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BIG DATA PHENOMENON IN BUSINESS: PROJECT PROCESS, GENERATION OF VALUE AND HUMAN-DATA MEDIATION: A STUDY OF INDIAN SME'S

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Chapter 1: Introduction

1.1 Background of the Study

The term Big Data is a term of Anglo-Saxon origin, whose translation into Spanish could be understood as "A set of data so large and complex that they require computer applications for data processing and development, which are far from the traditional tools to process this data. properly" as defined by Conecta Software on its website, the term accepted by the RAE to refer to the data set is Macro data. As it is not an exact science, it is not perfectly defined when a database by volume can be considered Big Data, but according to professionals in the sector, the range in which a database must oscillate to be considered Big Data by volume is from 50 Terabytes to several Petabytes.

Big Data has been gaining notoriety, and becoming a fundamental tool for business management due to the importance of analysing new data to discover the true value of these, to find relationships between data existing millions of these, it is impossible to use a conventional relational database, and due to this inefficiency of relational databases, this powerful business management tool arises, which has come to stay in the business field.

The purpose of Big Data is for companies to be able to group and understand relevant data, and establish relationships all between companies data that with incorporate similar characteristics, macro data analysis which is why programs achieve an advantageous competitive advantage over its competitors, due to the reduction of costs and information processing times that lead to greater operational efficiency and effectiveness, if we refer to the search for relationships between macro data for SMEsthe correct term that we must take into account is Small Data, the cheapest alternative for data processing, with characteristics similar to those of its "big brother", but with much lower information processing capacity, data volume, and processing speed, this type of data analysis program macro data is much more accessible to companies with fewer resources, even being offered as a free software tool business management.

1.2 Problem Statement

Big data is still a very foreign concept. Today, only 1.5 percent of all data is analysed. In fact, there is not even a definite definition of the subject. Data sets are getting bigger and more varied, and this data needs to be efficiently analysed. How will this be done? Is there any benefit to it? The subject is current and there are many indications that in the near future it will become important in many industries.

There is no single solution to the problem, but it can be solved in several ways. We intend to make the problem less alien by examining the situation according to our research questions, and thus gain insight into what the challenges and opportunities around big data are.

1.3 Scope of work

This study aims to provide an understanding and developed knowledge of what big data is and how it can be used by Indian SME's. The study also intends to answer whether there is in practice a business benefit, and what opportunities and challenges are associated with this, by interviewing experts at established companies that work with big data.

1.4 Objective of the project

- To analyse the concept of Big Data
- To analyse the evolution of Big Data
- To analyse the benefits of Big Data

- To analyse the potential application of Big Data to the sector of small and medium-sized companies

1.5 Structure of the Study
Chapter 1: Introduction
Chapter 2: Literature Review
Chapter 3: Research Methodology
Chapter 4: Findings and Analysis
Chapter 5: Conclusions and Recommendations

Chapter 2: Literature Review

The history of Big Data goes back to years before 1980, when computers were unthinkable to have all of us in our homes, and unthinkable to predict the amount of information that they can process in seconds, the data that these computers stored was stored exclusively in what were known as data centers, access to this data was limited to a very small level of the population, and understanding it was a laborious task.

From 1980 until the beginning of the 21st century, technological progress manifested itself in the growth of households that had a personal computer, data centers in turn evolved to become centralized and with the ability to distribute and analyze data. Thanks to the connection between personal computers, these data centers would become known as "Hubs" and allow the development of large industries such as film or music thanks to being able to analyze, store and interpret information, this in turn motivated by largely to the creation of microprocessors that allowed growth in data storage.

Finally, from 2000, the term Big data began to emerge gradually as time went by, data centers began to be developed in the cloud, therefore, they could store much more information than what they were handling until At that time, in addition to this, another series of devices connected to each other such as tablets, smartphones, etc., was added to the cloud in such a way that the cloud or Cloud Computing has become so important that there are different business models based on storage in the cloud, thus avoiding a large amount of paperwork by going from having a physical location to store the information to be stored in the cloud. Due to this change, there are large multinationals that knew how to be ahead of their time and take advantage of this cloud storage to generate and store large amounts of data that, thanks to Big Data, transform it into information about each client, knowing their tastes, habits and needs, to In this way, get more enjoyment from the Internet, for example, Google, Facebook or Amazon are three of the largest companies in the world that use cloud storage.

