Is Big data too Big for Swedish SMEs?
A quantitative study examining how the employees of small and medium-sized enterprises perceive Big data analytics

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Abstract

Background: Marketing is evolving because of Big data, and there are a lot of possibilities as well as challenges associated with Big data, especially for small and medium sized companies (SMEs), who face barriers that prevent them from taking advantage of Big data. For companies to analyze Big data, Big data analytics are used which helps companies analyze large amounts of data. However, previous research is lacking in regard to how SMEs can implement Big data analytics and how Big data analytics are perceived by SMEs.

Purpose: The purpose of this study is to investigate how the employees of Swedish SMEs perceive Big data analytics.

Research Questions: How do employees of Swedish SMEs perceive Big data analytics in their current work environment? How do the barriers impact the perceptions of Big data analytics?

Methodology: The research proposes a quantitative cross-sectional design as the source of empirical data. To gather the data, a survey was administered to the employees of Swedish companies that employed less than 250 people, these companies were regarded as SMEs. 139 answered the survey and out of those, the analysis was able to use 93 of the answers. The data was analyzed using previous theories, such as the Technology Acceptance Model (TAM).

Findings: The research concluded that the employees had positive perceptions about Big data analytics. Further, the research concluded that two of the barriers (security and resources) analyzed impacted the perceptions of the employees, whereas privacy of personal data did not.

Theoretical Implications: This study adds to the lacking Big data research, and improves the understanding of Big data and Big data analytics. The study also adds to the existing gap in literature to provide a more comprehensive view of Big data.

Limitations: The main limitation of the study were that previous literature has been vague and ambiguous and therefore may not be applicable.

Practical Implications: The study helps SMEs understand how to better implement Big data analytics and what barriers need to be prioritized regarding Big data analytics.

Originality: To the best of the author’s knowledge there is a significant lack of academic literature regarding Big data, Big data analytics and Swedish SMEs, therefore this study could be one of the pioneer studies examining these topics which will significantly contribute to current research.

Key words: Big data, Big data analytics, Technology Adoption Barriers, Technology Acceptance Model, Perception, SME, Sweden.
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Växjö 23rd of May 2018

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Appendix 1: Survey
1 Introduction

This chapter begins by presenting the background of Big data, how companies can use Big data and some problems with Big data. After the background, the problematizing of the subjects, the purpose of the study, the research questions, and the research delimitations are presented. The chapter concludes with an outline of the study.

1.1 Background

An enormous amount of electronic data is created worldwide every day, and at just the company YouTube more than 100 hours of video are uploaded every minute (Mousannif et al., 2016). Everyone who, “likes” or “follows” on social media, or interacts with a website contributes to Big data (Mousannif et al., 2016). Almost everyone who interacts with a website helps to contribute to a large amount of data gathered every day. Big data is a large amount of data that requires specific analysis methods and tools, due to the size and complexity of the data (De Mauro et al., 2016; Mengke et al., 2016). Big data cannot be analyzed using the same techniques and technologies used for small amounts of data and needs specific Big data analytics” for its analysis. Big data analytics are the techniques and technologies that are used by those who want to analyze Big data (Kwon et al., 2014). These can be programs, software or tools that are custom-made to handle large amounts of data (Kwon et al., 2014).

Furthermore, Big data analytics can provide companies with a sustainable competitive advantage by being at the forefront of this new technology (Pridmore & Hämäläinen, 2017; Côte-Real, Oliveira & Ruivo, 2017; Zhang et al., 2017). Both small and medium sized enterprises (SMEs) and large companies can benefit from using Big data to improve their business (Del Vecchio et al., 2018). Big data can change internal business strategies, it can help the companies in finding new markets, or it can help companies target their existing customers better (Erevelles et al., 2016). Moreover, around 99% businesses in The European Union qualify as micro, small or medium-sized enterprises (Nowicka, 2015). SMEs are essential for the European economy and account for more than half of the employment (Hessels & Parker, 2013).

Furthermore, marketing is changing because of Big data and companies can gain more insights than before (Liu & Burns, 2018). Changes has made the demand for Big data analytics increase
in recent years (Karamehmet, 2017). If the employees understand Big data Analytics (Google Analytics, Google AdWords, Facebook Analytics, LinkedIn Analytics), they can immensely improve a company’s marketing (Liu & Burns, 2018). An example of Big data analytics is “Google Analytics”. Google Analytics helps companies understand why and how someone buys a product/service using their site (Liu & Burns, 2018). It can demonstrate to companies how long a typical person is on their site, what products they bought, what products they looked at but did not buy and other consumer analytics (Gunter & Önder, 2016). Google Analytics is an essential tool for marketers who wish to gain insights about what the people on their site respond to (Liu & Burns, 2018; Gunter & Önder, 2016). Furthermore, Google Analytics is similar to another Google tool, Google AdWords (Liu & Burns, 2018). Google AdWords helps companies advertise on Google's different sites and for search engine marketing (SEM). A person who understands how Google Analytics and Google AdWords work are in high demand by companies, because this knowledge is valuable for the company (Liu & Burns, 2018). As mentioned earlier social media analytics are examples of Big data analytics, that help companies gain information about their customers and potential customers (Mackay, 2017; Liu & Burns, 2018). Two examples of social media analytics are “Facebook Analytics” and “LinkedIn Analytics”, where people share their thoughts, opinions, and ideas. A company can understand what their customers' opinions are without asking them directly and instead using social media and website analytics, to gain real-time insights. (Mackay, 2017). However, there have been concerns about how companies gather and analyze Big data (Hofacker et al., 2016).

These topics were discussed recently in April 2018 due to a scandal involving Facebook. Mark Zuckerberg, the CEO of Facebook, was asked questions regarding personal data, security and data mining by the United States Senate Commerce and Judiciary Committees on April 10th, 2018 (The Washington Post, 2018). It was revealed that Cambridge Analytica improperly accessed some of the user data Facebook stored. The statements made by the senators and Mark Zuckerberg show that there is a lot of confusion and concerns surrounding Big data. There were discussions about how data could be gathered and the need to protect personal information. Furthermore, privacy and security can be barriers for companies who want to implement Big data analytics (Alharthi et al., 2017). Security and privacy are just two of the barriers associated with Big data. Available resources, including financial and human, is also a significant barrier when implementing Big data analytics (Alharthi et al., 2017; Coleman et al., 2016). These barriers can make it difficult for companies to implement Big data analytics, although despite the barriers Big data is deemed as a big opportunity for SMEs (Alharthi et al., 2017; Coleman
et al., 2016). This confusion is also recurring in Big data research that is lacking and Big data is described as ambiguous (Wiencierz & Röttger, 2017; De Mauro et al., 2016). To the authors understanding this paper could be one of the pioneer papers regarding Big data and Swedish SMEs.

1.2 Problem discussion

Big data can be useful for companies who wish to improve their marketing, by using Big data analytics companies could improve their understanding of their consumers (Erevelles et al., 2016). Research and businesses are starting to use Big data analytics more than they previously have (Hofacker et al., 2016; Moreno et al., 2016). Before it was cheaper deleting data, compared to recent years, when it has been a transition towards it being cheaper to store data (Hofacker et al., 2016).

An example of how a company used Big data to target consumers in a practical way was by changing the price of baseball tickets based (Erevelles et al., 2016). The prices were set based upon different variables such as time, weather, what teams played, the potential for records during the event, how much social media discussion there was about the game and a variety of other factors. A massive amount of data that was gathered and analyzed helped the company price their tickets effectively. Using Big data will improve how every aspect of marketing is analyzed (Erevelles et al., 2016). With the development of user data collection methods, such as social media, companies can adopt more effective marketing strategies that include target marketing, segmentation and predictive analysis (Pridmore & Hämäläinen, 2017; Mousannif et al., 2016; Banerjee et al., 2013).

Despite the many advantages of Big data research claims that SMEs are not adopting it (Coleman et al., 2016). It can sometimes be challenging to implement Big data in an effective manner (Erevelles et al., 2016). Limited resources could be a significant problem for companies that aim to implement Big data. Barriers prevent SMEs from using Big data to the extent that large companies can (Del Vecchio et al., 2018; Coleman et al., 2016). The barriers SMEs have to overcome for implementing Big data are not as significant issues for large companies to overcome (Del Vecchio et al., 2018; Alharthi et al., 2017; Coleman et al., 2016). The barriers make SMEs slow adopters of the Big data (Del Vecchio et al., 2018; Coleman et al., 2016; Rehman et al., 2016). The adoption rate of Big data for UK SMEs was 0.2% compared to large
companies (businesses with over 1000 employees) that had an adoption rate of 25% (Coleman et al., 2016).

Moreover, there are many potential reasons for why businesses are not using Big data although the research is limited surrounding the perceptions of the users. Whenever a new technology emerges, it is crucial to understand how it is perceived. A person who has a positive perception of a system will relate to them using that system (Brock & Khan, 2017). These findings were first claimed by Fred Davis who suggested that the intention to use a technology was an indicator for if someone would or would not use that system (Davis et al., 1989). He developed the Technology Acceptance Model (TAM) that showed how the perceptions of technology relate to usage.

Furthermore, current research focuses on the barriers to implementing Big data (Del Vecchio et al., 2018; Alharthi et al., 2017; Coleman et al., 2016). Big data, in general, has been the focus of current; new research should examine Big data and specific problems (Moreno et al., 2016). The barriers are an indication of why SMEs are not implementing Big data analytics. However, the research is limited in regard to how the Big data analytics are perceived. The employees are the users of Big data analytics at SMEs, and their perceptions are important. A user who perceives technology as being difficult to use and not useful will have a lower chance of using that technology (Davis, 1989). By understanding the perceptions of Big data analytics will contribute towards understanding what needs to be improved for SMEs to implement Big data analytics.

As mentioned previously, Big data analytics is a growing market (Karamehmet, 2017). However, there needs to be more research made on the topic of Big data in general as well as Big data analytics surrounding SMEs. Big data analytics have not been discussed enough in scientific journals (Wiencierz & Röttger, 2017). Currently, there is a lack of empirical evidence surrounding Big data and Big data analytics in the context SMEs (Del Vecchio et al., 2018). There also needs to be more research made surrounding Big data and social media (Ducange et al., 2018). Big data is in its early development, and much research is ambiguous surrounding Big data, how to use it and how to define it (Wiencierz & Röttger, 2017).

