) - Correlation analysis	- Ability to query and request specific marketing information - Ad-hoc data querying	- Ability to pull and analyze information throughout the firm - Access to real time data
Data	- Limited access to data - Data available, but not utilized - Experience view	- Variety of data sources - Organized or structured data - Product level view	- Variety of data sources - Structured data from multiple sources - Business unit level view	- Data in a single, internal warehouse - Unstructured data incorporated - Firm level view

Figure 6. Stages of the Big Data Hierarchy (Sleep et al., 2019, p. 6)

Table 4. Transition capabilities (Sleep et al., 2019)

Transition capabilities	
Accessible data	*“Accessible and usable data serves as the foundation for data-oriented decision making. As a preliminary step, data collected from various sources should be combined into a single data source and made available, in a usable form, to the entire organization.”* (Sleep et al., 2019, p. 10)
Analytics tools	*“Because of the unique skill set needed to produce and interpret predictive analytics, managers must determine what analytic tools to provide. This decision depends not only on the selection of the tool but also on the combination of additional value to the firm and its compatibility with existing capabilities.”* (Sleep et al., 2019, p. 11)
Employee ability	*“When implementing a new technology or innovation, it is important to select the right team members and establish defined roles and responsibilities. Both the diversity of employees’ backgrounds and the current skill sets of the workforce can impact transition movement up the Big Data Hierarchy.”* (Sleep et al., 2019, p. 11)
Collaborative organisation	*“Developing a collaborative organization is another critical concern when implementing a more customer-centric, data-driven strategy. Successfully implementing a new technology requires the sharing of knowledge by encouraging free and open communication.”* (Sleep et al., 2019, p. 12)

2.5 Literature conclusion & hypotheses

To conclude, this literature research has shown that DDD can help organisations with improving their performance. Furthermore, looking at the literature regarding big data, data analytics, DDD, and the adoption of DDD, there are many factors which are overlapping between these concepts when adopting DDD. These overlapping factors are the difficulty of handling high volumes and variety of data, having the right organisation structure and management, the right analytics tools, and employees with the adequate skills. Research shows that organisations which are unable to achieve these aspects have difficulties with adopting DDD or gaining significant performance improvement after adopting DDD. This thesis will build further on the previous research by conducting a quantitative research about the factors that influence the adoption of DDD in the Netherlands. Additionally, the state of the influencing factors for DDD adoption will be studied within growing organisations.

Furthermore, based on the findings of the literature, hypotheses are formulated that will be tested. Certain factors from various literatures that measure the same aspect have been combined to one factor. This thesis will conduct multiple testing, because multiple factors influencing the adoption and rate of DDD will be tested. Multiple testing refers to the testing of more than one hypothesis at a time (Shaffer, 1995). The hypotheses concerning all the influencing factors of DDD adoption will be derived in the following sections. The hypotheses have been put into sequence by starting with internal factors followed by the external factors. Additionally, the internal factors have been divided in organisational and human factors based on their attributes. These factors are demonstrated in the research model in Figure 7.

Organisation size

Literature has shown that larger organisations are more likely to adopt new technologies, including DDD. In general, large organisations have typically more advanced use cases and needs influencing their adoption of emerging technologies. Larger organisations also have access to more resources such as money and workforce. Additionally, large organisations are more likely to increase IT budgets in the future, allowing them to simultaneously renovate outdated infrastructure and invest in innovation. Therefore, it expected that larger organisations are more likely to adopt DDD.

H1: The organisation size has a positive impact on the level of DDD adoption

Organisation structure (Hierarchy)

The structure of an organisation can have an impact on the adoption of DDD. Organisational structure can have an effect on companywide measures of performance, such profitability or speed in adopting productivity-enhancing innovations (DeCanio, Dibble, & Amir-Atefi, 2000). Firms with customer-centric structures are more likely to adopt a sing enterprise-wide view of the customer in terms of both data collection and an emphasis on cooperation between various internal departments (Sleep et al., 2019). For example, according to Schultz, Salomo, de Brentani, and Kleinschmidt (2013), an organisational structure based on formal control may increase innovative performance by enabling coordination among different functional units, increasing the level of cost effectiveness, decreasing uncertainty and minimising mistakes. However, studies of Hage and Aiken (1967) and Kalay and Gary (2015) have shown that formalisation can have a negative impact on innovation. Increasing formalisation reduces the extent of freedom of employees by prescribing procedures and potentially constraining employees' ability to engage in personal initiatives.

H2: The organisational structure has a positive impact on the level of DDD adoption

Investment in IT

Advances in IT have changed what is measurable, analysable, and communicable within organisations (Brynjolfsson & McElheran, 2016). Organisations that invest significantly in IT are more likely to have advanced technological capabilities and a greater volume of digitised information to draw on. Therefore, these organisations are expected to adopt new technologies including DDD more likely.

H3: The investment in IT has a positive impact on the level of DDD adoption

High educated workers

Previous studies have found that highly educated workers tend to adopt new technologies faster than those with less education (Riddell & Song, 2017). The study of Bartel and Lichtenberg (1987) has also shown that highly educated workers have a comparative advantage with respect to the adjustment to and implementation of new technologies. Therefore, it is expected that organisations with a higher rate of high educated workers are more likely to adopt DDD.

H4: The rate of high educated workers in an organisation has a positive impact on the level of DDD adoption

Executive commitment to data

Brown and Gottlieb (2016) state that transitioning to a fully data-driven organisation is a multi-year process that requires continual support from senior executives, adequate resources, a focus on change management, and the involvement of employees in the development and implementation of DDD. Executive Commitment to Data Executive commitment significantly impacts the firm's adoption of Big Data use in decision making. When data are a fundamental part of the decision-making process, that commitment is largely driven by the CEO and senior executives (Sleep et al., 2019). Therefore, it is expected that organisations with executives that are committed to data are more likely to adopt DDD.

H5: The executive commitment to data of an organisation has a positive impact on the level of DDD adoption

Interdepartmental dynamics

According to Sleep et al. (2019), how the departments of an organisation interact with each other also has an impact on the adoption of DDD. Those firms at the higher stages of the hierarchy view integration between marketing and data functions, such as information technology (IT), business intelligence (BI), and finance, as a critical component for providing strategic insights and improving firm performance (Sleep et al., 2019, p. 8). Therefore, it is expected that organisations with strong interdepartmental dynamics are more likely to adopt DDD.

H6: The interdepartmental dynamics of an organisation has a positive impact on the level of DDD adoption

Market type

The amounts and type of data available is influenced by the market type. Business-to-Consumer (B2C) firms have larger transaction volumes and less direct customer interaction, increasing the availability and use of data (Sleep et al., 2019). Business-to-Business (B2B) firms on the other hand, use less data because they rely on relationship selling for high revenue, low volume transactions and, thus, have greater knowledge of clients (Sleep et al., 2019). B2C has more data, because the transaction volume is very high and the customer volume is very high (Sleep et al., 2019). Therefore, it is expected that organisations that have a larger volume and diversity of data available are more likely to adopt DDD.

H7: The market type "Business-to-Consumer" has a positive impact on the level of DDD adoption

Competitive intensity

The level of competition an organisation is facing has a large impact on data adoption (Sleep et al., 2019). According to Sleep et al. (2019), organisations in a relatively stable, comfortable business environment, data can play a much less significant role than for organisations in a dynamic competitive environment. When the level of competition is higher, organisations are more open to innovation. Cornett, Erhemjamts, and Tehranian (2019) add to this by stating that when industry competition is high, it causes industry firms to increase innovation intensity to escape competition. Therefore, it is expected that organisations in a competitive environment are more likely to adopt DDD.

H8: The competitive intensity of the industry has a positive impact on the level of DDD adoption