The traditional information value chain describes how data is the basis for information that is transformed into knowledge. Knowledge is then the basis for decisions that result in actions (Abbasi, Sarker& Chiang 2016). The actions taken consequently result in results equal to value or additional data (Sharma, Mithas&Kankanhalli 2014). In Abbasi, Sarker and Chiang (2016) studies from 2016, they visualize a connection between how the information value chain looked like before and after big data became a decisive factor in the business market. The models demonstrate that different technologies are prominent within the different eras of the information value chain - while the chain itself is similar. The big difference lies in how knowledge is generated. It is still relevant to talk about data becoming information that forms knowledge, but with big data present, knowledge is created based on big data rather than limited and internally selected data.

The boundary where data - or data in normal dimensions - turns into big data is not obvious. In Abbasi, Sarker& Chiang (2016) publication from 2016, the authors describe how to separate big data from normal data through a set of characteristics. These characteristics are well known in the context and go by the collective name "The four Vs" (Abbasi et al. 2016). Big data's four v's refer to volume, variety, velocity and veracity, which are explained below.

Volume

Just as explained earlier, the amount of data circulating in a given business has increased significantly in recent years. In a 2011 study, it appears that the US Library of Congress has stored hundreds of

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terabytes of data from its operations that store both digital and offline content (Manyika et al. 2011). Despite this enormous amount of data, the same study shows that the average company operating in 15 out of 17 industrial sectors in the US stores more data than the US Library of Congress (Manyika et al. 2011). To further put this into perspective, McAfee and Brynjolfsson (2012) conducted a study in which it emerged that the retail chain Walmart stores 2.5 petabytes of data daily solely connected to the customer's transactions in connection with their purchase from the company, which consequently means that the annual storage of data can reach units such as exabytes. Here, possibly some new concepts are introduced that are relevant in a context of big data - peta- and exabytes. If megabytes were represented by sand, a tablespoon could hold its data, a terabyte in comparison is a rectangular sandbox with a length of just over 30 centimetres and a depth of just over 2.5 centimetres, while petabytes in the same metaphor would be represented by a 1.6-kilometre-long beach. Exabytes would in this metaphor be represented by a beach that stretches 1529 kilometres (Abbasi et al., 2016). Just as the text above suggests, volume refers to data being constantly growing (Chiang, Grover, Liang & Zhang 2018).

Variation

The reason why the amount of data circulating in organizations needs to be measured in the SI prefix exabyte is that companies today consider unstructured, semi-structured and structured data that is acquired both internally and externally from the operations (Abbasi et al., 2016). The variety of data that a company stores on a daily basis is of course dependent on the sector they are active in, but both Chen, Chiang and Storey (2012) and Abbasi, Sarker and Chiang (2016) include traditional transactional data, click-generated data from web and mobile devices , sensor-based data, data from user generated images, video and text, data from social media and spatial temporal data in the data variety that companies need to adapt to. The great variety of where available data can be collected from brings both challenges and opportunities for companies (Abbasi et al., 2016).

Velocity

Velocity aims to explain the speed of emergence of data, which is one of the clearest characteristics of big data. The data that companies are flooded with today comes frequently and at a high speed (Chiang et al. 2018). As previously mentioned, McAfee and Brynjolfsson (2012) illustrate this through their research where it emerged that Walmart alone produces 2.5 petabytes of data per day solely linked to the customer's transactions in connection with their purchase. In 2015, only three years later, Yin and Kaynak (2015) reported that the data produced by various machines, cloud-based solutions and enterprise governance annually generates a volume greater than 1000 exabytes. In the same article, they state that the amount of data is expected to increase twentyfold in the next 10 years. Thus, companies face a big task where they need to process and interpret data in a short time (Chiang et al. 2018).