Moreover, Sweden is one of the countries in Europe where most firms have websites (Falk & Hagsten, 2015). About 90% of firms in Sweden have a website, and Swedish firms are often
engaged in e-commerce activities. Although, there is limited research regarding Sweden and Big data. Because of the digital maturity in Sweden, it is a fitting country for analyzing Big data and Big data analytics. Big data has not been studied sufficiently in the context of Sweden, SMEs and from the perspective of the employees. Using Davis’ model will determine how Big data analytics are perceived and thus help SMEs understand what actions should be taken to improve Big data analytics implementation. Analyzing Big data analytics in a new context from the perception of the employees of Swedish SMEs will add to the existing literature that lacks empirical evidence. Previous research was characterized by ambiguity; therefore, it is important to conduct this research, and to analyze Big data in the context of Swedish SMEs which will fulfill the research gap.

1.3 Purpose

The purpose of this study is to investigate how the employees of Swedish SMEs perceive Big data analytics.

1.4 Research Questions

How do employees of Swedish SMEs perceive Big data analytics in their current work environment?

How do the barriers impact the perceptions of Big data analytics?

1.5 Delimitations

Big data can be problematic to define and encapsulates many different analytical tools and analysis methods that help companies in different ways. This paper is going to focus on Big data in the context of marketing, such as market segmentation, targeting customers and consumer behavior. Moreover, there are many different types of software, such as Hadoop and MapReduce. However, these types of Big data analytics will not be the focus of this paper, the tools that will be analyzed are Google AdWords, Facebook Analytics, Google Analytics and LinkedIn Analytics.

1.6 Outline of study

The first chapter introduces some of the topics that are essential for the paper. It explains why the perception of technology is important, a brief explanation of Big data and Big data analytics.
Furthermore, the introduction examines how Big data has previously been researched and discusses the gap of previous research. The literature review describes the concepts of perception and the Technology Acceptance Model which is used to analyze how a person perceives a technology. The literature also describes Big data and Big data analytics in depth to give the reader a comprehensive view of the topics. Further, the literature review presents the hypotheses throughout the text. Moreover, in the frame of references chapter, a model is developed based on the theory to give an in-depth view of the study. After which the methodology chapter is presented which discusses the data gathering process. The results are presented in the chapter following the methodology chapter, which presents the results of the study, with validity, reliability and hypotheses testing. After the results have been presented, the discussion chapter is presented which discusses the concepts based on the results and previous theory. Lastly, conclusions, managerial implications, theoretical implications, limitations and further studies are presented based upon the literature and the results of the study.
2 Literature review

In the literature review, the authors describe the theory and concepts surrounding Big data, SMEs, Technology Acceptance Model, adoption barriers, marketing, and perception, as well as defining the hypotheses.

2.1 Frame of literature

To answer the purpose and the research questions of this study, firstly, theory regarding Big data and Big data analytics are presented, secondly the Technology Acceptance Model is presented, and lastly barriers that make it difficult for SMEs to implement Big data are presented. Big data and Big data analytics are presented first to ensure these concepts are accurately explained. After the main concepts of this paper have been presented, the Technology Acceptance Model (TAM) is presented. The Technology Acceptance Model aims to describe the perceptions of technology users, which has different subsections, that are, Perceived Ease of Use, Perceived Usefulness, Attitude and Intention to Use. This theoretical framework aims to understand the perceptions of technology users, and in this paper, the technology users are the employees of Swedish SMEs who have used Big data analytics. Lastly the adoption barriers that SMEs face when implementing Big data are presented. The barriers are first described in a general sense, after which the different barriers are described more in-depth. The barriers analyzed are Financial and Human Resources, Security and Privacy of Personal Data. The frame of literature can be viewed in the figure below labeled "Figure 1: Frame of literature". 
2.2 What is Big data?

As mentioned earlier there is a lack of literature regarding the topics of Big data, Big data analytics and SMEs. Few academic journals have been published surrounding the topics. Using “OneSearch” searching for academic journals (19th of May), it was discovered that by searching for “SME” along with “Big data analytics” 88 results were provided. In the last year, 52 had been published out of those 88. “Big data” along with “SME” provided 212 results, and by searching a combination for “SME,” “Sweden” together with “Big data analytics” only provided 16 results, 11 of which had been published in the last year. Big data has not been studied enough and needs more academic research (Del Vecchio et al., 2018; Wiencierz & Röttger, 2017).
Defining Big data based solely on the volume of the data can be a limited definition (Gandomi & Haider, 2015). Big data is a debatable term which is often characterized of changing circumstances, and there is a discussion of how to accurately define Big data. Data can be considered large in a specific type of industry; however, in another, it may not be considered large. As stated, describing Big data based solely on the size of the data can be limiting and more factors need to be considered. What was once deemed to be massive amounts of data is today only a fraction of what would be considered a lot of data (Brock & Khan, 2017). All of the data created before 2003 is believed to be created every minute today. It is clear that Big data is difficult to define because there are no benchmarks to define what “fast” or “big” is in this context. The rapid size increase is one of the reasons why volume is not a useful metric for defining Big data (De Mauro et al., 2016; Wiencierz & Röttger, 2017). Big data is a “buzzword,” and Big data descriptions are often ambiguous (Wiencierz & Röttger, 2017). Big data has been lacking a formal definition and the definitions have been inconsistent (De Mauro et al., 2016). As can be seen in the table below there are many different definitions of Big data.

Table 1: Defining Big data

<table>
<thead>
<tr>
<th>Author(s), Year</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>George et al., 2014</td>
<td>“(..)offers voluminous quantities of data over multiple periods (whether seconds, minutes, hours, days, months, or years)” p.324</td>
</tr>
<tr>
<td>Wamba et al., 2015</td>
<td>“(…)a holistic approach to manage, process and analyze 5 Vs (i.e., volume, variety, velocity, veracity and value) in order to create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages” p.235</td>
</tr>
<tr>
<td>De Mauro et al., 2016</td>
<td>“(…)the Information asset characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value” p.22</td>
</tr>
<tr>
<td>Del Vecchio et al., 2018</td>
<td>“...refers to any set of data that, with traditional systems, would require large capabilities in terms of storage space and time to be analysed” p.6</td>
</tr>
</tbody>
</table>

For this study, Big data will be defined as “(…)the Information asset characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value” (De Mauro et al., 2016, p.22). Furthermore, Big data analytics can also be challenging to define. The table below labeled “Table 2: Defining Big data analytics” presents some definitions of Big data analytics.
Table 2: Defining Big data analytics

<table>
<thead>
<tr>
<th>Author(s), Year</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwon et al., 2014</td>
<td>“(..)technologies (e.g., database and data mining tools) and techniques (e.g., analytical methods) that a company can employ to analyze large scale, complex data for various applications intended to augment firm performance in various dimensions” p.387</td>
</tr>
<tr>
<td>Gandomi &amp; Haider, 2015</td>
<td>“(..)techniques used to analyze and acquire intelligence from big data” p.140</td>
</tr>
<tr>
<td>Coleman et al., 2016</td>
<td>“(..)that is, analytical tools and libraries, which support exploratory, descriptive, predictive, statistical analysis and machine learning” (p.2155).</td>
</tr>
<tr>
<td>Wamba et al., 2017</td>
<td>“(..)a holistic approach to managing, processing and analyzing the 5 V data-related dimensions (i.e., volume, variety, velocity, veracity and value) to create actionable ideas for delivering sustained value, measuring performance and establishing competitive advantages” p. 356</td>
</tr>
</tbody>
</table>

As can be seen in “Table 1: Defining Big data” along with “Table 2: Defining Big data analytics”, Wamba et al., (2017) used the same definition for Big data analytics as they previously had used for Big data in 2015 (Wamba et al., 2015), and there are many different ways that Big data analytics and Big data can be defined. For this study, Big data analytics will be defined as “(..)techniques used to analyze and acquire intelligence from big data” (Gandomi & Haider, 2015, p. 140).

2.3 Dimensions of Big data

Big data have many dimensions which help to explain it (Brock & Khan, 2017). However, there is not a consensus and different researchers have different dimensions (Gandomi & Haider, 2015). The main concepts of Big data are the three V’s known as volume, variety, and velocity (Brock & Khan, 2017; Coleman et al., 2016; Gandomi & Haider, 2015). For this study, Big data will be defined based on the three V’s and the definition discussed in previous chapters. The different dimensions of Big data can be seen in the table below, labeled “Table 3: Dimensions of Big data”.
### Table 3: Dimensions of Big data

<table>
<thead>
<tr>
<th>Author(s), Year</th>
<th>Dimension</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gandomi &amp; Haider (2015); Brock &amp; Khan (2017)</td>
<td>Volume</td>
<td>Data can be considered Big data if it is deemed large in volume.</td>
</tr>
<tr>
<td>Coleman et al., (2016)</td>
<td>Variety</td>
<td>Big data consists of data from different sources with a lot of different formats that can be structured, semi-structured and unstructured.</td>
</tr>
<tr>
<td>Gandomi &amp; Haider (2015); Brock &amp; Khan (2017)</td>
<td>Velocity</td>
<td>Big data is gathered and analyzed at high speed.</td>
</tr>
</tbody>
</table>

### 2.4 Big data and changing marketing strategies

There are three ways that companies can implement Big data that are In-house, public cloud or a hybrid approach (Mousannif et al., 2016). The method is decided based on cost, technical requirement, project longevity, security size of company and resources. In some industries, Big data has led to the creation of entirely new business models (Mousannif et al., 2016). Companies can use data to make more informed decisions and increase their performance (Hartmann et al., 2016).

Furthermore, companies can use Big data to improve their PR and marketing communication (Wiencierz & Röttger, 2017). Analyzing data from social media and websites has been regarded as necessary for successful future marketing strategies (Ducange et al., 2018). Social media Big data has the capabilities to change marketing strategies drastically and, companies can utilize social media and website analysis to change their products, gather customer insights and develop new marketing strategies. Therefore, Big data can help to improve various aspects of company’s marketing strategies (Karamehmet, 2017). Due to Big data, marketing is going to change drastically in the future. Using Big data to mine massive amounts of data will help companies to improve their marketing and better reach customers. In the tourism sector, Big data was analyzed using tourism websites, such as, “Tripadvisor.com, Agoda.com, Yelp.com and Booking.com” (Karamehmet, 2017). These were analyzed by the companies to view what improvements were needed to satisfy their customers better. Once a company starts gathering more data they will need specific Big data analytics to analyze the data, because manually
analyzing reviews can be difficult or impossible at that point. Big data can aid companies in several ways, such as improving their communication strategies (Ducange et al., 2018). It is important that Big data analytics are useful and easy to understand for them to be used, although analytics that are both easy to understand and useful are rare (Coleman et al., 2016).