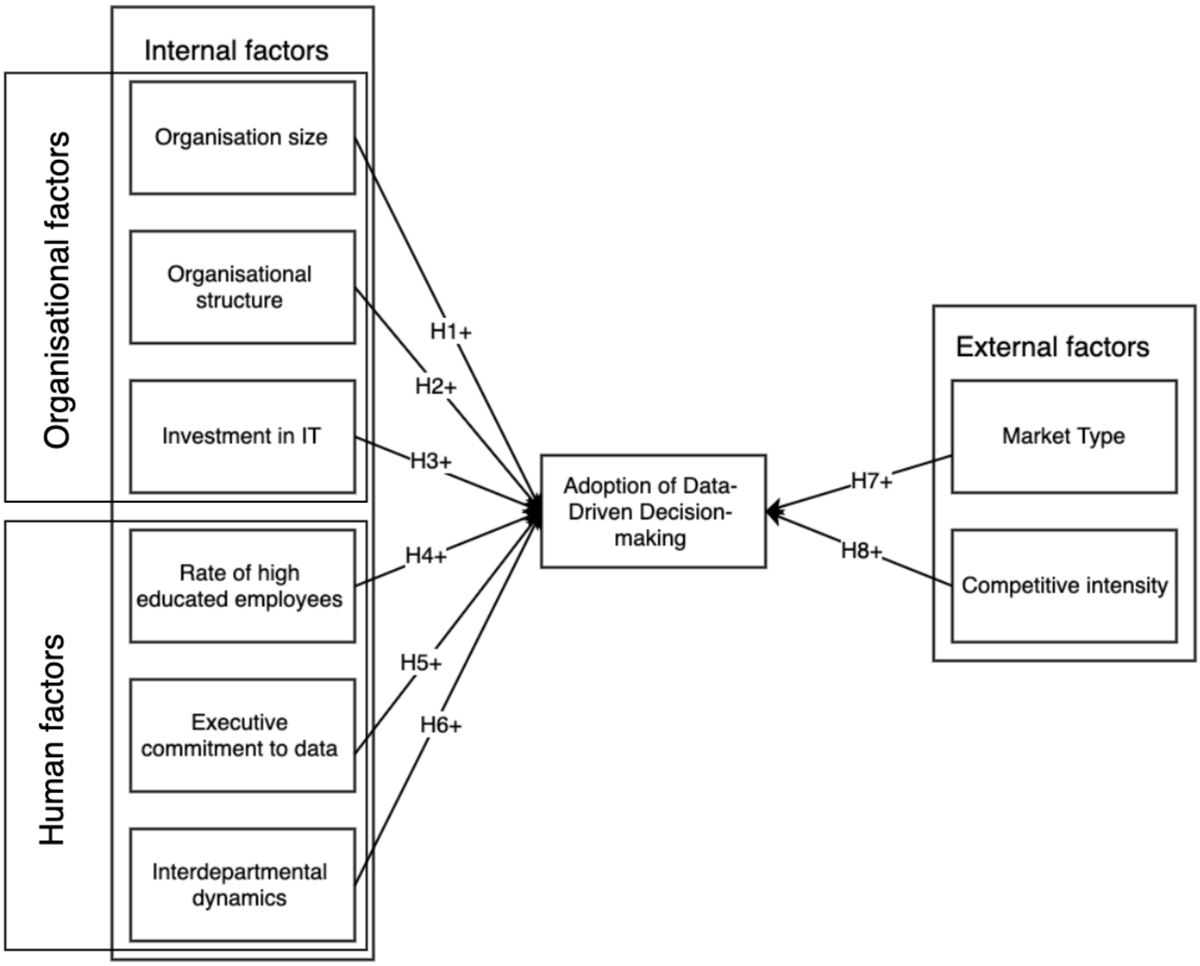

Figure 7. Conceptual model: the influencing factors of DDD adoption

3. Research Methodology

This chapter introduces the research method of this thesis. Firstly, the research design of this study will be described. As second, the way data will be collected is described. Thereafter, the way in which the collected data will be analysed is described. Lastly, it will be described how the reliability and the validity of this research will be maintained.

3.1 Research design

To answer the research question, a quantitative research is conducted. Descriptive research seeks to describe the status of an identified variable. These research projects are designed to provide systematic information about a phenomenon (A Bryman & Bell, 2007). Systematic collection of information requires careful selection of the units studied and careful measurement of each variable (Alan Bryman, 2016). Quantitative research is a research strategy that focuses on quantifying the collection and analysis of data (Alan Bryman, 2016). Associated with the natural, applied, formal and social sciences, this research strategy promotes the objective empirical investigation of observable phenomena to understand relationships (Alan Bryman, 2016). The choice to conduct a quantitative research instead of a qualitative research is because the aim is to produce generalisable information about the causes of the concepts and constructs, as well as identifying patterns and relationships (Watson, 2015). The possibility to reach a higher sample size is an important advantage of quantitative research, because this allows to better generalise conclusions. However, quantitative research generally does not consider the deeper reasoning for certain phenomena, therefore, it is not able to measure this deeper reasoning (Schofield, 1993). Thus, quantitative research shows a single moment, a picture of phenomena, with no dynamics and poor of details (Schofield, 1993).

3.2 Sample definition & data collection

The data for this quantitative research is collected through surveys. The research design of this paper is inspired by the previously conducted research of Brynjolfsson and McElheran (2016) and Sleep et al. (2019). The study of Brynjolfsson and McElheran (2016) targets American manufacturing establishments through a large-scale survey to examine the phenomena of DDD adoption within these establishments. For this thesis, the surveys are distributed digitally since the needed number of respondents is relatively high. Digital distribution of surveys makes it easier to send out more survey to respondents and to save time, because of the time limitation. The surveys contained closed-ended questions. The questions of the survey can be found in appendix I. The factors that are researched to influence the adoption of DDD of organisations in the Netherlands are based on the findings of the literature research. These factors are organisation size, organisational structure, Investment in IT, employee ability, market characteristic, and competitive intensity. Due to time constraints and limitation, not every single influential factor for DDD adoption is studied, but only those that have the most impact according to literature. The questions of the survey are a mixture of multiple-choice questions and rating scale questions based on the information that is needed. To generalise from the sample to the population, the sample has to be representative of the population. To ensure this, a stratified random selection procedure is chosen to make sure that proportional representation of various industries will be included. The variables for this study have been defined based on the factors influencing the adoption of DDD from the literature review. These variables can be found in table 5. Additionally, there are questions formulated concerning the views and goals of organisations regarding their organisational performance, decision-making, plans for future innovation and views on the importance of Data-Driven Decision-making.

Table 5. All variables and measurements

Variables	*Measurement*
Independent Variables	
Organisation size (Brynjolfsson & McElheran, 2016)	• Number of employees
Organisational structure (Sleep et al., 2019)	• Hierarchical • Non-Hierarchical
Investment in Information Technology (Brynjolfsson & McElheran, 2016)	• IT Capital stock (hardware and software) investment in Euros per year
Rate of high educated workers (employee ability) (Brynjolfsson & McElheran, 2016)	• Percentage of employees with bachelor's degree or higher
Executive commitment to data (Sleep et al., 2019)	Based on the Likert scale whether the executives are committed to use of data: • Score 1 (Strongly disagree) • Score 2 (Disagree) • Score 3 (Neither disagree nor agree) • Score 4 (Agree) • Score 5 (Strongly agree)
Interdepartmental dynamics (Sleep et al., 2019)	Based on the Likert scale whether there is interdepartmental dynamics: • Score 1 (Strongly disagree) • Score 2 (Disagree) • Score 3 (Neither disagree nor agree) • Score 4 (Agree) • Score 5 (Strongly agree)
Market characteristic (Sleep et al., 2019)	• Business-to-business • Business-to-consumer • Both
Competitive intensity of the market (Sleep et al., 2019)	• Low • Medium • High
Dependent variables	
Level of DDD adoption	Based on the Likert scale whether the organisation is using DDD: • Score 1 (Strongly disagree) • Score 2 (Disagree) • Score 3 (Neither disagree nor agree) • Score 4 (Agree) • Score 5 (Strongly agree)

The sample for this thesis were organisations in the Netherlands from various industries. This thesis aimed for a sample size of 100 respondents. The organisations were approached with e-mails, as well as through social media connections, such as LinkedIn. A template e-mail was developed with the purpose of the research and the link to the survey tool Qualtrics. To increase the response rate, the mails were sent directly to the managers within the organisations. If the contact information of the manager was not available, then the mail was sent to the general mail of the organisation with the question to forward the mail to the concerned manager within the organisation. Every email that was sent to directly to the managers was personalised with a personal greeting to increase the response rate. Additionally, managers whose name was known within a certain organisation, but did not have any contact information were contacted through LinkedIn.

The response rate was expected to be around 10%, therefore the survey was to send to approximately 900 organisations in the Netherlands. Because of the time limitation and to reach out to as many organisations as possible, convenience sampling was also used. This means that the organisations who have received the survey were asked to send out the survey to other organisations whom they work or have a relationship with. The survey has been sent in Dutch, because the target organisations are all based in the Netherlands. The organisations are mainly found through a list of top 250 growing companies of the Netherlands for each year. The lists for these companies are available for the year 2020, 2019 and 2018. This makes it approximately 750 companies, because a few companies appear in the lists of multiple years. The top growing companies are chosen, because multiple reports, among which that of Accenture (2019) have shown that such companies are more likely to embrace and adopt new technologies. Additionally, 150 Data & Technology organisations have been approached for this research. The list of organisations that are approached can be found in appendix II.

During the three weeks that the questionnaire was open, 115 responses were received. After the first two weeks, there were approximately 75 responses. Therefore, in the third week, a reminder was sent to all the correspondents. Additionally, the survey has been sent out to 150 Data & Technology organisations, because looking at the respondents of the first two weeks, the responses showed that organisations which responded were largely organisations that worked with or had some sort of interest in DDD. This is considered when analysing the results. This can also be seen looking at the rate of respondents per industry in figure 8. The respondents from the “Other” industry were approximately 70% organisations from the IT industry. Afterwards, 12 surveys have been taken out due to missing values and self-reported insufficient knowledge about their organisation and DDD.