Veracity

Reliability refers to the distinction between uncertainty and unreliability in the data collected (Chiang et al. 2018). The credibility of the data included in big data can vary significantly (Abbasi, Sarker& Chiang 2016). For example, Abbasi and Adjeroh (2014) state in their study from 2014 that 20 percent of all data that exists on the web comes from spam accounts on social media, which then generates unreliable data. That (Abbasi, Sarker& Chiang 2016).

In Chiang et al. (2018) study from 2018, the authors describe how a fifth characteristic was considered to be added to the four already recognized characteristics that define big data - also the initial letter of this characteristic is of course V. Chiang et al. (2018) describes how value - or Value - was considered to be added to the characteristics that describe big data, since analysis of big data that does not generate value is of no use to companies that use big data with the aim of creating value for the business regardless of the size of the data that is available to the business.

According to Seddon et al. (2016) data is the prerequisite for all analytical things and describes the extent to which relevant and accurate data is available for analysis inside and outside the organization. Provided that appropriate board arrangements are in place to ensure data availability. In the same study, the authors define a number of models of different factors that business analysis helps bring value. The authors themselves then develop a model that is intended to specify particularly important insights from business analysis. Their belief is that their model can provide better explanations of what companies need to do to achieve more benefits from business analytics. Furthermore, the authors show how stories from 100 successful businesses were evaluated according to a process model. The study shows, for example, how 100% of the respondents mention how enabling technology is an important factor for success, while only 12% of the respondents mention analytical competence among the staff as important for success. 98% mention that the use of data-based business analysis is an aspect that has contributed to the success of business operations. 89% say insights as a result of business analysis tools are important and 81% mention decision-making with the just-mentioned insights as the basis for the success of the business. With this study as a basis, it is made clear that a clear majority of the successful companies with the help of business analysis and big data can be given insights that are the basis for positive decision-making.

Also, Acharya et al. (2018) study the effect of big data on the SME's and conduct a study that is rooted in decision making. The authors' presented conclusions show that it is possible to extract knowledge through the interaction between the company's staff and its customers and that generated knowledge can provide value-creating insights. In Jain et al. (2017) study shows how companies in the SME's that fail to adapt their range to the customer's ever-changing tastes and preferences are at risk of declining its profitability. The study examines how SME's work to adapt their range to the customer's premises and identifies that insights through big data as an opportunity to succeed with customer adaptation. The insights can then form the basis of a trend analysis, which enables customer adaptation.

Chapter 3: Research Methodology

3.1 Scientific approach

According to Patel and Davidsson (2011), there are essentially three approaches to approaching an empirical reality, inductive, deductive and abductive, which is a combination of the two previously mentioned. The study applies a deductive approach as the approach to the work has gone from theory to empiricism in order to subsequently strengthen the empirical assumptions against acquired theory (Jacobsen & Andersson 2017). Furthermore, a deductive approach enables the development of existing research, which we strived for.

The approach of the deductive process is distinguished by the procedure of initially studying existing knowledge and theory, to enable comparisons of existing models and theories to thus illuminate essential variables and create a theoretical starting point for the study. Furthermore, interview questions are anchored in a theoretical foundation to enable comparisons of existing theories and hypotheses that arose in connection with interviews. In order to analyse whether the answers differ from previously studied theory.

3.2 Qualitative method

With the starting point of investigating the underlying causes and meaning, an investigation of a qualitative nature is carried out. According to Christensen et al. (2016), qualitative methods can be used to create conceptual descriptions of reality and thus highlight and illuminate the connections that emerge, with a primary focus on the whole and the context rather than specific parts. The reason for this is that the study investigates phenomena that are not generalizable, as Eliasson (2010) indicates in his book Quantitative method from the beginning. With the aim of gaining a deeper understanding of how the company worked with data-driven business analysis, a quantitative method was not relevant.