Furthermore, Big data research in regard to large companies and SMEs determined that both could benefit from this new technology (Del Vecchio et al., 2018). Big data was said to improve the innovation strategies for a company. Big data opportunities are deemed endless and can apply to almost all industries in some fashion. SMEs can significantly benefit from Big data by innovation (Del Vecchio et al., 2018). SMEs can often use Big data as large companies, although, the barriers that SMEs face are not as significant for large companies. Often it is easier for large companies to develop economies of scale and this is a problem in regard to Big data for SMEs (Del Vecchio et al., 2018). SMEs need to be careful if they decide to implement new technologies because they have limited resources (Del Vecchio et al., 2018).

2.5 Technology Acceptance Model (TAM)

A model used in information technology (IT) and information system (IS) research is the Technology Acceptance Model (TAM) which was developed by Fred Davis in 1986 (Davis et al., 1989). TRA (Theory of reasoned action) was the basis for TAM, which is similar to TAM with the exceptions that TAM is more focused on technology whereas TRA is a more generic model. TAM was designed to improve TRA except designed for how users perceived an information system. The model claims that there is a relationship from if a user perceives a technology as being easy to use and usefulness to the user’s Attitude (A) of that technology (Davis et al., 1989). A user who thinks that a technology is easy to use and useful will according to TAM have a positive Attitude of that technology. The Attitude, in turn, is connected to the Intention to Use (IU) the technology and a user who has a positive Attitude of a technology will intend to use that technology (Davis et al., 1989). The model below presents all the variables associated with TAM. (Figure 2).
The perceived usefulness (PU) influences the Intention to Use a technology whereas the Perceived Ease of Use (PEOU) only influences the Attitude (Davis et al., 1989). Someone who perceives a technology as being useful will have a high Intention to Use that technology. The Ease of Use determines the user perception of how well they can use the technology with ease (Brock & Khan, 2017). A user who perceives a specific technology as being easy to use will lead to a more positive Attitude of the technology, and a user who perceives the technology as being difficult to use will lead to the user having a more negative Attitude of the technology (Davis et al., 1989). Although, as can be viewed in the model, the Perceived Ease of Use does not influence the Intention to Use directly as the Perceived Usefulness does (Davis et al., 1989).

TAM is a model that has been used extensively in technology research and is still being used today (Brock & Khan, 2017; Folsinshteyn & Lennon, 2016; Bruner & Kumar, 2005). It was recently used to analyze bitcoin and block chain technologies (Folsinshteyn & Lennon, 2016). Although, there are sometimes problems regarding TAM (Brock & Khan, 2017). TAM can provide misleading results if the person providing their opinions about a technology are not knowledgeable about the technology. It is useful if the person providing opinions about the technology have used the technology before or are knowledgeable about the technology to give credible results (Brock & Khan, 2017).

TAM will be used to determine how the employees of SMEs perceive Big data analytics. TAM claims that when a user perceives a technology as being easy to use the user will also perceive
it as being more useful (Davis et al. 1989). TAM will provide insights into how the different perceptions of the users are influenced by each other.

The TAM model claims that the Perceived Ease of Use influences the Perceived Usefulness which developed the following hypothesis:

**H1:** The Perceived Ease of Use of Big data analytics positively influences the Perceived Usefulness of Big data analytics.

2.5.1 Attitude

The Attitude that users have regarding technology is constantly changing because of changing markets (Ratten, 2015). According to the Theory of Reasoned Action (TRA), Attitude can be described as how a technology will be beneficial (Davis et al., 1989). The perceptions a person has will influence their Attitude (A) (Davis et al., 1989). A user who has a positive Attitude of a technology will be more inclined to intent to use it. As previously stated the Perceived Usefulness and Perceived Ease of Use influences the Attitude (Davis et al., 1989).

The TAM model claims that the Perceived Ease of Use and the Perceived Usefulness influences the Attitude which developed the following hypothesis:

**H2:** The Perceived Usefulness of Big data analytics positively influences the Attitude of Big data analytics.

**H3:** The Perceived Ease of Use of Big data analytics positively influences the Attitude of Big data analytics.

2.5.2 Intention to use

A person who has a positive Attitude towards a technology and perceives it as being useful will be inclined to intend to use it (Davis et al., 1989). Depending what Attitude the user has of a technology will influence if they will use it. A negative Attitude will make them less likely to intend to use it whereas a positive Attitude will make them more inclined to use it. As previously mentioned Perceived Usefulness and the Attitude influences the Intention to Use (Davis et al., 1989).
The TAM model claims that the Perceived Usefulness and the Attitude influence the Intention to Use which developed the following hypothesis:

**H4:** *The Perceived Usefulness of Big data analytics positively influences the Intention to Use Big data analytics.*

**H5:** *The Attitude of Big data analytics positively influences the Intention to Use Big data analytics.*

### 2.6 Technology Adoption Barriers

Sometimes barriers prohibit companies from implementing Big data (Alharthi et al., 2017). MacGregor & Vrazalic (2005) researched how Swedish and Australian small businesses (less than 50 employees) implemented E-commerce. SMEs perceived there to be barriers that made it difficult to implement new technology. There were several reasons for why it was difficult to implement new technology for the SMEs. Some of these barriers included that it was complicated, they did not think they had the technical knowledge or there was a high financial investment. Barriers similar to these are now recurring in the literature regarding SMEs and Big data analytics (Coleman et al., 2016).

#### 2.6.1 Financial and Human Resources

For an SME to invest in Big data, it is necessary that they have the sufficient resources to do so and many times the resources of SMEs are limited (Del Vecchio et al., 2018; Coleman et al., 2016). Even companies that use third-party cloud services still have to invest human and financial resources setting up and maintaining the data systems (Coleman et al., 2016). Limited resources cause SMEs to be careful about new investments because they need to choose what technologies are worth investing in and what are not based on their available resources. SMEs sometimes do not have the available financial and human resources to make substantial investments in Big data (Del Vecchio et al., 2018; Alharthi et al., 2017; Coleman et al., 2016). Investing in Big data analytics can be more difficult for SMEs than for large companies due to these limited resources. There may be a need to invest in software, hardware, and human resources to use the Big data analytics effectively.

Furthermore, it is crucial for companies to realize that if they handle Big data in the wrong way, they may be violating laws (Moreno et al., 2016; Tankard, 2012). The company needs to be
aware of the privacy laws, security laws and other laws associated with data handling to make sure that they are not infringing on any laws. A company intending to use Big data analytics may need human resources in other areas than just IT, such as the legal department (Alharthi et al., 2017; Moreno et al., 2016; Tankard, 2012).

2.6.2 Security

Security is an important topic when discussing Big data (Mengke et al., 2016). Enterprises need to be aware of the security issues that exist when analyzing Big data. If enterprises are not careful, they may risk facing security concerns such as information leaking and malware (viruses, spyware, worms, trojans) (Mengke et al., 2016). These security issues can sometimes hinder enterprises from implementing Big data because they perceive them as being problems. Big data can be difficult to secure due to its volume, variety, and velocity (Mengke et al., 2016; Kshetri, 2014). Currently, companies are not sufficiently implementing security options designed for Big data (Kshetri, 2014). Big data needs to be protected and secured so that no information is destroyed or released to those who should not have it (Moreno et al., 2016). If a company has personal information about its customers, this may be valuable for hackers. Hackers can target Big data companies to gain the customer’s private information. If personal information is released, it can be devastating for the company and the consumer. Although, those who analyze Big data can also gain advantages when it comes to security, by mining large amounts of data, the companies can interpret the data and find these threats before they happen (Tankard, 2012).

2.6.3 Privacy of Personal data

Privacy of personal data is essential and can be a barrier for those who wish to analyze Big data because of the volume, veracity, and velocity of Big data, there is going to be a substantial amount of data to analyze (Alharthi et al., 2017). When large amounts of data are analyzed, some of the data is going to contain personal information. If the company does not adequately handle the personal data they may face legal actions or their company may face scrutiny from the customers (Alharthi et al., 2017). Companies need to be transparent about how they analyze, store and gather their data, so that customer’s privacy is not being infringed on. Privacy is a significant barrier that may stop companies from using Big data analytics and, if the company makes a mistake regarding personal data they may run the risk of not only facing legal actions, it can lead to bad relationships with their consumers who may feel as though their personal
information has not been handled properly (Hofacker et al., 2016). Privacy will be a significant challenge in the years to come regarding Big data (Wiencierz & Röttger, 2017).

These three barriers are important to consider when implementing Big data analytics. Although, there has not been a sufficient discussion regarding the perception of these topics. Based on the security, the privacy of personal data and financial and human resources the following hypotheses has been developed:

**H6:** Low perceived levels of adoption barriers positively influence the Perceived Usefulness of Big data analytics.

**H7:** Low perceived levels of adoption barriers positively influence the Perceived Ease of Use of Big data analytics.
3 Conceptual framework

In this chapter, the authors discuss their research model. The authors also show the variables measured along with the conceptual and operational definitions.

3.1 Research model

The study aimed to analyze what perceptions the employees had of Big data analytics and to examine barriers that hinder SMEs from implementing Big data analytics. The study focused on the employees and their perceptions about Big data using the Technology Acceptance Model as a theoretical base. The Perceived Usefulness, Perceived Ease of Use, Attitude, and Intention to Use which are all part of the Technology Acceptance Model, were used to analyze the perceptions of the employees. TAM and the barriers that SMEs face when implementing Big data analytics was the basis for the research model, which shows how the different concepts are influenced by each other. The researchers used previous theory to form the hypotheses associated with TAM as well as two new hypotheses that test how the employees of SMEs perceive the barriers to implementing Big data analytics. The barriers are believed to influence the Perceived Usefulness of Big data analytics (PU-BDA) and the Perceived Ease of Use of Big data analytics (PEOU-BDA). The model proposes that if someone believes that there are low barriers for implementing Big data analytics, the person will also have a positive perception of Big data analytics and perceive Big data analytics as being useful, easy to use and will, in turn, intend to use it. The four concepts explained in the theory, Attitude, Perceived Usefulness, Perceived Ease of Use, and Barriers will according to this model influence if an employee will have the Intention to Use Big data analytics (IU-BDA). The model will attempt to offer insights to how employees perceive Big data, if they will intend to use Big data and how these concepts are influenced by each other. The model can be viewed below, labeled "Figure 3: Conceptual model"
Figure 3: Conceptual model (Self-made, adapted from Folkinshteyn & Lennon, 2016; Davis et al., 1989)
4 Methodology

In this chapter, the authors discuss the chosen methodology as well as state their chosen research approach and research design.