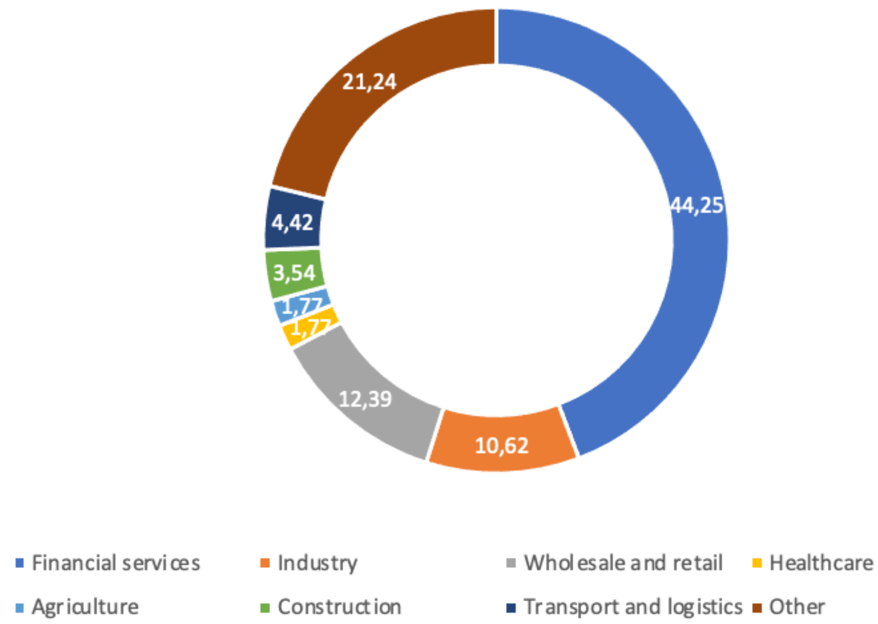

Figure 8. The rate of respondents per industry in percentages

Furthermore, looking at the size of the organisations of the respondents, of the 103 valid responses, 44 are small organisations with a maximum of 100 employees (42,2% of responses), 34 are medium sized organisations with a size between 101 and 250 employees (33,3% of responses), and lastly 25 of the responses are from large organisations with an organisation size of more than 250 employees (24,5% of responses). This frequency can be seen in table 6.

Table 6. Frequency of organisation size of respondents

	Frequency	***Percent***	***Cumulative percent***
Small organisations	44	42,7%	42,7%
Medium sized organisations	34	33,0%	75,7%
Large organisations	25	24,3%	100%
Total	103		

3.3 Data analysis

The hypotheses were specified in chapter two that need to be confirmed or rejected. The data was collected with a survey that measures attributes of organisations and gathers opinions of manager regarding their organisation. This process is followed by an analysis of the collected information through statistical procedures and hypothesis testing which will provide averages, frequencies, patterns, and correlations between variables. The software that is used for the analysis of the collected data is SPSS.

First a preliminary test was conducted with Cronbach's alpha. Cronbach's alpha is a measure of internal consistency, which is a measure of scale reliability. Cronbach's Alpha is most used to assess the internal consistency of a questionnaire that is made up of multiple Likert scales and items. To measure the consistency for the questions within the questionnaire that are based on the Likert Scale, the variables are divided into three groups which are for this measurement referred to as: Current data usage, Innovation and DDD challenges. The general rule of thumb is that a Cronbach's alpha of 0.7 indicates an acceptable level of reliability. The groups with their variables and the reliability measures can be seen in table 7. The exact variable codes and the SPSS output for the reliability measurement can be found in the appendix III. Additionally, to achieve reliability in this thesis, all the respondents have received the same survey and the respondents of the organisations that has been reached out to had more or less the same position in their organisations. To achieve validity in this thesis, the questions of the survey have to measure the intended construct. Validity is defined as the extent to which a concept is accurately measured in a quantitative study (Heale & Twycross, 2015). A pilot survey strategy is used to test the validity of the questionnaire using of sample 10 respondents compared to the planned sample size of 100 respondents.

Thereafter, a common method bias is assessed using Harman's one-factor test. Common method bias happens when variations in responses are caused by the instrument rather than the actual predispositions of the respondents that the instrument attempts to uncover(Chin, Thatcher, & Wright, 2012). If the total variance extracted by one factor exceeds 50%, common method bias is present. The total variance extracted by one factor in the data of this study is 25,46%, thus there is no problem with common method bias in this data. Additionally, a rotated component matrix has been analysed using the varimax rotation. The output of the Harman's one factor test for common method bias, the rotated component matrix and the correlation table can also be found in appendix III.

Table 7. Internal consistency measurement with Cronbach's alpha

Group name	***Variables***	***Cronbach's Alpha***
Current Data Usage	• Importance of Data • Current decision making • Use of analytics • Analytics for decision making • Analytics for performance	0,810
Innovation	• Innovation stimulation • Executive commitment to innovation • Goal to become data-driven	0,775
DDD barriers	• Lacking skills • Budget • IT infrastructure • Data accessibility • Data usability • Time • Change management	0,785
		Criteria > 0.7

Furthermore, the formulated hypotheses were tested though a multiple linear regression analysis. Regression analysis is a method to identify which variables have impact on a topic of interest. The process of performing a regression allows to confidently determine which factors matter most, which factors can be ignored, and how these factors influence each other. Multiple regression is an extension of linear regression, and it is used to predict the value of a variable based on two or more variables (Uyanık & Güler, 2013, p. 1). Regression models with one dependent variable and more than one independent variable are called multilinear regression. The factors (independent variables) which are assumed to have an influence on the adoption of Data-Driven Decision-making (dependent variable) are tested in the multiple regression analysis using SPSS. The output of the multiple regression analysis is interpreted by analysing the R Square value, the statistical significance of the regression model, and the Coefficients. This can be seen in table 8. Additionally, the answers regarding the challenges on DDD adoption have been analysed with cross tabs. The output of the multiple regression analysis can be found in appendix IV.

Table 8. The independent and dependent variables for the hypotheses

Hypothesis	***Variables***
H1	Organisation size → Data-Driven Decision-making adoption
H2	Organisational structure → Data-Driven Decision-making adoption
H3	Investment in IT → Data-Driven Decision-making adoption
H4	Rate of high educated employees → Data-Driven Decision-making adoption
H5	Executive commitment to data → Data-Driven Decision-making adoption
H6	Interdepartmental dynamics → Data-Driven Decision-making adoption
H7	Market type → Data-Driven Decision-making adoption
H8	Competitive intensity → Data-Driven Decision-making adoption

4. Results

This chapter presents the results of the data analysis after the data is collected in which the formulated hypotheses are tested. The literature review in chapter two has shown various influencing factors of Data-Driven Decision-making adoption. All the output for the multiple regression analysis can be found in Appendix IV.

The multiple regression analysis shows the overall fit statistics. The adjusted R2 of the model is 0,441 with the R2 of 0,485. This means that the multiple linear regression explains 44,1% of the variance in data. The next test is the F-test. The linear regression's F-test has the null hypothesis that the model explains zero variance in the dependent variable. The F-test for this model is highly significant, thus it can be assumed that the model explains significant amount of the variance in the adoption of Data-Driven Decision making.

As follows, the statistically significant impact of the independent variables on the dependent variables are tested. The p-value for each independent variable tests the null hypothesis that the variable has no correlation with the dependent variable (Aiken, West, Pitts, Baraldi, & Wurpts, 2012, p. 7). If the p-value for a variable is less than the significance level of 0,05, then the sample data provides enough evidence to reject the null hypothesis. The significance level, also denoted as alpha, is a measure of the strength of the evidence that must be present in the sample before rejecting the null hypothesis and concluding that the effect is statistically significant (Aiken et al., 2012, p. 5). Therefore, the impact of a variable is considered significant if the p-value for a variable is less than 0,05. The results of the multiple regression analysis are shown in table 9.

Table 9. Results of multiple linear regression model

Hypothesis	***Variables***	***β***	***p-value***
H1	Organisation size → DDD adoption	**0,174**	**0,045**
H2	Organisational structure → DDD adoption	0,022	0,820
H3	Investment in IT → DDD adoption	0,117	0,175
H4	Rate of high educated employees → DDD adoption	**0,247**	**0,011**
H5	Executive commitment to data → DDD adoption	**0,307**	**0,001**
H6	Interdepartmental dynamics → DDD adoption	**0,297**	**0,002**
H7	Market type → DDD adoption	-0,030	0,704
H8	Competitive intensity → DDD adoption	0,007	0,929

Looking at all the independent variables and their impact on the adoption of Data-Driven Decision-making, strong evidence shows that executive commitment to data has the most significant positive impact on the adoption of Data-Driven Decision making (H5: β=0,316) in this sample. Furthermore, a significant positive impact can be seen at the rate of high educated workers (H4: β=0,247) and the interdepartmental dynamics (H6: β=0,297) of an organisation on the adoption of Data-Driven Decision making. Additionally, a significant positive significant impact can be seen at the organisation size (H1: β=0,174) on the adoption of Data-Driven Decision-making, even though the effect is weaker. On the other hand, in this sample there was no significant impact of organisational structure (H2: β=0,022), amount of investment in IT (H3: β=0,117), the market type (H7: β=-0,030), and the competitive intensity of the market (H8: β=0,007) on the adoption of Data-Driven Decision-making.

The results of the impact of all the independent variables are visualised in the conceptual model in figure 9. In the figure, the solid arrows represent a significant effect, while the arrows with broken lines represent insignificant effects.