Like Saura et al. (2021) use a qualitative research method to enrich the answers obtained from interviews, we use a similar method in the study, with the aim of gaining a deeper understanding of the investigated phenomenon rather than statistically generated significance of results. The method is also characterized by semi-structured interviews with open questions, which also reflects the study carried out by Saura et al. (2021) the main reason is thus that open questions can deal with a wider spectrum of experiences and phenomena. Furthermore, the interviews have been transcribed and coded according to themes.

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3.3 Data collection method

Secondary data in the form of previous research was initially collected from a journal published in the field of informatics and information systems. The reason for this was to create a theoretical foundation to enable comparison of previous research and collected empirical data. In order to collect the empirical data in the study, semi-structured interviews were used with an identified company active in the textile industry. Due to the fact that we wanted to have the opportunity to ask follow-up questions in cases where we considered it relevant, we considered that semi structured interviews were the most appropriate form of interview for the study. Furthermore, semi-structured interviews enable a way for the respondents to answer the questions in a rich and unrestricted way, in addition we who conduct the interviews are given space to respond to the questions with supplementary questions to obtain relevant information (Christensen et al. 2016). With the help of this data collection method, we hoped to obtain as good conditions as possible to answer the problem formulation and purpose, as well as test the hypotheses collected from the theory against the empirical material and discover differences and similarities.

Through this collection method, interactions and group dynamics are created, which leads to developing discussions. Furthermore, an unbalanced focus group can mean that some individuals take up more space than others and therefore steer the discussion in the wrong direction. In order to increase the validity of the study, we therefore believe that semi-structured interviews were the most suitable alternative as we as researchers could to some extent control the interviews so that the report's question formulation could be answered (Christensen et al. 2016). There is a risk with semi-structured interviews for the reason that knowledge of the business's approach is limited. This would be able to indicate that interviews with a lower degree of structuring should be used in order not to risk that too controlled questions could lead to data collection being hampered. On the other hand, we needed to get answers to questions relating to a specific issue, which means that we need the interview's questions to be angled to answer specific points, and thus the choice fell on a semi structured interview.

3.4 Data collection

The interviews were conducted via computer in the form of digital meetings with the respondents at the company. All interviews were conducted in the meeting tool Microsoft Teams, which enabled the recording of all interviews. With the help of the recording function offered by Microsoft Teams, we were able to easily transcribe the interviews afterwards.

The first interview was conducted at the company's CFO. Primarily, the respondent answered questions regarding the company's strategies, objectives, software programs and working methods. The respondent provided us with supplementary email responses regarding data collection methods to which the person did not have an answer during the course of the interview. The company's CSO was then interviewed, who answered questions regarding roles and skills that the company possesses. The respondent was also asked to list software programs that were used in order to evaluate the company's infrastructural maturity and identify the company's functions. Two different controllers were then interviewed regarding the software program and the type of data analysed was determined. Initially, the questions and question wording were identical for these two interviews, but as the interview form is semi-structured, this meant that the supplementary follow-up questions differed. Consequently, a market analyst was interviewed with the aim of identifying how the company works to increase its market shares as well as how they identify profitable markets.

3.5 Analysis

After the interviews were completed, the analysis work and transcription started. When qualitative interviews were conducted, central quotes could be picked out and worked on further. When analysing the collected data, the underlying meaning has been considered and categorized according to codes and quotes. Graneheim&Lundman (2004) explain in their study on qualitative content analysis that themes cannot be objects or things, but answer the question "How?". Because the data has several meanings, the themes are not exclusive and categories are placed within several themes. The interviews that were conducted were reviewed several times to create a sense of the whole and subsequently compiled into texts. This became the basis for the analysis unit and in this way comparisons of differences and similarities between theory and empirical work were made possible. Based on the quotes the results could be produced, which then led to analysis and discussion. Finally, conclusions and future research proposals could be presented based on the quotes. Conducted interviews have been analysed step by step as below:

Step 1: Recorded interviews were transcribed.

Step 2: Based on the interviews, central quotes were selected for further analysis and discussion.

Step 3: The empirical material is interpreted and compared against theory.

Step 4: Analysis and discussion could present proposals for future research.