4.1 Research Approach

Depending on the objective of the research different approaches should be used. A deductive approach is an approach where the research examines previous theories which are used to develop hypotheses (Bryman & Bell, 2015). The hypotheses are then tested based on empirical results. This research used a deductive approach by analyzing previous theories about Big data, Big data analytics, and perception to form hypotheses. The hypotheses were tested using a survey to verify if they were significant or not.

Furthermore, it is appropriate to use a quantitative approach if one deems to test hypotheses based on existing theory (Bryman & Bell, 2015). Because of this, the study used a quantitative approach where the employees of SMEs answered a survey, which was deemed to be the most appropriate choice. A quantitative approach focuses on statistical analysis that measures how variables influence each other which is what this study aimed to test.

4.2 Research Design

When conducting research, an exploratory design or a conclusive design are the two main designs that can be used (Malhotra, 2010). These concepts can be subdivided. How this study chose to break down the research design and research approach can be viewed in the table labeled “Figure 4: Methodology breakdown”. This study aimed to use a quantitative approach with a self-completion survey. The quantitative approach and the conclusive design are closely connected. The literature review determined the hypotheses and the survey aimed to test those hypotheses, these reasons made the conclusive design fit the objective of the research. The conclusive design is used for testing or verifying hypotheses which made it an appropriate choice of research design for this study. The conclusive design is often used to examine a population and make conclusions based on quantifiable data (Malhotra, 2010), which made it an appropriate design for the purpose of this paper. The full methodology breakdown can be viewed in the figure below, labeled “Figure 4: Methodology breakdown”.

Moreover, the conclusive design can be further broken down into other categories (Malhotra, 2010). One of the ways that conclusive design can be subdivided further is the descriptive design. The descriptive designs objective is to describe something (Malhotra, 2010). This type of design fits the purpose of this paper that aims to describe how employees of Swedish SMEs perceive Big data analytics.

Finally, the research design can be broken down further depending on the time frame of the data gathering. A cross-sectional design is a design that examines the chosen sample at a single point in time (Malhotra, 2010). A cross-sectional design fit this research because the research aimed to examine the perceptions of the employees at one point in time and not over a period.

4.3 Sampling

The entire population refers to all who are a part of a specific group (Bryman & Bell, 2015). It is crucial that the study represents the entire population and it is essential to provide a reliable sample. If the research aims to get insights of a population without analyzing the entire population a sample of the population can be analyzed. For this study, the population referred to those who were employed at a Swedish SME and had used one of the Big data analytics mentioned (Facebook Analytics, LinkedIn Analytics, Google Analytics or Google AdWords).

The research used a non-probability sample instead of a random sample. A non-probability sample is a sample that is not random but still tries to represent the population effectively (Bryman & Bell, 2015). This research used purposive sampling along with some elements of snowball sampling and convenience sampling. The research used a database that listed
companies in Sweden that had less than 250 employees, who were listed in Swedish municipalities (Business Update System), for its purposive sampling. The database existed of 555 contacts, which consisted of 135 in the IT industry, 208 in consulting, 110 in marketing, 72 in the service industry and 30 in merchandising. Approximately 139 answered the survey. Some of the municipalities which used this database were Växjö municipality, Sala municipality, Nyköping municipality along with several other municipalities throughout Sweden. The database existed of municipalities throughout Sweden which ensured that responses came from different regions in Sweden. The researchers sent emails to the companies; however, few answered the survey after the first email. After the first email, the researchers called the companies in the database, and the research was explained. The telephone calls helped the employees make an informed decision if they wished to partake. To ensure a more random sample, the companies were not called in chronological order, instead, every seventh company on the database list was called. This approach ensured that the SMEs called were as random as possible. After calling the employees from the database more of the employees answered the survey.

Furthermore, as stated convenience and snowball sampling were used which are not as reliable as a random sample, and these types of sampling may work if it is difficult to achieve a random sample (Bryman & Bell, 2015). The convenience sample was done by asking acquaintances of the researchers to answer the survey and by visiting companies in the same city (Växjö municipality, Sweden) as the researchers whose employees were asked to answer the survey. Moreover, there was an element of snowball sampling because the people who answered the survey were encouraged to spread the survey to other employees at their companies who used Big data analytics (Bryman & Bell, 2015).

4.4 Data collection method

The data that was gathered and used in this paper came from primary sources. The survey that was distributed to the employees of Swedish SMEs was the primary source of data. The survey started with a short description of the research along with contact information of the researchers. In the description, it was stated that the research was anonymous, and there was an option of giving an email address to be able to win a monetary prize (1000 SEK) to increase survey respondents. After the description, there was a kick out question that asked: “Are you currently employed by or own a company that employs less than 250 people?”. If the survey respondent
answered “yes” they could proceed to the next section of the survey and if they answered “no” they would not be able to proceed.

The next section asked the respondents if they had ever used any of the Big data analytics examples mentioned and what country their company was based in. The third section consisted of the statements in the operationalization table. The statements could be graded on a 7 point Likert (LK) scale format from 1-strongly disagree to 7-strongly agree. Lastly, some demographic questions were asked, that included, what business they worked for, the role they had at their company, their age, gender and country of citizenship. In Appendix 1 the complete survey is presented.

4.5 Operationalization

Below the operationalization table is presented labeled “Table 4: Operationalization table”. The table describes the variables along with the conceptual definitions and operational definitions. The items used in this research were adopted from previous research such as the example of “I like using Google applications” (Cheung & Vogel, 2013) that was adopted to “I like using Big data analysis.” This approach helped to assure that the questions were easy to understand and ensured the validity of the survey questions.

<table>
<thead>
<tr>
<th>Theory</th>
<th>Conceptual definition</th>
<th>Operational definition</th>
<th>Original Items</th>
<th>Adapted Items</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Businesses</td>
<td>SME</td>
<td>A company that employs less than 250 people (SCB, 2016)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Big data</td>
<td>“(...)the Information asset characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value” (De Mauro, Greco &amp; Grimaldi, 2016, p.22).</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Big data Analytics</td>
<td>“(...) techniques used to analyze and acquire intelligence from Big data” (Gandomi &amp; Haider, 2015, p. 140).</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>-------------------</td>
<td>----------------------------------------------------------------------------------------------------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td></td>
</tr>
<tr>
<td>Technology Acceptance Model</td>
<td>Perceived Usefulness</td>
<td>“(...) the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context” (Davis et al., 1989, P.985)</td>
<td>1. Using electronic mail allows me to accomplish more work than would otherwise be possible. (Davis et al., 1989)</td>
<td>1. Using Big data analytics allows me to accomplish more work than would otherwise be possible.</td>
<td>LK</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Overall, I find the electronic mail system useful in my job. (Davis et al., 1989)</td>
<td>2. Overall, I find Big data analytics useful in my job</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Using electronic mail enhances my effectiveness on the job. (Davis et al., 1989)</td>
<td>3. Using Big data analytics enhances my effectiveness on the job</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. Electronic mail enables me to accomplish tasks more quickly. (Davis et al., 1989)</td>
<td>4. Big data analytics enables me to accomplish tasks more quickly</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Perceived Ease of Use</td>
<td>“(...) the degree to which the prospective user expects the target system to be free of effort” (Davis et al., 1989, P. 985)</td>
<td>1. Overall, I find the electronic mail system easy to use (Davis et al., 1989)</td>
<td>1. Overall, I find Big data analytics easy to use</td>
<td>LK</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. I find it easy to get the electronic mail system to do what I want (Davis et al., 1989)</td>
<td>2. I find it easy to get Big data analytics to do what I want</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. The electronic mail system provides helpful guidance in performing tasks (Davis et al., 1989)</td>
<td>3. Big data analytics provides helpful guidance in performing tasks</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. My interaction with the electronic mail system is easy for me to understand (Davis et al., 1989)</td>
<td>4. My interaction with Big data analytics is easy for me to understand</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Attitude</td>
<td>“(...) the degree to which a user is interested in using the system ” (Cheung &amp; Vogel, 2013, P. 164)</td>
<td>1. Using Google Applications is a good idea. (Cheung &amp; Vogel, 2013)</td>
<td>1. Using Big data analytics is a good idea</td>
<td>LK</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. I like using Google applications (Cheung &amp; Vogel, 2013)</td>
<td>2. I like using Big data analytics</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. It is desirable to use Google applications (Cheung &amp; Vogel, 2013)</td>
<td>3. It is desirable to use Big data analytics</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. I believe that Big data analytics can</td>
<td>4. I believe that Big data analytics can</td>
<td></td>
</tr>
</tbody>
</table>
4. I believe computers in general practice can contribute to diagnosis (Ridderikhoff et al., 1999)

| Intention to use | “(...) a measure of the strength of one’s intention to perform a specified behavior” (Davis et al., 1989) | 1. All things considered, I expect to continue using Google Applications for the project (Cheung & Vogel, 2013)
2. If I could, I would like to continue my use of Google Applications for the project (Cheung & Vogel, 2013)
3. My intentions are to continue using OBD than use any alternative means (traditional banking) (Bhattacherjee, 2001)
4. I will recommend other people to play the game I play (Zhu, Lin & Hsu, 2012) | 1. I expect to use Big data analytics
2. I would like to continue my use of Big data analytics
3. I would prefer using Big data analytics over alternative means of analysis
4. I will recommend using Big data analytics to other people |

| Barriers | Data security | Data security refers to how well a system prevents unauthorized access to data | 1. E-commerce is not secure (MacGregor & Vrazalic, 2005)
2. “(...)malware has been an ever growing threat to data security” (Sivarajah et al., 2017, P.274)
3. The web site has adequate security features (Ha, & Stoel, 2009)
4. “The gathering of data inevitably increases the risk of information leakage” (Mengke et al., 2016, P195) | 1. Big data analytics is not secure
2. There is a risk of malware (e.g. viruses, spyware, worms, trojans etc.) when using Big data Analytics
3. Big data analytics does not have adequate security features
4. There is a risk of information leakage when using Big data analytics |

| Resources | Financial and Human resources | 1. The financial investment required to implement e-commerce is too high for us (MacGregor & Vrazalic, 2005)
2. We do not have the technical knowledge in the organisation to implement e-commerce (MacGregor & Vrazalic, 2005) | 1. The financial investment required to implement Big data analytics is too high for the company I work for
2. We do not have the technical knowledge in the organisation to implement big data analytics |
3. We do not have the technical knowledge in the organisation to implement e-commerce (MacGregor & Vrazalic, 2005)