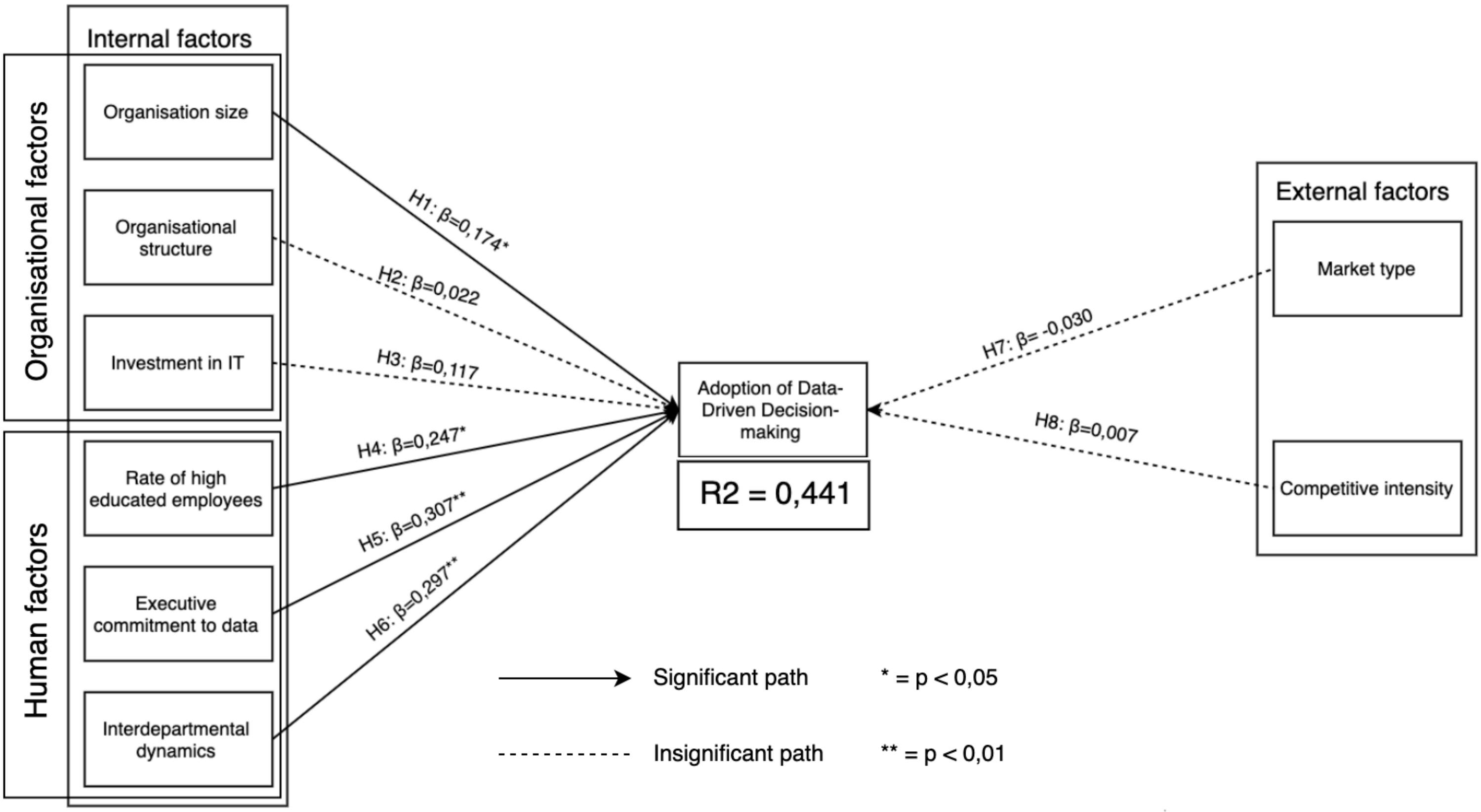

Figure 9. Results: The influencing factors of Data-Driven Decision-making adoption

In addition, this thesis included the barriers and challenges of adopting Data-Driven Decision-making according to the literature review. These barriers are included in the questionnaire to analyse which barriers and challengers are acknowledged as obstacles for becoming data-driven according to the responding organisations by the organisations in this sample. The responses regarding the barriers and challenges of becoming data-driven are analysed with cross tabulations. In this sample, the barrier which is most relevant for the respondents is the lack of adequate skills and staff. 74% of the respondents in this sample consider the lack of adequate skills and staff as a significant barrier when it comes to adopting Data-Driven Decision-making. While only 27% of the respondents consider budget as a barrier when it comes to the adoption of Data-Driven Decision making. Additionally, a noticeable number of respondents also indicated in the open answers that the large volume of data was a barrier for adopting Data-Driven Decision-making. The results of the answers of the respondent regarding the all the barriers of adopting Data-Driven Decision making can be seen in figure 10. The percentages in figure 10 are a representation of respondents who answered agree or strongly agree for a certain potential barrier. The output of the cross tabulation in SPSS can be found in appendix V.

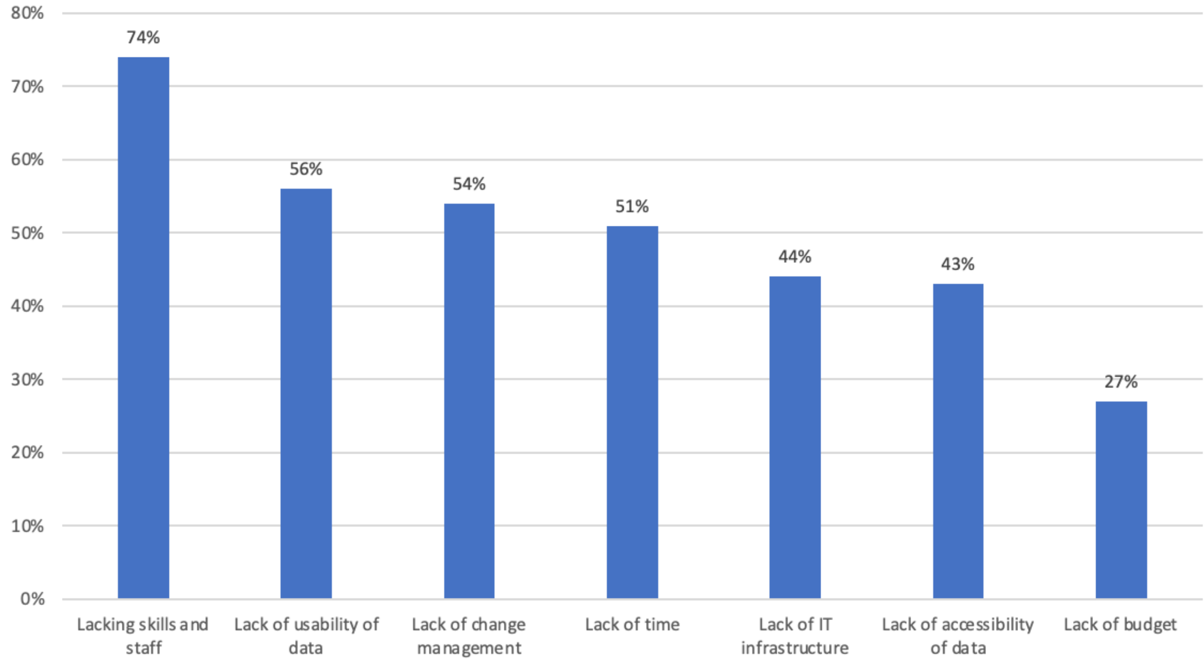

Figure 10. Respondent answer rates of Data-Driven Decision-making adoption barriers

5. Discussion

Based on the literature review, eight factors that have an influence on the adoption of Data-Driven Decision-making have been identified, and a conceptual model has been generated for this research. Afterward, this model was tested and revised using data collected from various organisations in the Netherlands. From the analysis that is conducted, it can be concluded that four factors have a significantly positive impact on the adoption of Data-Driven Decision-making. However, in contrary to the literature review, the remaining four factors did not show any significant effect on the adoption of Data-Driven Decision-making. In this chapter, the results will be discussed and compared with existing literature.

The positive impact of organisation size on the adoption of Data-Driven Decision-making in this thesis supports the studies of Brynjolfsson and McElheran (2016) and Sleep et al. (2019). An explanation for this can be that larger organisations have more resources. Organisational size has been defined as the organisation's resources, transaction volumes, or workforce size (Kimberly & Evanisko, 1981; Lee & Xia, 2006, p. 1). It is therefore a substitute for total and slack resources that represent the organisation's economies of scales (Moch & Morse, 1977). Additionally, the study of Yao, Xu, Liu, and Lu (2003) has shown that there is a statistically significant relationship between university size and ATM technology adoption, and that size can serve as a predictor of other IT adoptions in other settings, such as in firms and financial institutions. However, according to the study of Lee and Xia (2006), the empirical results on the relationship between organisation size and IT innovation adoption are disturbingly mixed and inconsistent. Lee and Xia (2006, p. 9) suggest that the direction and strength of the relationship between organisational size and IT innovation adoptions depends on the type of innovation, type of adoption organisation, adoption stage, scope of size measure, and type of size measure. These factors or a combination of them may have also been the reason for the significant positive effect in this thesis of organisational size on the adoption of Data-Driven Decision-making.