3.6 Ethical considerations

Just as Christensen et al. (2016) suggests, investigations are dependent on public participation and we as investigators are thus forced to take a stand on various ethical aspects. Ethical considerations considered during the course of the study can be specified as follows: possible respondents were asked via email and attached was also the interview guide and the purpose of the study, this approach created a basis for the respondent to assess the study and later stand up of their own free will. Before each conducted interview, respondents have been asked if recording is permitted and if anonymity is desired. In each case, the respondents wanted anonymity and from special requests from a high-ranking manager also for the organization. The recorded material was approved by all respondents before the interviews began, this to fulfil the requirement for consent. The confidentiality criterion was met by storing the recorded interviews in such a way that they were only available to us researchers in the study.

Chapter 4: Findings and Analysis

4.1 Infrastructure

Grover et al. (2018) write how the integration between internal selected data and externally acquired data contributes to rare insights which can be the basis for value-creating decision-making and with the completed study as a basis, we believe that the company has the infrastructural conditions to acquire external data, present it in software program as well as the analytical competence to bring in a value based onthe insights. What is particularly distinctive about the company's infrastructure can be found in the analysis portfolio, where social media as a platform for external data acquisition is a central part of the company's path towards increased profitability.

Regarding the degree of infrastructural maturity, previous studies (Grover et al. 2018) indicate that this part is absolutely decisive for whether a business will succeed in extracting value with the help of Big Data. LaValle et al. (2011) study shows that the majority of the 3000 business leaders, managers and analysts surveyed work in companies where the quantitative amount of data is greater than they can handle. The studies do not define a clear level of infrastructural maturity that companies need to achieve for the infrastructure to be sufficient to enable strategic business value.

The results obtained from the qualitative study indicate that the company is aware that investments in the infrastructure are necessary for the business to be able to work with big data. For example, the respondent mentions how the company strives to become more data-driven and to make decisions based on data. The respondents' words are also supported by the fact that the IT department at the company has grown significantly in recent years, as recently as 2021 additional analytical skills were recruited in the form of an in-house BI developer. In addition, there are areas where the company chooses to outsource parts of the analytical activities. In parallel with these investments, both earnings and turnover have increased. In 2018, the company had a turnover of just under 290 million INR, while in 2019 they increased to a turnover of approx. 350 million INR.

At the time this study was conducted, the analyzed business was able to handle the amount of data flowing into the company's software system. As the study explains in the results chapter, the company is aware that analytical competence, analytical software and big data assets are required to consequently generate valuable insights. The reason why the time aspect is made clear is because we believe that this is not a constant state - a company can of course, in its pursuit of further insights, choose to work with more big data assets, which can result in the company outgrowing its existing infrastructural asset. However, previous studies indicate that in such an event, the company can hire more analytical people and more analytical software solutions that can process the increased amount of data.

Conducted study shows that what distinguishes the analyzed business is the amount of data collected from social media and influencer collaborations, as well as the importance of the acquired data. This is confirmed by the fact that despite the company's relatively few employees (49), it includes the analytical competence in the company's infrastructure services that work with generating insights from social media and influencer collaborations. User-generated data is also something that the company values highly in its quest to improve the customer experience - but we consider user-generated data to be more frequent in all industries that work with sales of any kind. This is confirmed by Acharya et al. (2018) whose study showed that user-generated data is frequent in companies since the introduction of big data.

On the other hand, we believe that in the context of the fact that the functional value of profitability is of thehighest importance for the company, there are increased margins to be brought into the infrastructure forthe company. In the short term, outsourced departments are considered to be more profitable thanmaintaining the competence within the business, but in the long term it is usually more expensive to hirethe competence. There may be a correlation between the company outsourcing parts of the business andthe fact that the company was forced to notify roughly 30 employees in 2020 and that post-covid-19 they are working torebuild the company. A sign that the business strives to increase analytical competence and preserve competence within the company is that in 2021 they hired a BI analyst to select and present relevant data to the company's controllers.