4. We do not have time to implement e-commerce (MacGregor & Vrazalic, 2005)

5. E-commerce is too complicated to implement (MacGregor & Vrazalic, 2005)

3. We do not have the legal knowledge in the organisation to implement Big data analytics

4. There is not enough time to implement Big data analytics at work

5. Big data analytics is too complicated to implement

Privacy of personal data

“personal data’ means any information relating to an identified or identifiable natural person (’data subject’); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person” (General Data Protection Regulation EU, 2016/679)

1. Companies should not use personal information for any purpose unless it has been authorized by the individuals who provided the information. (Smith, Milberg, & Burke. 1996, P. 170)

2. Companies should devote more time and effort to preventing unauthorized access to personal information. (Smith, Milberg, & Burke. 1996, P. 170)

3. When people give personal information to a company for some reason, the company should never use the information for any other reason. (Smith, Milberg, & Burke. 1996, P. 170)

4. Companies should never sell the personal information in their computer databases to other companies. (Smith, Milberg, & Burke. 1996, P. 170)

1. Companies should not use personal information for any purpose unless it has been authorized by the individuals who provided the information

2. Companies should devote more time and effort to preventing unauthorized access to personal information

3. When people give personal information to a company for some reason, the company should never use the information for any other reason

4. Companies should never sell the personal information in their computer databases to other companies

4.6 Quality Criteria

To ensure that the quality of the research was sufficient the validity and the reliability was measured, which are important criteria for making sure that research upholds to the standards necessary for it to be analyzed (Bryman & Bell, 2015). The internal reliability of a study is
essential because in quantitative research it shows if the variables were consistent (Bryman & Bell, 2015). A consistent variable measure what it is supposed to measure, and by testing the reliability, the researcher can examine if the variables are consistent. The internal reliability was measured using Cronbach’s alpha, which tests the internal reliability to ensure the variables measure the correct concepts. A Cronbach’s alpha value of 0.8 is generally considered strong, and 0.7 is deemed acceptable (Bryman & Bell, 2015).

Furthermore, the validity was measured, which made sure the concepts measure what they were supposed to measure (Bryman & Bell, 2015). Validity is crucial because sometimes a researcher believes a concept measures something when in reality it measures something else. For this research face validity and construct validity were measured, and these types of validity tests fit the research design, and the research approach used for this research. The construct validity ensures the validity of the constructs (Bryman & Bell, 2015). A Pearson’s correlation test was done to ensure the construct validity of the research. Furthermore, measuring the face validity also helped ensure the validity, which ensures the validity of research by examining the concepts intuitively (Bryman & Bell, 2015). By doing a pre-test, the face validity of the research was ensured, by asking people from the sample of the population along with experts in the field.

4.7 Pre-test

To ensure that the questions were perceived as intended a pre-test was made. Five people of the sample were asked to answer the survey and provide feedback. These five people were currently employed by a Swedish SME and had used Big data analytics. After discussing the pre-test with the respondents from the sample, it was concluded that they were using Big data analytics, although, they were not referring to it as Big data analytics and an explanation containing different examples of Big data analytics were added at the beginning of the survey. The explanation ensured that the respondents understood how the concepts were defined in this research. To make sure the questions were understandable language changes were made. The new questions were sent to five experts within the field, after which the questions were improved, rewritten and some questions were removed. The questions were sent to five people of the sample again who provided feedback who thought the questions were clear and understandable. Finally, the survey was sent to one of the experts in the field again. When the survey had been sent the last time, no further changes were made, and the survey was completed. After the survey was completed, it was sent to the employees of the SMEs.
4.8 Data Analysis Method

The analysis was made using IBM SPSS Statistics. SPSS was used to organize and analyze the data gathered from the survey. 139 people answered the survey. Out of those 139, seven people were not currently employed by a company with less than 250 employees, 33 were removed because their company was based in another country other than Sweden or because they answered “No” to the question “Have you ever analyzed Big data using Google AdWords, Google Analytics, Facebook Analytics or LinkedIn Analytics?”. After these respondents were removed this left 97 answers for the analysis, although there were four extreme outliers. Sometimes all extreme outliers are removed, and sometimes the numbers can be changed slightly to fit the research (Pallant, 2007). For this study, all extreme outliers were removed from further analysis, which left the sample with 93 respondents.

First some descriptive statistics were presented which included the position at the company, what kind of Big data analytics were used, age, gender, what kind of business the respondents worked for and what country the respondent had as citizenship. The mean values of the different concepts were measured along with the standard deviations.

Moreover, a reliability analysis was made using Cronbach’s Alpha coefficients to ensure that the constructs and statements from the survey were measured as intended. A correlation analysis was made to determine the construct validity. These tests ensured the validity and reliability of the research so that the results could be analyzed appropriately.

To test hypotheses, regression analyses were made which determined if the hypotheses were accepted, rejected or partially accepted. Simple regression was done to test how the concepts of TAM influenced each other. Moreover, multiple regression was done to test how the barriers influenced the PEOU-BDA and PU-BDA. The regression analysis determined the R-square values and the standardized coefficient betas.

4.9 Ethical Considerations

For research to be ethical, the study needs to adhere to certain criteria. The study cannot harm the participants, it is important to make sure that the participants have given their consent, the
privacy of the participants cannot be invaded, and the study cannot deceive the participants (Bryman & Bell, 2015). The ethical criteria of the research were achieved by providing the respondents information about the goals of the study, what the information would be used for was stated, the anonymity was highlighted, and the study did not aim to deceive the participants. By given the participants this information, they could make an informed decision whether they wanted to participate. The precautions made by the researchers ensured that the participants did not provide any information they were not comfortable with disclosing. Because the survey was a self-completion survey, the participants could decide for themselves if they wanted to participate. The ethics of the study was tested by doing a pretest that ensured that the questions were explained sufficiently, and if the explanation of the study was done sufficiently so that the participants could make an informed decision of participating or not.
5 Data analysis and results

The data analysis and results chapter explains the results gathered using IBM SPSS Statistics. The chapter contains descriptive statistics of the sample, validity tests, reliability tests and a regression analysis that tested the hypotheses of this study.

5.1 Descriptive statistics

65 out of the respondents were male, and 28 of the respondents were female. None of the respondents answered, “Prefer not to say.” The sample consisted of approximately 70% male respondents and 30% female. 84 out of the respondents had Swedish citizenship and 9 worked at a Swedish company, although they did not have Swedish citizenship. The age of the respondents consisted of, 5(≈5%) respondents who were 18-25, 44(≈47%) respondents who were 26-35, 38(≈40%) respondents who were 36-45, 5(≈5%) respondents who were 46-55 and 1(≈1%) respondents who were 55 or older.

Moreover, the types of businesses included the service business 27(≈29%), merchandising business 9 (≈10%), manufacturing business 6 (≈6%), consulting 43 (≈46%), marketing 5(≈5%) and IT 3 (≈3%). The roles the respondents had was CEO/Owner 35 (≈38%), Marketing related 14 (≈15%), IT related 17 (≈18%), Sales 9 (≈10%), Manager/supervisor 11 (≈12%) and other 7 (≈8%).

Furthermore, 53 (≈57%) of the respondents had used Google AdWords, 57 (≈61%) out of the respondents had used Google Analytics, 76(≈82%) of the respondents had used Facebook Analytics, and 44 (≈47%) out of the respondents had used LinkedIn Analytics. The table below labeled “Table 5: Descriptive statistics of Survey Respondents” presents all of the descriptive statistics gathered from the survey.
Table 5: Descriptive statistics of Survey Respondents (N=93)

<table>
<thead>
<tr>
<th>Descriptive statistics</th>
<th>n</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>65</td>
<td>≈70</td>
</tr>
<tr>
<td>Female</td>
<td>28</td>
<td>≈30</td>
</tr>
<tr>
<td><strong>Citizenship</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sweden</td>
<td>84</td>
<td>≈90</td>
</tr>
<tr>
<td>Other</td>
<td>9</td>
<td>≈10</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-25</td>
<td>5</td>
<td>≈5</td>
</tr>
<tr>
<td>26-35</td>
<td>44</td>
<td>≈47</td>
</tr>
<tr>
<td>36-45</td>
<td>38</td>
<td>≈40</td>
</tr>
<tr>
<td>46-55</td>
<td>5</td>
<td>≈5</td>
</tr>
<tr>
<td>55+</td>
<td>1</td>
<td>≈1</td>
</tr>
<tr>
<td><strong>Role in business</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CEO/Owner</td>
<td>35</td>
<td>≈38</td>
</tr>
<tr>
<td>Marketing related</td>
<td>14</td>
<td>≈15</td>
</tr>
<tr>
<td>IT</td>
<td>17</td>
<td>≈18</td>
</tr>
<tr>
<td>Sales</td>
<td>9</td>
<td>≈10</td>
</tr>
<tr>
<td>Manager/Supervisor</td>
<td>11</td>
<td>≈12</td>
</tr>
<tr>
<td>Other</td>
<td>7</td>
<td>≈8</td>
</tr>
<tr>
<td><strong>Big data Analytics used</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Google AdWords</td>
<td>53</td>
<td>≈57</td>
</tr>
<tr>
<td>Google Analytics</td>
<td>57</td>
<td>≈61</td>
</tr>
<tr>
<td>Facebook Analytics</td>
<td>76</td>
<td>≈82</td>
</tr>
<tr>
<td>LinkedIn Analytics</td>
<td>44</td>
<td>≈47</td>
</tr>
<tr>
<td><strong>Type of Business</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Service</td>
<td>27</td>
<td>≈29</td>
</tr>
<tr>
<td>Merchandising</td>
<td>9</td>
<td>≈10</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>6</td>
<td>≈6</td>
</tr>
<tr>
<td>Consulting</td>
<td>43</td>
<td>≈46</td>
</tr>
<tr>
<td>Marketing</td>
<td>5</td>
<td>≈5</td>
</tr>
<tr>
<td>IT</td>
<td>3</td>
<td>≈3</td>
</tr>
</tbody>
</table>
The mean values along with the standard deviations are presented in the table below labeled “Table 6: Mean values”. The components of the Technology Acceptance Model were higher than 4 which indicated that the respondents had a favorable view of Big data analytics. The barriers were low indicated that the respondents did not agree with the statements associated with barriers except for privacy. Privacy had the highest mean value (6.081) out of all of the questions indicating that the respondents agreed with the statements regarding privacy. The standard deviations were low (.7111-1.048) compared to the mean values which indicated that the mean values could be used for analysis.