In contrast to earlier findings of Sleep et al. (2019) and Brynjolfsson and McElheran (2016), this thesis failed to find a significant positive impact of organisational structure on the adoption of Data-Driven Decision-making. A possible explanation for these results may be that the respondents within organisations were at a managerial level. The managers answered the questions whether the organisation had a hierarchical or non-hierarchical structure. The study of Keeton and Mengistu (1992) shows that managers at different levels in an organisation have different perspectives concerning that organisation, and therefore hold somewhat different views of the organisation's structure and culture. The responding managers may have a different perception on the reality of the organisation's structure. However, there are also contradicting views regarding the effect of organisational structure on the adoption of innovation. For example, the study of Schultz et al. (2013) shows that an organisational structure based on formal control may increase innovative performance by enabling coordination among different functional units, increasing the level of cost effectiveness, decreasing uncertainty and minimising mistakes. On the other hand, studies of Hage and Aiken (1967) and Kalay and Gary (2015) have shown that formalisation can have a negative impact on innovation. Increasing formalisation reduces the extent of freedom of employees by prescribing procedure. These studies provide more insight on why this thesis failed to find a significant positive impact of organisational structure on the adoption of Data-Driven Decision-making.

Neither did this study find a significant impact of investment in IT on the adoption of Data-Driven Decision making as the study of Brynjolfsson and McElheran (2016) has shown. A recent study of Nwankpa and Merhout (2020) supports the study of Brynjolfsson and McElheran (2016) by stating that there is a positive relationship between digital investment and IT innovation. According to Nwankpa and Merhout (2020, p. 20), organisations embark on digital transformation by investing in such emerging digital technologies as big data, analytics, social media, the cloud, and embedded systems. A possible explanation for the absence of a significant effect of investment in IT on the adoption of Data-Driven Decision-making may be because of the convenience sampling of this study. The sample for this study were mainly in the top 250 growing organisations within the last 3 years. Regardless of their size and investment budget, these “fast-growing” organisations may already have been adopting Data-Driven Decision-making more rapidly in comparison to “regular” organisation, because of their knowledge and competences.

The significant positive impact of the rate of high educated employees in an organisation on the adoption of Data-Driven Decision-making in this sample supports the studies of Brynjolfsson and McElheran (2016) and Sleep et al. (2019). Early studies of Bartel and Lichtenberg (1987) and Chun (2003) support this by stating that highly educated workers have a comparative advantage with respect to the adjustment to and implementation of new technologies. The results of the questionnaire also show that 74% of the respondents see the lacking skills and employees as a barrier for adopting Data-Driven Decision-making. A possible explanation for this may be that the adoption of new technologies accelerates the demand for educated workers. The study of Chun (2003) supports this by stating that new technologies require educated or skilled workers for the successful adoption of the new technology.

The significant positive impact of executive commitment to data on the adoption of Data-Driven Decision making in this sample supports the studies of Brynjolfsson and McElheran (2016) and Sleep et al. (2019). A possible explanation for this is that the top-level management have a significant amount of influence on the organisation to change its course. An organisation with a management that is committed to innovation or data may be more likely to adopt Data-Driven Decision-making or any other new technology. This is supported by an early study of Daellenbach, McCarthy, and Schoenecker (1999) which states that the perceptual lens of the top management team and the team’s dynamics are of great significance to have a direct impact on the organisation’s commitment to innovation. The study of Khanagha, Volberda, Sidhu, and Oshri (2013) adds to this by stating that managerial initiatives can be an integral part of the technological change process. Managerial interventions are crucial in organisational routines in order to overcome ineffectiveness of familiar practices of organisations for dealing with a new technology (Khanagha et al., 2013, p. 15).

Another significant finding which supports both the studies of Brynjolfsson and McElheran (2016) and Sleep et al. (2019), is the impact of interdepartmental dynamics on the adoption of Data-Driven Decision making. A possible explanation for this can be that teams that work collaboratively have better communication with each other and share knowledge about the possibilities and challenges within the organisation. Effective interdepartmental collaboration may also keep information moving within the organisation. The study of Sleep et al. (2019) states integration between departments such as marketing, Information technology, business intelligence, and finance as a critical component for providing strategic insights and improving firm performance. The study of Cuijpers, Guenter, and Hussinger (2011) adds to this by stating that interdepartmental collaboration increases the exchange of information thereby benefitting innovation processes and outcomes. However, Cuijpers et al. (2011) also mention that interdepartmental collaboration can be a source of increased costs.

An example of these costs are project delays. Project delays can arise, because departments can set different task priorities and pursue conflicting objectives. These delays can also arise because of differences in the educational backgrounds of employees. In the worst case, these differences between departments can cause dysfunctional conflicts that may lead to innovation project terminations (Cuijpers et al., 2011).

Surprisingly, this study did not find a significant impact of the market type on the adoption of Data-Driven Decision-making. It was expected that the market Business-to-consumer would have a positive impact on the adoption of Data-Driven Decision-making, because Business-to-consumer firms have larger transaction volumes and less direct customer interaction, increasing the availability and use of data (Sleep et al., 2019, p. 7). Additionally, according to Sleep et al. (2019, p. 7) Business-to-business firms use less data, because they rely on relationship selling for high revenue, low volume transactions and, thus, have greater knowledge of clients. However, a recent study of Troisi, Maione, Grimaldi, and Loia (2020) shows that Business-to-business firms are using Data-Driven Decision-making to generate multiple advantages throughout the entire supply chain and in the enhancement of relationships with customers. Additionally, Cuzzocrea, Loia, and Tommasetti (2017) mention that Data-Driven Business-to-business firms can reduce costs, rise competitiveness, reinforce service quality and promptness in procurement, logistics, delivery and post-delivery assistance. This may be an explanation on why the market type did not have any significant effect on the adoption of Data-Driven Decision-making, because Business-to-business organisations are adopting Data-Driven Decision-making more than expected based on the study of Sleep et al. (2019).

Lastly, this thesis did not find a significant impact of the competitive intensity on the adoption of Data-Driven Decision making, which is stated in the study of Sleep et al. (2019). This phenomenon is also supported by the studies of Sharpe and Currie (2008), which states that competitive intensity has a strong positive effect on innovation and productivity. The study of Kretschmer, Miravete, and Pernías (2012) supports this by stating that competitive pressure translates into a change in adoption behaviour. Competitive pressure leads to a change in adoption behaviour as scale and the adoption of demand-enhancing software are complements, while organisations tend to substitute demand-enhancing and cost-reducing innovations (Kretschmer et al., 2012, p. 41). An explanation for this difference may be differences in country and industry in which the research has been conducted.

All in all, this thesis has confirmed some of the hypotheses, while rejecting some hypotheses which were based on findings in the literature review. However, looking at the independent variables that indeed have a significant positive impact, it is noticeable that the majority of these factors are “human” or “soft” aspects of an organisation. This is mostly in line with the study of Sleep et al. (2019) in which the emphasis is on human capabilities and human factors. The differences in the findings between the empirical research and the literature research may also be explained by the difference in countries and/or industries of the organisations that participated in this research and the research of the literature review.

6. Conclusion

The objective of this thesis was to answer the main research questions: *"What are the influencing factors of Data-Driven Decision-making adoption for organisations in the Netherlands?".* First, a literature research has been conducted regarding relevant topics such as Big Data, data analytics, Data-Driven Decision-making, and the influencing factors of Data-Driven Decision-making according to previous literature research. Thereafter, several hypotheses were made based on previous literature which helped to provide an answer for the research question, as well as questionnaires were developed where the provided answers served as the basis for the analysis. A total amount of 115 responses were collected, but 12 surveys have been taken out due to missing values and self-reported insufficient knowledge about their organisation and DDD. Multiple SPSS techniques were used to analyse the data and test the hypotheses which provided valuable findings and insights.

Looking at the results of the multiple regression analysis of this sample where the effect of multiple independent variables on the adoption of Data-Driven Decision-making is measured, evidence has been found that organisation size, executive commitment to data, rate of high educated workers, and interdepartmental dynamics all have a positive impact. Moreover, according to previous literature research, organisational structure, amount of investment in IT, the market type, and the competitive intensity of the market should also have a positive impact on the adoption of Data-Driven Decision making. However, this thesis has failed to find a significant impact of these factors on the adoption of Data-Driven Decision-making. Looking at factors which have a significant effect in this sample, the importance of human capabilities and factors on the adoption of Data-Driven Decision-making have emerged in this research.

Additionally, the literature research has shown that there are certain barriers for adopting Data-Driven Decision-making. These findings are mostly based on human and technological barriers. This study provided an overview on what the organisations in this sample consider as barriers when trying to adopt Data-Driven Decision-making. These barriers are a lack of skills/staff, budget, IT infrastructure, accessibility of data, usability of data, time, and change management. Most of the respondents considered lack of skills and workers as the biggest barrier for adopting Data-Driven Decision-making.