In Grover et al. (2018) study, the authors refer to previously completed studies that demonstrate that an increased amount of external data is not synonymous with increased value - it is the way businesses use the existing data that is decisive for the outcome. Which means that even if an increased amount of purchased data could generate increased value for the company, there are studies that indicate that the correlation between the amount of data acquired does not necessarily generate increased value.

Text analysis

The analysed business continuously works with user-generated data to adapt its range to customers.If companies that carry out text analysis select data based on the content of words, they risk missing out on relevant data as words on public digital platforms tend to be misspelled, grammatically incorrect and written in jargon that is difficult to interpret. This may become a growing problem for the company as they expand - but currently one of the respondents describes how they have roles that work closely relevant to the platforms which suggests that it is currently rather the competence of individual workers who can do that companies are missing out on valuable insights from users.

Predictive analysis

The study explains how it is possible to distinguish from conducted interviews that predictive analysis is particularly distinctive among the company's value-creating mechanisms. Predictive analysis, as explained earlier, is about - using historical events as a basis - predicting the customer's future actions. As the results section explains, the company works with predictive analytics in a variety of ways that are reflected in the literature. A concrete example of approach is how the company transforms external data from social media into insights.

4.2 Functions

Deviation detection, social media analysis, and visualization tools were identified with the company's infrastructural conditions. The particularly distinctive features are compared with previous studies and discussed below.

As mentioned in the theory section, visualization tools can be a contributing factor to the functionality required to obtain value according to the organization's Big Data functions, above all by adapting the organization's analytical tools to a more comprehensive use, i n the form of mobile devices and visually appealing interfaces with the aim of eliciting more frequent analyses. Despite the benefits outlined in the theory, the organization today has not implemented mobile devices in its arsenal of analytical tools.

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Innovative solutions like mobile applications and tablets would have been another instrument to enable more frequent analyses, encourage discussion, collaboration and engage users i n an interactive way. However, the organization's previous software program (Excel) has been replaced by more modern, graphically appealing software such as Qlikview and Qliksense to enable the handling of large data volumes and subsequently create better conditions for understanding market trends, business models and customer behaviour. Something that Grover et al. (2018) suggest is a foundation for developing actionable insights to obtain streamlined business processes. The analytical software the organization uses also contributes to the identification of diversified data in real time and can thus create value for the organization by obtaining data at high speed (Velocity). Furthermore, the tools offer easy access to business analysis and enable analyses that were previously not possible to carry out via Excel, which is proven by analyses in the form of past, present and future in order to identify where, how and what value is created. Despite the fact that the organization has not chosen to implement mobile devices in daily work, there is a clear indication that the company seeks more modern solutions to support the expected BA growth and subsequently create value through more detailed analyses.

Social media analysis is seen as one of the organization's primary sources of valuable insights as the company's social media analysis helps the company understand customer needs and trends. These insights later form the basis for understanding consumption behaviour. The strategy is supported by Grover et al. (2018) who in his study insinuates that social media is a platform filled with valuable information. Data derived from social media thus creates a foundation for decision-making regarding assortment and sales as it can indicate various trends.

Businesses that work with external data from social media in various respects need to be prepared for the problems that can arise with data generated from social media. Like Sivarajah et al. (2017) describe that the majority of surveyed organizations receive more data than they can handle, the valuable insights sought from social media can be hampered to some extent due to the amount of unstructured data that may need to undergo further processing to filter out irrelevant information. The fact that 90% of all data produced online is unstructured (Sivarajah et al. 2017) combined with the fact that everything written online is not true or is written with a sarcastic tone that can be difficult to decipher can iead to problems when a business has to analyse online content.

Insights may be based on false and sarcastic claims which may generate insights that do not reflect reality.

The company's insights from influencer collaborations are an interesting aspect in this analysis as previous research articles did not touch on this as a function that businesses can extract data from.

One respondent explained how the business contracts influencers and public figures that fit their identified target audience to market their products. Based on a given influencer, the company can generate insights such as exposure, engagement, sales figures and the profitability of a collaboration.