<table>
<thead>
<tr>
<th>Mean values</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Usefulness</td>
<td>2</td>
<td>7</td>
<td>4.984</td>
<td>.9723</td>
</tr>
<tr>
<td>Perceived Ease of Use</td>
<td>2</td>
<td>7</td>
<td>5.298</td>
<td>.8864</td>
</tr>
<tr>
<td>Attitude</td>
<td>3</td>
<td>7</td>
<td>5.637</td>
<td>.8304</td>
</tr>
<tr>
<td>Intention to Use</td>
<td>2</td>
<td>7</td>
<td>5.272</td>
<td>.9833</td>
</tr>
<tr>
<td>Privacy</td>
<td>3</td>
<td>7</td>
<td>6.081</td>
<td>.7111</td>
</tr>
<tr>
<td>Security</td>
<td>1</td>
<td>7</td>
<td>3.575</td>
<td>1.048</td>
</tr>
<tr>
<td>Resources</td>
<td>1</td>
<td>7</td>
<td>3.043</td>
<td>.9074</td>
</tr>
</tbody>
</table>

5.2 Construct Reliability

Security, Attitude and Intention to Use had Cronbach’s alpha coefficients above 0.8 which indicated strong internal reliability. All values were above 0.7 which indicated a sufficient internal consistency of the variables based on the criteria discussed by Bryman and Bell (2015) and Pallant (2007). All Cronbach’s alpha coefficients of this research can be viewed in the table below labeled ”Table 7: Cronbach’s alpha coefficients”
5.3 Pearson Correlation

According to Pallant (2007) if the variables have a value of above 0.9, this can be a sign of multicollinearity, although none of the variables measured had a value of 0.9 or above. All of the variables were significantly correlated with each other except for privacy. All variables were correlated at the 99% level except for security with PU-BDA that was correlated at the 95% level. All variables were correlated positively with each other except for security and resources. These barriers were negatively correlated with the other variables. A correlation of 0.10 to 0.29 can be regarded as small, a correlation of 0.30 to 0.49 can be regarded as medium, and a correlation of 0.50 to 1.0 can be regarded as strong (Cohen, 1988). All of the variables were correlated at a medium to strong level except for four; security with (PU-BDA), security with Attitude, security with resources and (PU-BDA) with PEOU-BDA. Moreover, as is viewed in the correlation table (“Table 8: Pearson Correlation”) security and resources were positively correlated at the 99% level. Security and resources were correlated, although because it was only a small correlation the variables were not removed from barriers in the multiple regression analysis. The results of the Pearson Correlation ensured that all of the variables had a sufficient construct validity. The Pearson Correlation further ensured that the barriers were not correlated by a large amount and could thus be analyzed together using multiple regression.

### Table 7: Cronbach’s alpha coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cronbach’s alpha coefficient</th>
<th>Number of Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Usefulness</td>
<td>0.746</td>
<td>4</td>
</tr>
<tr>
<td>Perceived Ease of Use</td>
<td>0.784</td>
<td>4</td>
</tr>
<tr>
<td>Attitude</td>
<td>0.810</td>
<td>4</td>
</tr>
<tr>
<td>Intention to Use</td>
<td>0.825</td>
<td>4</td>
</tr>
<tr>
<td>Privacy</td>
<td>0.733</td>
<td>4</td>
</tr>
<tr>
<td>Resources</td>
<td>0.701</td>
<td>5</td>
</tr>
<tr>
<td>Security</td>
<td>0.837</td>
<td>4</td>
</tr>
</tbody>
</table>
Table 8: Pearson Correlation

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Perceived Usefulness</th>
<th>Perceived Ease of Use</th>
<th>Attitude</th>
<th>Intention to Use</th>
<th>Security</th>
<th>Resources</th>
<th>Privacy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Usefulness</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived Ease of Use</td>
<td>.273**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attitude</td>
<td>.558**</td>
<td>.307**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intention to Use</td>
<td>.648**</td>
<td>.466**</td>
<td>.723**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Security</td>
<td>-.235*</td>
<td>-.473**</td>
<td>-.286**</td>
<td>-.393**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resources</td>
<td>-.436**</td>
<td>-.386**</td>
<td>-.429**</td>
<td>-.422**</td>
<td>.270**</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Privacy</td>
<td>.081</td>
<td>.044</td>
<td>.148</td>
<td>.076</td>
<td>-.051</td>
<td>-.047</td>
<td>1</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed) * Correlation is significant at the 0.05 level (2-tailed)

5.4 Hypothesis testing

Pallant (2007) states that the R square value can be converted to a percentage to view how much of the variance in the dependent variable can be explained by the independent variables. As can be viewed in the table below labeled "Table 9: Hypothesis regression analysis", the barriers can explain 21% of the PU-BDA, and 29.8% of the PEOU-BDA. The PEOU-BDA can explain 9.5% of the Attitude and 7.4% of the PU-BDA. The PU-BDA can explain 31.1% of the A-BDA, and 42% of the IU-BDA. The IU-BDA can explain 52.2% of the A-BDA.

The standardized coefficients beta where also measured. These showed that security and resources influenced the PEOU-BDA, whereas privacy did not. Further, security and privacy did not influence the PU-BDA whereas resources did.
Table 9: Hypothesis regression analysis

<table>
<thead>
<tr>
<th>Hypothesis regression analysis</th>
<th>Standardized coefficients Beta</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H1:</strong> The perceived ease of use of Big data analytics positively influences the perceived usefulness of Big data analytics.</td>
<td>.273**</td>
<td>.074**</td>
</tr>
<tr>
<td><strong>H2:</strong> The perceived usefulness of Big data analytics positively influences the attitude of Big data analytics.</td>
<td>.558**</td>
<td>.311**</td>
</tr>
<tr>
<td><strong>H3:</strong> The perceived ease of use of Big data analytics positively influences the attitude of Big data analytics.</td>
<td>.307**</td>
<td>.095**</td>
</tr>
<tr>
<td><strong>H4:</strong> The perceived usefulness of Big data analytics positively influences the intention to use Big data analytics.</td>
<td>.648**</td>
<td>.420**</td>
</tr>
<tr>
<td><strong>H5:</strong> The attitude of Big data analytics positively influences the intention to use Big data analytics.</td>
<td>.723**</td>
<td>.522**</td>
</tr>
</tbody>
</table>
| **H6:** Low perceived levels of adoption barriers positively influence the perceived usefulness of Big data analytics. | Security: -.132  
Resources: -.397**  
Privacy: .069 | .210** |
| **H7:** Low perceived levels of adoption barriers positively influence the perceived ease of use of Big data analytics. | Security: -.401**  
Resources: -.275**  
Privacy: .052 | .298** |

**. Correlation is significant at the 0.01 level (2-tailed)

Based on the regression analysis H1-H5 were accepted at the 0.01 level (2-tailed). The table below labeled “Table 10: Hypothesis testing results” shows the hypothesis testing results. As one variable increases so do the other variables, meaning that H1-H5 were accepted. The variables positively influenced the other variables and were deemed accepted.

Moreover, H6-H7 were deemed partially accepted. Privacy and security did not influence PU-BDA, although resources did, therefore H6 was partially accepted. Security and resources influenced the PEOU-BDA although privacy did not, therefore H7 was partially accepted as well. The items were negatively correlated meaning the PU-BDA and the PEOU-BDA would be negatively influenced if the user perceived there to be high adoption barriers.
### Table 10: Hypothesis testing results

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Acceptance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H1</strong>: The perceived ease of use of Big data analytics positively influences the perceived usefulness of Big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>H2</strong>: The perceived usefulness of Big data analytics positively influences the attitude of Big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>H3</strong>: The perceived ease of use of Big data analytics positively influences the attitude of Big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>H4</strong>: The perceived usefulness of Big data analytics positively influences the intention to use Big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>H5</strong>: The attitude of Big data analytics positively influences the intention to use Big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>H6</strong>: Low perceived levels of adoption barriers positively influence the perceived usefulness of Big data analytics.</td>
<td>Partially Accepted</td>
</tr>
<tr>
<td><strong>H7</strong>: Low perceived levels of adoption barriers positively influence the perceived ease of use of Big data analytics.</td>
<td>Partially Accepted</td>
</tr>
</tbody>
</table>
6 Discussion

The discussion chapter is based on the hypotheses and presents a detailed discussion based on previous research and the results of this study.

The PEOU-BDA helped to form the PU-BDA of the employees. Although, the PEOU-BDA was not the most influential concept in forming the A-BDA, the strongest determinant towards the A-BDA was the PU-BDA. A person who has a strong PU-BDA would more likely have a positive A-BDA, as indicated by the high correlation between PU-BDA and the A-BDA. As can also be seen, the IU-BDA was strongly formed by the PU-BDA and the A-BDA, and these findings comply with the previous research by Davis et al. (1989), who stated that the A, the IU, the PEOU and the PU positively influences each other.

Previous research indicated that SMEs would have problems implementing Big data because it was considered difficult to use (Del Vecchio et al., 2018; Alharthi et al., 2017; Coleman et al., 2016). However, this research indicated that the users at Swedish SMEs did not perceive the types Big data analytics studied as being difficult to use. Instead, most of the respondents perceived Big data analytics as being easy to use, as indicated by the high mean value. Alharthi et al. (2017) and Coleman et al. (2016) claimed that SMEs would find Big data more difficult to use than large companies. Even though this study cannot provide comparisons between large companies and SMEs, the results indicated that SMEs did not find Big data analytics difficult to use. Coleman et al. (2016) stated that software that is both easy to understand and useful is rare, although the employees of SMEs did not confirm this claim, because they perceived Big data analytics as being both useful and easy to use.