This study might be interesting for the managers of organisations who want to improve their decision making by implementing data analytics. The factors in this study which have a significant positive impact on the adoption of Data-Driven Decision-making can be used as a guideline by managers to aim for these internal conditions in their organisations. Therefore, managers change their organisations by creating an environment where various teams work closely together and share knowledge and information between departments. Additionally, the management should ensure that the right people and skills are available for the adoption of Data-Driven Decision-making. This can be achieved by providing training and development opportunities for their employees or hiring new staff with the adequate skillsets. All in all, organisations need to focus on creating business value with the possibilities that are created by adopting Data-Driven Decision-making. The adoption of Data-Driven Decision-making should not be a goal in itself.

7. Future research and limitations

This thesis had some limitations when it comes to the various aspects of the research. In this final chapter, the limitations of this research will be discussed, and suggestions will be made for possible future research.

The first and most notable limitation for this research is the number of respondents. For this thesis, the sample consisted of 103 respondents, because of time constraints. Having a higher sample size would increase the significance level of the findings, since the confidence of the results are likely to increase with a higher sample size. This is to be expected, because larger the sample size, the more accurately it is expected to mirror the behaviour of the whole population.

Secondly, respondents who are evenly spread across various industries would give a better a more balanced view on the influencing factors of Data-Driven Decision-making adoption. Approximately, 60 percent of all the respondents were active in the financial services and IT industry. During the data collection phase, it was also noticeable that many respondents who answered the survey were working with Data-Driven Decision-making or were interest in some kind of way. This is based on the feedback from e-mails and the commentary in the surveys. Therefore, it is assumed that many respondents were already familiar with data analytics and Data-Driven Decision-making. This may also explain the low rate of respondents who answered that they did not have any knowledge regarding Data-Driven Decision-making. Having an equal number of respondents from every industry may give a more general view on the influencing factors of Data-Driven Decision-making adoption. Therefore, it is difficult to make assumptions about specific factors that may influence a specific industry or organisation. Examples of studies where the adoption of certain technologies across industries are compared in a more balanced way, are the studies of Oliveira and Martins (2010) and King and Gribbins (2002). The respondents of these studies are divided proportionally across industries. Therefore, with samples like these, it is more appropriate to make assumptions for certain factors based on specific industries.

Furthermore, another limitation was the knowledge of the respondents regarding certain topics. A topic that particularly stood out is the amount of IT investment of organisations. A significant number of respondents indicated that they did not know how much their organisations invested in IT, thus they gave a rough estimate as answer, which they mentioned in the comments and e-mails. This may also explain the reason why this study did not find a significant effect of IT investment on the adoption of Data-Driven Decision-making.

Lastly, a research that may be interesting in the future, is an industry specific research in the Netherlands on the adoption of Data-Driven Decision-making. Given the possibility, conducting further research on the adoption of Data-Driven Decision-making within the healthcare industry would be the choice. A comparable study is that of Länsisalmi, Kivimäki, Aalto, and Ruoranen (2006), in which the adoption of innovation in healthcare has been studied. This will provide deeper insights on the various influencing factors, which may be more practical for potential adopters of Data-Driven Decision-making in that specific industry.

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Appendix

Appendix I. Survey questions & answer choices

Question	***Dimension***	***Answer scale***
Hoe groot is de organisatie qua aantal werknemers?	Internal (organisational)	Slider + open answer
In welke branche is de organisatie actief?	Internal (organisational)	Multiple choice
Hoeveel wordt er circa gemiddeld per jaar geïnvesteerd in IT (Denk hierbij aan investeringen voor hard- en software)	Internal (organisational)	Slider + open answer
De organisatie heeft een hierarchische structuur	Internal (organisational)	Strongly disagree – Strongly agree (1-5)

Question	***Dimension***	***Answer scale***
Wat is het percentage van hoogopgeleide werknemers (HBO of hoger) in verhouding met alle personeel?	Internal (human)	Slider with percentage
Binnen de organisatie is er een hechte samenwerking tussen de verschillende afdelingen.	Internal (human)	Strongly disagree – Strongly agree (1-5)
Hoe worden innovaties binnen de organisatie gestimuleerd?	Internal (human)	Top-down – Bottom-up (1-5)
De leidinggevenden zetten zich in voor het stimuleren van innovatie	Internal (human)	Strongly disagree – Strongly agree (1-5)

Question	***Dimension***	***Answer scale***
In welke markt is uw organisatie actief?	External	Business-business – Business-to-customer (1-5)
De intensiteit van de concurrentie is hoog in de markt waarin de organisatie actief is.	External	Strongly disagree – Strongly agree (1-5)

Question	***Dimension***	***Answer scale***
Het gebruik van data is belangrijk binnen de huidige activiteiten van de organisatie.	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)
Binnen de organisatie hebben wij een goede besluitvorming.	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)

Binnen de organisatie wordt er gebruik gemaakt van data analytics voor de besluitvorming.	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)
Het gebruik van data analytics is belangrijk voor de besluitvorming in de organisatie	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)
Het gebruik van data analytics voor de besluitvorming verbetert de performance van de organisatie	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)
Binnen de organisatie staat data gedreven besluitvorming hoog op de agenda	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)
Binnen de organisatie is er als doel om de komende jaren data gedreven te worden.	Internal (Data usage)	Strongly disagree – Strongly agree (1-5)
Binnen hoeveel jaar verwacht u dat de besluitvorming binnen de organisatie data gedreven zal zijn?	Internal (Data usage)	Slider with number of years

Question	***Dimension***	***Answer scale***
Het ontbreken van de benodigde mensen en skills waren/zijn een belemmering voor de organisatie om data gedreven te worden	Barriers	Strongly disagree – Strongly agree (1-5)
Het budget van de organisatie was/is een belemmering om data gedreven te worden	Barriers	Strongly disagree – Strongly agree (1-5)
De IT-infrastructuur van de organisatie was/is een belemmering om data gedreven te worden.	Barriers	Strongly disagree – Strongly agree (1-5)
De toegankelijkheid van data was/is een belemmering om data gedreven te worden.	Barriers	Strongly disagree – Strongly agree (1-5)
De bruikbaarheid van data was/is een belemmering om data gedreven te worden.	Barriers	Strongly disagree – Strongly agree (1-5)
Tijd was/is een belemmering voor de organisatie om data gedreven te worden.	Barriers	Strongly disagree – Strongly agree (1-5)
Het managen van verandering binnen de organisatie was/is een belemmering om data gedreven te worden.	Barriers	Strongly disagree – Strongly agree (1-5)
Welke belemmeringen waren er nog meer om data gedreven te worden?	Barriers	Strongly disagree – Strongly agree (1-5)
Ik had genoeg kennis over mijn bedrijf en data gedreven besluitvorming om de vragen in deze enquête te kunnen beantwoorden.	Confirmation	Strongly disagree – Strongly agree (1-5)

Appendix II. List of approached organisations

List	***Link***
Top 250 growing companies 2020	https://www.nlgroeit.nl/groeicontent/top-250-groeibedrijven-2020
Top 250 growing companies 2019	https://www.nlgroeit.nl/groeicontent/top-250-groeibedrijven-2019
Top 250 growing companies 2018	https://www.nlgroeit.nl/groeicontent/top-250-groeibedrijven-2018
List of Data Science companies	https://www.consultancy.nl/rankings/beste-adviesbureaus-per-vakgebied/data-science

Appendix III. Reliability measurement – Cronbach's Alpha

Case Processing Summary

		N	%
Cases	Valid	103	100,0
	Excluded[a]	0	,0
	Total	103	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,810	5

Item Statistics

	Mean	Std. Deviation	N
Het gebruik van data is belangrijk binnen de huidige activiteiten van de organisatie.	4,43	,762	103
Binnen de organisatie hebben wij een goede besluitvorming.	3,81	,780	103
Binnen de organisatie wordt er gebruik gemaakt van data analytics voor de besluitvorming.	3,47	1,092	103
Het gebruik van data analytics is belangrijk voor de besluitvorming in de organisatie.	4,04	,816	103
Het gebruik van data analytics voor de besluitvorming verbetert de performance van de organisatie.	4,35	,667	103

Case Processing Summary

		N	%
Cases	Valid	103	100,0
	Excluded[a]	0	,0
	Total	103	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,775	3

Item Statistics

	Mean	Std. Deviation	N
De leidinggevenden zetten zich in voor het stimuleren van innovatie.	4,05	,821	103
Binnen de organisatie staat data gedreven besluitvorming hoog op de agenda.	3,65	1,026	103
Binnen de organisatie is er als doel om in de komende jaren data gedreven te worden.	3,89	,999	103

Case Processing Summary

		N	%
Cases	Valid	103	100,0
	Excluded[a]	0	,0
	Total	103	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,785	7

Item Statistics

	Mean	Std. Deviation	N
Het ontbreken van de benodigde mensen en skills waren/zijn een belemmering voor de organisatie om data gedreven te worden.	3,89	1,179	103
Het budget van de organisatie was/is een belemmering om data gedreven te worden.	2,84	,947	103
De IT infrastructuur van de organisatie was/is een belemmering om data gedreven te worden.	3,17	1,224	103
De toegankelijkheid van data was/is een belemmering om data gedreven te worden.	3,15	1,106	103
De bruikbaarheid van data was/is een belemmering om data gedreven te worden.	3,48	1,074	103
Tijd was/is een belemmering voor de organisatie om data gedreven te worden.	3,37	,907	103
Het managen van verandering binnen de organisatie was/is een belemmering om data gedreven te worden.	3,52	1,203	103