Furthermore, previous research stated that SMEs would have to overcome barriers to implement new technology (Alharthi et al., 2017; Macgregor & Vrazalic, 2005). The multiple regression analysis of the barriers with the PEOU-BDA and the PU-BDA indicated that there was a medium negative correlation between the security and the resources with the PEOU-BDA, there was also a medium negative correlation between the resources and the PU-BDA. These results contributed towards verifying previous research that stated the barriers could be significant problems when implementing new technology (Alharthi et al., 2017; Macgregor & Vrazalic, 2005). If the employees perceived resources as a concern it would influence their perceptions of Big data analytics negatively to a medium degree. According to Del Vecchio et al. (2018);
Coleman et al. (2016) the limited resources SMEs have make it difficult for them to implement Big data analytics, however, this study indicates that this is not always true. In regard to the Big data analytics analyzed, the resources were not a considerable concern for the employees. This study indicates that Big data analytics do not require as much resources as previously stated by Del Vecchio et al. (2018), Alharthi et al. (2017) and Coleman et al. (2016). Del Vecchio et al. (2018) stated that SMEs would have a disadvantage because of their limited resources, and SMEs would have difficulty developing economies of scale using Big data. According to the perceptions of the employees, SMEs had the necessary resources for using Big data analytics. In previous research resources were vital in the context of Big data and innovation (Del Vecchio et al., 2018) However, in this study, as previously stated, the employees answered low regarding resources, meaning they did not agree with the statements associated with resources. Most of the employees’ opinions were that their company had the necessary resources for Big data analytics. Moreover, by examining the research of Macgregor and Vrazalic (2005), it is clear that some of the barriers regarding E-commerce are applicable to Big data analytics. Barriers for implementing E-commerce in 2005 are similar to barriers of implementing Big data in 2018, and analyzing the results along with previous research indicates that these barriers may not be specific towards Big data or E-commerce. These types of barriers could be factors that affect SMEs whenever a new technology is being implemented.

Furthermore, the barrier privacy was not an indicator of how Big data analytics were perceived in this study. Most employees agreed that privacy was an important issue, which was indicated by them answering very high on the statements associated with privacy, although privacy did not affect the employee’s perception of Big data analytics (PU-BDA, PEOU-BDA, A-BDA, IU-BDA). Alharthi et al. (2017), Wiencierz & Röttger (2017) and (Hofacker et al., 2016) stated that privacy was an important issue, although in this study privacy did not influence the employee’s perception of Big data analytics. Privacy may therefore not be an important factor when implementing Big data in regard to the employees, although it may still be an important factor when implementing Big data in regard to the customers and legal threats. Alharthi et al. (2017) and Hofacker et al. (2016) stated that a good privacy strategy was needed to not receive backlash from customers or face legal ramifications. Therefore, privacy cannot be regarded as an unimportant barrier, although this research indicated that privacy is not an important factor in regard to how Big data analytics are perceived.
As mentioned by Del Vecchio et al. (2018) SMEs can benefit from using Big data. The perceptions of the employees fit with these claims. Employees who had used Big data analytics felt as though it is useful and easy to use. These findings fit the previous research about Big data and Big data analytics being useful for SMEs. The barriers did, in fact, contribute towards determining the perception of the employees as was shown in the hypothesis testing. However, this research states that all barriers are not as crucial for SMEs and the barriers SMEs should focus on primarily when implementing Big data analytics are the resources along with security. These two barriers influenced the employees’ perception of Big data analytics, whereas privacy did not.
7 Conclusions

This chapter states a summarized view of the research. The main findings are concluded based on the purpose and research questions.

The purpose of this study was to investigate how the employees of Swedish SMEs perceive Big data analytics. The results of this study indicated that Big data analytics were perceived positively by the employees of Swedish SMEs. All of the means associated with Big data analytics were higher than 4 which indicated that Big data analytics was viewed positively. The users had positive Attitude towards Big data analytics, found it easy to use, useful and they had the intention to use it. The PU-BDA was the most reliable indicator of how the Attitude was formed and if the employees intended to use it.

Moreover, if a person believed the resources and security were barriers to implementing Big data analytics, they would have a more negative view of the Big data analytics. People who perceived Big data analytics as having low adoption barriers would have a more positive view of Big data analytics. Security and resources were barriers for employees from having positive Attitude about Big data analytics. Security and resources were important factors for determining how Big data analytics were perceived. It was apparent that for SMEs to implement Big data analytics effectively, they would have to be aware of the barriers. Although, even though privacy was not a significant factor for determining the perceptions of Big data analytics, the employees thought that privacy was important.

In conclusion, the employees perceived Big data analytics positively. The PU-BDA was the most reliable indication of how Big data analytics were perceived. Security and resources impacted how the employees perceived Big data analytics whereas privacy did not. This study indicates that SMEs have favorable perceptions of Big data analytics and that SMEs need to be aware of the barriers.
8 Implications, limitations, and further studies

This chapter presents the implications of the study. The chapter also presents the limitations of the study, along with how future research can expand on the findings.

8.1 Managerial implications

As stated throughout the research Big data has not been sufficiently studied. Previous studies lack empirical evidence as stated by Del Vecchio et al. (2018), and Wiencierz and Röttger (2017). The results presented in this study improve businesses’ understanding of how Big data analytics can be applied, because the perceptions indicated that employees of SMEs had a favorable view of the technology. By understanding the perceptions of the employees; managers and SMEs as a whole will be able to improve the implementation of Big data analytics. This research contributes towards SMEs understanding what barriers needs to be prioritized and what aspects of Big data analytics need to be focused on for successful implementation.

As stated previously, Big data can be important for marketing, although, it could be challenging to implement Big data (Erevelles et al., 2016). Erevelles et al. (2016) stated that there were barriers to using Big data to improve consumer analysis, and the resources were a significant hindrance for implementing Big data. According to this research companies can utilize aspects of Big data with limited resources. Resources were deemed very important in previous research by Erevelles et al. (2016), although, in this study, the employees did not perceive resources as important, although there was still a strong relationship between available resources and the perceptions. The findings indicated that SMEs may be able to implement Big data easier than previous research has stated, although it also indicates that SMEs need to be aware of the barriers because there is a relationship between the barriers and the perception of Big data analytics. These findings are important for managers at SMEs who are contemplating if they should implement Big data analytics.

It is important to note that PEOU-BDA was not the best indicator of the user’s A-BDA and IU-BDA, the users were more concerned with Big data analytics as being useful than it being easy to use. As stated by Coleman et al. (2016) it was important that Big data analytics were both useful and easy to use, and Big data analytics that were both useful and easy to use was rare.
As stated previously, this research indicates that the employees perceived Big data analytics as being both easy to use and useful, and this contradicts previous research that claimed Big data analytics would be difficult for SMEs to implement (Coleman et al., 2016). Previous research claimed that Big data was not implemented enough by SMEs because Big data analytics are seldom both easy to use and useful (Coleman et al., 2016). The results of this study contradict previous studies and can assist SMEs who are unsure how to implement Big data, who could attempt to use website and social media analytics because according to the results of this study, these types of Big data are easy to use and useful.

Previous research stated that privacy was important (Alharthi et al., 2017; Hofacker et al., 2016), although, in this study, privacy did not affect how the employees perceived Big data analytics. Privacy may still be a barrier for SMEs when implementing Big data analytics in regard to public relations, legal threats, advertising, and various other customer relationships. However, this study indicates that SMEs do not need to focus on privacy when implementing Big data analytics with their employees.

8.2 Theoretical implications

To the authors understanding previous research is rare and thin. Also, to the authors understanding previous papers surrounding Big data has not been applied to the context of Swedish SMEs. Because of the significant lack of literature, the results presented in this study are unique and valuable for new research. As viewed in the literature review of this paper Big data and Big data analytics are difficult to define, and different research use different definitions (Wamba et al., 2017; De Mauro et al., 2016; Coleman et al., 2016; Gandomi & Haider, 2015; George et al., 2014; Kwon et al., 2014). Big data and Big data analytics have not existed for many years, and the definitions are still evolving, and currently the definitions are vague and ambiguous (Wiencierz & Röttger, 2017). Wamba et al. (2017) used a very similar definition (see Table 1: Defining Big data and Table 2: Defining Big data analytics) for Big data analytics as they had previously used for Big data. De Mauro et al. (2016) stated that Big data did not have a formal definition and was inconsistent. This claim was made in 2016 and even though Big data has been researched more since then, it still seems as though the concepts are plagued by ambiguity. As stated by Wiencierz & Röttger (2017) Big data is a “buzzword” and this research has determined that the concepts continue to be problematic to define. The ambiguity contributes to many problems, such as stating that SMEs rarely adopt Big data, as stated by
Coleman et al. (2016) and Del Vecchio et al. (2018), can be true or false based on what definition of Big data and Big data analytics is used. Moreover, most of the definitions are based upon volume, velocity, and variety, and the definitions are made on a case by case basis (Brock & Khan, 2017; Coleman et al. 2016; Gandomi & Haider, 2015). As stated, there is no way to understand what constitutes as “big” (Wiencierz & Röttger, 2017). This provides problems that have not been addressed enough in previous research. Depending on the industry, goal and what analytics are used, “big” means different things. The analytics analyzed in this thesis may not necessitate the same capabilities and resources as more advanced analytics. If there is a difference between the perceptions of different Big data analytics, one type of Big data research may not apply to other Big data research. A definition that changes depending on many factors may contribute to confusion about Big data. This study highlights some of the problems with current definitions and contributes towards defining the concepts. An example of a problem defining Big data was presented in this research were most of the respondents had used Big data, however, in previous research it was stated that Big data had had a slow adoption rate among SMEs (Coleman et al., 2016). The large difference may be due to different definitions, which cause the results to significantly differ.

Furthermore, the research determined that the TAM model is still an effective model for analyzing technologies. The research contributes towards TAM research and perception research in general. The claims made by Davis in 1989 are still relevant today which shows that TAM can still be used in research regarding new technologies regardless of changes in society between 1989 and 2018.

8.3 Limitations

Other Big data analytics may be more difficult to use or not perceived as useful, as social media and website Big data analytics. As stated a company can use different approaches for their Big data implementation (Mousannif et al., 2016). Other Big data analytics may not be perceived as the Big data analytics analyzed in this study, therefore the findings might not apply to other types of Big data analytics.

Out of everyone asked on a database list of 555, 139 answered the survey, and these responses also included the respondents achieved from convenience sampling. A limitation of this study was that out of all of the respondents surveyed, only 93 could be examined, and a majority of
8.4 Further studies

Future research could recreate this research with a larger sample along with other demographics. A larger sample size with different demographics could determine if there are differences in perception based upon other factors, such as education and income. The given research found that more males than females answered the survey. The difference between males and females could be an indication that more males use Big data analytics. However, the sample was too small to verify this claim. Future research could investigate if there are any differences, and if so, why, between male and females using Big data analytics.

As mentioned previously, future research needs to define the terms Big data and Big data analytics more clearly. An established definition ensures that different researchers have the same definition and discuss the topics from a similar point of view. This research contributes towards the definitions of Big data and Big data analytics, although, future research could expand on this research to define the topics more clearly.

Out of the respondents, 97 out of 139 had used Big data analytics (Facebook Analytics, Google Analytics, Google AdWords, LinkedIn Analytics). This indicates that the adoption rate is higher than previously stated, and was not as low as 0.2% in the UK, as stated by Coleman et al. (2016). There may be a difference between UK adoption rate and Swedish adoption rate or there could be a big difference depending on the type of Big data analytics used. Future studies could investigate what the adoption rates are for different types of Big data analytics and the potential differences between countries regarding Big data. Future research could attempt to recreate this analysis with the same model to gain insight of how other Big data analytics are perceived, as stated, cloud computing works very differently to large in-house gathering (Mousannif et al., 2016), thus there may be differences in perception.
Future research could examine the perceptions of employees who have never used Big data analytics, and how their perceptions differ from those who have used Big data analytics. A qualitative study could expand on this research, by comparing the perceptions of non-users of Big data analytics and users of Big data analytics, which could provide a more comprehensive view of the topics.
9 References


Appendix 1: Survey

<table>
<thead>
<tr>
<th>Big data</th>
</tr>
</thead>
</table>

Dear Survey-Participant,

We are two students from Linnaeus University in Växjö who are currently working on our thesis surrounding Big data and small-medium sized businesses. We want to investigate how Big data analytics is perceived by the employees of small and medium sized businesses.

We ask you to please answer the following questions about Big data and Big data analytics.

All of the answers are anonymous and it will take around 5 minutes to fill out the entire survey. If you fill out the survey you have a chance to win a gift card of your choice (1000 kr/100 €) for participating.

Thank you!

If there are any questions you can contact Lukas or Ronja.
Lukas Danielsson: ld222fk@student.lnu.se 076-848 92 92
Ronja Toss: rt222cz@student.lnu.se 072-852 74 12

Q1. Are you currently employed by or own a company that employs less than 250 people?
   - Yes
   - No

Q2. In what country is the company you work for (or own) based?
   - Sweden
   - Other

Q3. Have you ever analyzed Big data* using Google AdWords, Google Analytics, Facebook Analytics or LinkedIn Analytics?
   *Big data are datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze.
   - Yes
   - No

Q4. Which Big data analytics have you used?
   (Multiple answers possible)
   - Google AdWords
   - Google Analytics
   - Facebook Analytics
   - LinkedIn Analytics
   - I have never used Big data Analytics
For this research, Big data Analytics refers to: Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics

<table>
<thead>
<tr>
<th>Question</th>
<th>Description</th>
<th>Rating Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q5.</td>
<td>Using Big data analytics* allows me to accomplish more work than would otherwise be possible</td>
<td>1. Disagree entirely 2 3 4 5 6 7 Agree entirely</td>
</tr>
<tr>
<td>Q6.</td>
<td>Overall, I find Big data analytics* useful in my job</td>
<td>1. Disagree entirely 2 3 4 5 6 7 Agree entirely</td>
</tr>
<tr>
<td>Q7.</td>
<td>Using Big data analytics* enhances my effectiveness on the job</td>
<td>1. Disagree entirely 2 3 4 5 6 7 Agree entirely</td>
</tr>
<tr>
<td>Q8.</td>
<td>Big data analytics* enables me to accomplish tasks more quickly</td>
<td>1. Disagree entirely 2 3 4 5 6 7 Agree entirely</td>
</tr>
<tr>
<td>Q9.</td>
<td>Overall, I find Big data analytics* easy to use</td>
<td>1. Disagree entirely 2 3 4 5</td>
</tr>
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</tr>
<tr>
<td>6</td>
<td>7 Agree entirely</td>
<td></td>
</tr>
</tbody>
</table>

Q10. I find it easy to get Big data analytics* to do what I want  
*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics  
• 1 Disagree entirely  
• 2  
• 3  
• 4  
• 5  
• 6  
• 7 Agree entirely

Q11. Big data analytics* provides helpful guidance in performing tasks  
*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics  
• 1 Disagree entirely  
• 2  
• 3  
• 4  
• 5  
• 6  
• 7 Agree entirely

Q12. My interaction with Big data analytics* is easy for me to understand  
*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics  
• 1 Disagree entirely  
• 2  
• 3  
• 4  
• 5  
• 6  
• 7 Agree entirely

Q13. Using Big data analytics* is a good idea  
*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics  
• 1 Disagree entirely  
• 2  
• 3  
• 4  
• 5  
• 6  
• 7 Agree entirely

Q14. I like using Big data analytics*  
*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics  
• 1 Disagree entirely  
• 2  
• 3  
• 4  
• 5  
• 6
<table>
<thead>
<tr>
<th>Q15. It is desirable to use Big data analytics*</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics</td>
<td></td>
</tr>
<tr>
<td>• 1 Disagree entirely</td>
<td></td>
</tr>
<tr>
<td>• 2</td>
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<td>• 3</td>
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<td>• 5</td>
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<td>• 6</td>
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<tr>
<td>• 7 Agree entirely</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Q16. I believe that Big data analytics* can contribute towards better analysis</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics</td>
<td></td>
</tr>
<tr>
<td>• 1 Disagree entirely</td>
<td></td>
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<tr>
<td>• 2</td>
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<td>• 6</td>
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<tr>
<td>• 7 Agree entirely</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Q17. I expect to use Big data analytics*</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics</td>
<td></td>
</tr>
<tr>
<td>• 1 Disagree entirely</td>
<td></td>
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<tr>
<td>• 2</td>
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<td>• 3</td>
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<td>• 6</td>
<td></td>
</tr>
<tr>
<td>• 7 Agree entirely</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Q18. I would like to continue my use of Big data analytics*</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics</td>
<td></td>
</tr>
<tr>
<td>• 1 Disagree entirely</td>
<td></td>
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<td>• 2</td>
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<td>• 6</td>
<td></td>
</tr>
<tr>
<td>• 7 Agree entirely</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Q19. I would prefer using Big data analytics* over alternative means of analysis</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics</td>
<td></td>
</tr>
<tr>
<td>• 1 Disagree entirely</td>
<td></td>
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<td>• 2</td>
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<td>• 6</td>
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<tr>
<td>• 7 Agree entirely</td>
<td></td>
</tr>
<tr>
<td>Question</td>
<td></td>
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<td>----------</td>
<td></td>
</tr>
</tbody>
</table>
| **Q20. I will recommend using Big data analytics* to other people**  
  *Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics** |
| 1. Disagree entirely  
  2  
  3  
  4  
  5  
  6  
  7 Agree entirely |
| **Q21. Big data analytics* is not secure**  
  *Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics** |
| 1. Disagree entirely  
  2  
  3  
  4  
  5  
  6  
  7 Agree entirely |
| **Q22. There is a risk of malware (e.g. viruses, spyware, worms, trojans etc.) when using Big data Analytics*  
  *Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics** |
| 1. Disagree entirely  
  2  
  3  
  4  
  5  
  6  
  7 Agree entirely |
| **Q23. Big data analytics* does not have adequate security features**  
  *Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics** |
| 1. Disagree entirely  
  2  
  3  
  4  
  5  
  6  
  7 Agree entirely |
| **Q24. There is a risk of information leakage when using Big data analytics*  
  *Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics** |
| 1. Disagree entirely  
  2  
  3  
  4  
  5  
  6  
  7 Agree entirely |
<table>
<thead>
<tr>
<th>Question</th>
<th>Description</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q25</td>
<td>The financial investment required to implement Big data analytics* is too high for the company I work for</td>
<td>1-7</td>
</tr>
<tr>
<td>Q26</td>
<td>We do not have the technical knowledge in the organization to implement big data analytics*</td>
<td>1-7</td>
</tr>
<tr>
<td>Q27</td>
<td>We do not have the legal knowledge in the organization to implement Big data analytics*</td>
<td>1-7</td>
</tr>
<tr>
<td>Q28</td>
<td>There is not enough time to implement Big data analytics*</td>
<td>1-7</td>
</tr>
<tr>
<td>Q29</td>
<td>Big data analytics* is too complicated to implement</td>
<td>1-7</td>
</tr>
</tbody>
</table>

*Google AdWords, Google Analytics, Facebook Analytics and LinkedIn Analytics
Q30. Companies should not use personal information for any purpose unless it has been authorized by the individuals who provided the information
   - 1 Disagree entirely
   - 2
   - 3
   - 4
   - 5
   - 6
   - 7 Agree entirely

Q31. Companies should devote more time and effort to preventing unauthorized access to personal info
   - 1 Disagree entirely
   - 2
   - 3
   - 4
   - 5
   - 6
   - 7 Agree entirely

Q32. When people give personal information to a company for some reason, the company should never use the information for any other reason
   - 1 Disagree entirely
   - 2
   - 3
   - 4
   - 5
   - 6
   - 7 Agree entirely

Q33. Companies should never sell the personal information in their computer databases to other companies
   - 1 Disagree entirely
   - 2
   - 3
   - 4
   - 5
   - 6
   - 7 Agree entirely

Q34. What kind of business do you work for?
   - Service business
   - Merchandising business
   - Manufacturing business
   - Consulting
   - Other

Q.37 What is your role at the company? (short text answer)
Q35. Age
- 18–25
- 26–35
- 36–45
- 46–55
- 55+

Q36. Gender
- Male
- Female
- Prefer not to say

Q37. Country of citizenship
- Sweden
- Other

• Thank you for your participation!