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5,733	28,665	28,665	5,093	25,464	25,464
2	3,217	16,083	44,748			
3	1,555	7,773	52,521			
4	1,294	6,472	58,993			
5	1,127	5,634	64,627			
6	1,023	5,114	69,742			
7	,971	4,856	74,598			
8	,840	4,199	78,797			
9	,744	3,718	82,515			
10	,513	2,565	85,080			
11	,473	2,364	87,444			
12	,436	2,179	89,623			
13	,391	1,954	91,577			
14	,320	1,602	93,179			
15	,314	1,571	94,750			
16	,279	1,395	96,146			
17	,266	1,329	97,475			
18	,213	1,063	98,537			
19	,172	,858	99,396			
20	,121	,604	100,000			

Extraction Method: Principal Axis Factoring.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
Lack of skills/staff	,835			
Lack of IT infrastructure	,786			
Lack of usability of data	,636	-,333		
Lack of accessbility of data	,571	-,312		,319
High educated staff	-,568	,437		
Lack of budget	,566			,548
Executive commitment to data		,802		
Interdepartmental dynamics		,799		
Data-Driven Decision-making Adoption		,714		-,333
Lack of change management	,529	-,577		
Organisational structure	,317	-,539	,331	
Organisation Size			,804	
Amount of IT investment			,736	
Competitive intensity			,498	
Lack of time				,899

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

		Organisation Size	Amount of IT investment	High educated staff	Organisational structure	Interdepartmental dynamics	Competitive intensity	Data-Driven Decision-making Adoption	Executive commitment to data
Correlation	Organisation Size	1,000	,416	-,186	,188	-,009	,174	,184	,009
	Amount of IT investment	,416	1,000	,028	,025	,126	,202	,285	,141
	High educated staff	-,186	,028	1,000	-,576	,309	-,109	,382	,253
	Organisational structure	,188	,025	-,576	1,000	-,249	,217	-,267	-,337
	Interdepartmental dynamics	-,009	,126	,309	-,249	1,000	,098	,551	,557
	Competitive intensity	,174	,202	-,109	,217	,098	1,000	,097	,097
	Data-Driven Decision-making Adoption	,184	,285	,382	-,267	,551	,097	1,000	,543
	Executive commitment to data	,009	,141	,253	-,337	,557	,097	,543	1,000
	Lack of skills/staff	-,038	,029	-,415	,169	-,200	,145	-,106	-,096
	Lack of budget	-,018	-,038	-,247	-,001	,048	,082	-,185	,010
	Lack of IT infrastructure	-,106	-,044	-,508	,327	-,108	,034	-,216	-,243
	Lack of accessbility of data	,097	,037	-,471	,300	-,315	,176	-,243	-,245
	Lack of usability of data	,151	,004	-,406	,191	-,343	,108	-,266	-,349
	Lack of time	-,070	,032	-,165	-,033	-,025	-,042	-,294	-,103
	Lack of change management	,001	-,020	-,411	,476	-,480	,056	-,397	-,473

		Lack of skills/staff	Lack of budget	Lack of IT infrastructure	Lack of accessbility of data	Lack of usability of data	Lack of time	Lack of change management
Correlation	Organisation Size	-,038	-,018	-,106	,097	,151	-,070	,001
	Amount of IT investment	,029	-,038	-,044	,037	,004	,032	-,020
	High educated staff	-,415	-,247	-,508	-,471	-,406	-,165	-,411
	Organisational structure	,169	-,001	,327	,300	,191	-,033	,476
	Interdepartmental dynamics	-,200	,048	-,108	-,315	-,343	-,025	-,480
	Competitive intensity	,145	,082	,034	,176	,108	-,042	,056
	Data-Driven Decision-making Adoption	-,106	-,185	-,216	-,243	-,266	-,294	-,397
	Executive commitment to data	-,096	,010	-,243	-,245	-,349	-,103	-,473
	Lack of skills/staff	1,000	,398	,536	,388	,482	,001	,489
	Lack of budget	,398	1,000	,353	,312	,285	,307	,184
	Lack of IT infrastructure	,536	,353	1,000	,394	,436	,074	,436
	Lack of accessbility of data	,388	,312	,394	1,000	,576	,268	,421
	Lack of usability of data	,482	,285	,436	,576	1,000	,029	,473
	Lack of time	,001	,307	,074	,268	,029	1,000	,144
	Lack of change management	,489	,184	,436	,421	,473	,144	1,000

Appendix IV. Output Multiple regression analysis

Descriptive Statistics

	Mean	Std. Deviation	N
Data-Driven Decision-making Adoption	3,47	1,092	103
Organisation Size	560,8544	1599,46150	103
Organisational structure	2,62	1,173	103
Amount of IT investment	390,2621	1243,73400	103
High educated staff	66,8058	29,13729	103
Executive commitment to data	4,05	,821	103
Interdepartmental dynamics	4,05	,809	103
Competitive intensity	4,28	,692	103
Market type	1,6117	1,09574	103

Correlations

		Data-Driven Decision-making Adoption	Organisation Size	Organisational structure	Amount of IT investment	High educated staff	Executive commitment to data	Interdepartmental dynamics	Competitive intensity	Market type
Pearson Correlation	Data-Driven Decision-making Adoption	1,000	,184	-,267	,264	,382	,543	,551	,097	-,085
	Organisation Size	,184	1,000	,188	,436	-,186	,009	-,009	,174	-,002
	Organisational structure	-,267	,188	1,000	,016	-,576	-,337	-,249	,217	,159
	Amount of IT investment	,264	,436	,016	1,000	,032	,117	,101	,196	,113
	High educated staff	,382	-,186	-,576	,032	1,000	,253	,309	-,109	-,248
	Executive commitment to data	,543	,009	-,337	,117	,253	1,000	,557	,097	,010
	Interdepartmental dynamics	,551	-,009	-,249	,101	,309	,557	1,000	,098	-,045
	Competitive intensity	,097	,174	,217	,196	-,109	,097	,098	1,000	-,010
	Market type	-,085	-,002	,159	,113	-,248	,010	-,045	-,010	1,000
Sig. (1-tailed)	Data-Driven Decision-making Adoption	.	,031	,003	,003	,000	,000	,000	,165	,197
	Organisation Size	,031	.	,029	,000	,030	,465	,464	,039	,494
	Organisational structure	,003	,029	.	,437	,000	,000	,006	,014	,054
	Amount of IT investment	,003	,000	,437	.	,375	,121	,155	,023	,129
	High educated staff	,000	,030	,000	,375	.	,005	,001	,137	,006
	Executive commitment to data	,000	,465	,000	,121	,005	.	,000	,166	,459
	Interdepartmental dynamics	,000	,464	,006	,155	,001	,000	.	,162	,326
	Competitive intensity	,165	,039	,014	,023	,137	,166	,162	.	,462
	Market type	,197	,494	,054	,129	,006	,459	,326	,462	.
N	Data-Driven Decision-making Adoption	103	103	103	103	103	103	103	103	103
	Organisation Size	103	103	103	103	103	103	103	103	103
	Organisational structure	103	103	103	103	103	103	103	103	103
	Amount of IT investment	103	103	103	103	103	103	103	103	103
	High educated staff	103	103	103	103	103	103	103	103	103
	Executive commitment to data	103	103	103	103	103	103	103	103	103
	Interdepartmental dynamics	103	103	103	103	103	103	103	103	103
	Competitive intensity	103	103	103	103	103	103	103	103	103
	Market type	103	103	103	103	103	103	103	103	103

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Market type, Organisation Size, Executive commitment to data, Competitive intensity, High educated staff , Amount of IT investment, Interdepartmental dynamics, Organisational structure[b]	.	Enter

a. Dependent Variable: Data-Driven Decision-making Adoption

b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,696[a]	,485	,441	,816	,485	11,070	8	94	,000

a. Predictors: (Constant), Market type, Organisation Size, Executive commitment to data, Competitive intensity, High educated staff , Amount of IT investment, Interdepartmental dynamics, Organisational structure

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	59,004	8	7,376	11,070	,000[b]
	Residual	62,627	94	,666		
	Total	121,631	102			

a. Dependent Variable: Data-Driven Decision-making Adoption

b. Predictors: (Constant), Market type, Organisation Size, Executive commitment to data, Competitive intensity, High educated staff , Amount of IT investment, Interdepartmental dynamics, Organisational structure

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-,588	,772		-,762	,448					
	Organisation Size	,000	,000	,174	2,035	,045	,184	,205	,151	,749	1,335
	Organisational structure	,020	,090	,022	,228	,820	-,267	,023	,017	,588	1,700
	Amount of IT investment	,000	,000	,117	1,366	,175	,264	,139	,101	,752	1,329
	High educated staff	,009	,004	,247	2,581	,011	,382	,257	,191	,597	1,675
	Executive commitment to data	,408	,124	,307	3,293	,001	,543	,322	,244	,630	1,587
	Interdepartmental dynamics	,401	,124	,297	3,242	,002	,551	,317	,240	,653	1,530
	Competitive intensity	,011	,125	,007	,089	,929	,097	,009	,007	,879	1,138
	Market type	-,030	,078	-,030	-,381	,704	-,085	-,039	-,028	,900	1,111

a. Dependent Variable: Data-Driven Decision-making Adoption

Appendix V. Output cross tabulation of barriers of becoming data-driven

Lack of skills/staff * GroupOrganisations Crosstabulation

			GroupOrganisations			
			Small	SME	Large	Total
Lack of skills/staff	Helemaal niet eens	Count	4	0	0	4
		% within Lack of skills/staff	100,0%	0,0%	0,0%	100,0%
		% within GroupOrganisations	9,1%	0,0%	0,0%	3,9%
	Oneens	Count	12	2	1	15
		% within Lack of skills/staff	80,0%	13,3%	6,7%	100,0%
		% within GroupOrganisations	27,3%	5,9%	4,0%	14,6%
	Neutraal	Count	4	3	1	8
		% within Lack of skills/staff	50,0%	37,5%	12,5%	100,0%
		% within GroupOrganisations	9,1%	8,8%	4,0%	7,8%
	Eens	Count	14	10	13	37
		% within Lack of skills/staff	37,8%	27,0%	35,1%	100,0%
		% within GroupOrganisations	31,8%	29,4%	52,0%	35,9%
	Helemaal eens	Count	10	19	10	39
		% within Lack of skills/staff	25,6%	48,7%	25,6%	100,0%
		% within GroupOrganisations	22,7%	55,9%	40,0%	37,9%
Total		Count	44	34	25	103
		% within Lack of skills/staff	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%

Lack of budget * GroupOrganisations Crosstabulation

			GroupOrganisations			
			Small	SME	Large	Total
Lack of budget	Helemaal niet eens	Count	4	0	1	5
		% within Lack of budget	80,0%	0,0%	20,0%	100,0%
		% within GroupOrganisations	9,1%	0,0%	4,0%	4,9%
	Oneens	Count	17	11	9	37
		% within Lack of budget	45,9%	29,7%	24,3%	100,0%
		% within GroupOrganisations	38,6%	32,4%	36,0%	35,9%
	Neutraal	Count	6	16	11	33
		% within Lack of budget	18,2%	48,5%	33,3%	100,0%
		% within GroupOrganisations	13,6%	47,1%	44,0%	32,0%
	Eens	Count	15	6	4	25
		% within Lack of budget	60,0%	24,0%	16,0%	100,0%
		% within GroupOrganisations	34,1%	17,6%	16,0%	24,3%
	Helemaal eens	Count	2	1	0	3
		% within Lack of budget	66,7%	33,3%	0,0%	100,0%
		% within GroupOrganisations	4,5%	2,9%	0,0%	2,9%
Total		Count	44	34	25	103
		% within Lack of budget	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%

Lack of IT infrastructure * GroupOrganisations Crosstabulation

			GroupOrganisations			
			Small	SME	Large	Total
Lack of IT infrastructure	Helemaal niet eens	Count	9	1	0	10
		% within Lack of IT infrastructure	90,0%	10,0%	0,0%	100,0%
		% within GroupOrganisations	20,5%	2,9%	0,0%	9,7%
	Oneens	Count	9	7	7	23
		% within Lack of IT infrastructure	39,1%	30,4%	30,4%	100,0%
		% within GroupOrganisations	20,5%	20,6%	28,0%	22,3%
	Neutraal	Count	13	9	3	25
		% within Lack of IT infrastructure	52,0%	36,0%	12,0%	100,0%
		% within GroupOrganisations	29,5%	26,5%	12,0%	24,3%
	Eens	Count	12	8	9	29
		% within Lack of IT infrastructure	41,4%	27,6%	31,0%	100,0%
		% within GroupOrganisations	27,3%	23,5%	36,0%	28,2%
	Helemaal eens	Count	1	9	6	16
		% within Lack of IT infrastructure	6,3%	56,3%	37,5%	100,0%
		% within GroupOrganisations	2,3%	26,5%	24,0%	15,5%
Total		Count	44	34	25	103
		% within Lack of IT infrastructure	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%

Lack of accessbility of data * GroupOrganisations Crosstabulation

			GroupOrganisations			
			Small	SME	Large	Total
Lack of accessbility of data	Helemaal niet eens	Count	7	0	0	7
		% within Lack of accessbility of data	100,0%	0,0%	0,0%	100,0%
		% within GroupOrganisations	15,9%	0,0%	0,0%	6,8%
	Oneens	Count	14	7	4	25
		% within Lack of accessbility of data	56,0%	28,0%	16,0%	100,0%
		% within GroupOrganisations	31,8%	20,6%	16,0%	24,3%
	Neutraal	Count	8	10	9	27
		% within Lack of accessbility of data	29,6%	37,0%	33,3%	100,0%
		% within GroupOrganisations	18,2%	29,4%	36,0%	26,2%
	Eens	Count	13	14	7	34
		% within Lack of accessbility of data	38,2%	41,2%	20,6%	100,0%
		% within GroupOrganisations	29,5%	41,2%	28,0%	33,0%
	Helemaal eens	Count	2	3	5	10
		% within Lack of accessbility of data	20,0%	30,0%	50,0%	100,0%
		% within GroupOrganisations	4,5%	8,8%	20,0%	9,7%
Total		Count	44	34	25	103
		% within Lack of accessbility of data	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%

Lack of usability of data * GroupOrganisations Crosstabulation

			GroupOrganisations			
			Small	SME	Large	Total
Lack of usability of data	Helemaal niet eens	Count	3	0	0	3
		% within Lack of usability of data	100,0%	0,0%	0,0%	100,0%
		% within GroupOrganisations	6,8%	0,0%	0,0%	2,9%
	Oneens	Count	15	2	3	20
		% within Lack of usability of data	75,0%	10,0%	15,0%	100,0%
		% within GroupOrganisations	34,1%	5,9%	12,0%	19,4%
	Neutraal	Count	7	8	7	22
		% within Lack of usability of data	31,8%	36,4%	31,8%	100,0%
		% within GroupOrganisations	15,9%	23,5%	28,0%	21,4%
	Eens	Count	18	16	7	41
		% within Lack of usability of data	43,9%	39,0%	17,1%	100,0%
		% within GroupOrganisations	40,9%	47,1%	28,0%	39,8%
	Helemaal eens	Count	1	8	8	17
		% within Lack of usability of data	5,9%	47,1%	47,1%	100,0%
		% within GroupOrganisations	2,3%	23,5%	32,0%	16,5%
Total		Count	44	34	25	103
		% within Lack of usability of data	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%

Lack of time * GroupOrganisations Crosstabulation

			GroupOrganisations			
			Small	SME	Large	Total
Lack of time	Helemaal niet eens	Count	2	0	0	2
		% within Lack of time	100,0%	0,0%	0,0%	100,0%
		% within GroupOrganisations	4,5%	0,0%	0,0%	1,9%
	Oneens	Count	9	4	4	17
		% within Lack of time	52,9%	23,5%	23,5%	100,0%
		% within GroupOrganisations	20,5%	11,8%	16,0%	16,5%
	Neutraal	Count	7	16	9	32
		% within Lack of time	21,9%	50,0%	28,1%	100,0%
		% within GroupOrganisations	15,9%	47,1%	36,0%	31,1%
	Eens	Count	25	11	9	45
		% within Lack of time	55,6%	24,4%	20,0%	100,0%
		% within GroupOrganisations	56,8%	32,4%	36,0%	43,7%
	Helemaal eens	Count	1	3	3	7
		% within Lack of time	14,3%	42,9%	42,9%	100,0%
		% within GroupOrganisations	2,3%	8,8%	12,0%	6,8%
Total		Count	44	34	25	103
		% within Lack of time	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%

Lack of change management * GroupOrganisations Crosstabulation

			GroupOrganisations			Total
			Small	SME	Large	
Lack of change management	Helemaal niet eens	Count	5	0	1	6
		% within Lack of change management	83,3%	0,0%	16,7%	100,0%
		% within GroupOrganisations	11,4%	0,0%	4,0%	5,8%
	Oneens	Count	13	3	0	16
		% within Lack of change management	81,3%	18,8%	0,0%	100,0%
		% within GroupOrganisations	29,5%	8,8%	0,0%	15,5%
	Neutraal	Count	11	7	8	26
		% within Lack of change management	42,3%	26,9%	30,8%	100,0%
		% within GroupOrganisations	25,0%	20,6%	32,0%	25,2%
	Eens	Count	10	8	10	28
		% within Lack of change management	35,7%	28,6%	35,7%	100,0%
		% within GroupOrganisations	22,7%	23,5%	40,0%	27,2%
	Helemaal eens	Count	5	16	6	27
		% within Lack of change management	18,5%	59,3%	22,2%	100,0%
		% within GroupOrganisations	11,4%	47,1%	24,0%	26,2%
Total		Count	44	34	25	103
		% within Lack of change management	42,7%	33,0%	24,3%	100,0%
		% within GroupOrganisations	100,0%	100,0%	100,0%	100,0%