4.3 Value-creating mechanisms

The identifiedvalue mechanisms based on the results of the interview are: customer adaptation, targeting, prediction and availability. A table is listed below to clarify what the expected effect of working with a given value- creating mechanism is and what the actual effect is for the analysed business.

Value creation mechanism	**Expected effect**	**Actual effect**
Customer customization	Customer customization and targeting strengthen customer relationships and are the basis for an improved customer experience.	Customer adaptation and targeting are used in the case of the analysed business in order to create the symbolic value of customer experience and customer satisfaction.
Targeting	Customer adaptation and targeting strengthen customer relationships and are the basis	Customer adaptation and targeting are used in the case of the analyzed business in order

	for an improved customer experience.	to create the symbolic value of customer experience and customer satisfaction.
Prediction	Prediction generates a value by predicting the probability of an event in the future, which can generate valuable insights that can be the basis for taking suitable action.	Prediction as a value-creating mechanism is used in the case of theanalysed business to predict the probability of an event in the future, the insights resulting from the prediction are the basis for decision-making in the business.
Availability	By making data available in the business, transparency is provided for the company's employees regarding the company's business processes and results.	The company uses data visualization programs in the form of Qlik Sense and the Harmony business system to transparently share)the company's results with employees. Qlik Sense also makes it possible to evaluate the company's well-being using real-time data as a basis.

Table 1: Expected effect and actual effect of value-creating mechanisms (Self prepared)

As the table above shows, the actual effect of using customization, targeting, prediction and availability as value creation mechanisms is strikingly similar to the theoreticalthe effect. The analysed business works with the mentioned value creation mechanisms for the same reason as the theory defines its value creation.

However, previous studies have established that companies can automate processes in various businesses with the help of machine learning and AI (artificial intelligence). We would not say that it is surprising that the company itself has not developed such mechanisms for, for example, text analysis that they work with to generate valuable insights from users since the company, as previously defined, has a relatively low turnover. However, it would be interesting to see if the insights would be more or different if the business decided to implement machine learning as a value-creating mechanism.

4.4 Values

Thevalues of the business studied are, just as the framework by Grover et al (2018) makes clear, strongly rooted in its value-creating mechanisms. The company's visualization tools and work with accessibility and transparency realize the company's vision of improving decision-making in the business. With the help of Qlik Sense, the company can provide its employees with real-time data about the company's performance.

The company also works with price optimization, but for the analysed business this is a predictive analysis with internally generated data from sales statistics. It would of course have been desirable to be able to predict at as early a stage as possible whether a product will sell well or not and to be able to act proactively regarding pricing. Grover et al. (2018) write that big data can generate insights based on external user-generated data from online reviews in combination with internal data to adjust prices for services and products, however, this is not something that emerges that any of the companies from the case study use despite the fact that two of the companies work with optimization as a value-creating mechanism.

In Jain et al. (2017), the authors describe how customers today expect a product or service to be adapted to their liking and taste. The analysed business works with this by adapting both interfaces and products to the likes and tastes of their target group via externally generated user data and customer surveys. This is summarized as service and product innovation as a value goal, which can also be linked to the company's pursuit of a good customer experience and good reputation.

4.5 Effects

As the results chapter explains, the company's work with data-driven business analysis results in both functional values and symbolic values. Just as in the Simchi-Levi and Wu (2017) study that defined that retailers are constantly working to improve revenue, margins and increase market share, the business in this study is working to increase profitability and increase theirmarket share. One strategy the company has to increase profitability is precisely by improving margins.

Functional value

The company's actions and deeds are usually done with the aim of increasing the company's profitability. A strategy that the company uses due to increased profitability is to increase its market shares and work with strategies that make the brand widely known. One feature used by the company to accomplish this is social media analytics and influencer collaborations. Currently, it is a manual process for the company to extract valuable insights from these collaborations and platforms. In Grover et al. (2018) study, the authors explain how a company automated the social media analysis used in their business to scan users'online publications that comment, tweet, tag or otherwise write the company's name online and then automatically generate promotional mailings about the company's products to users. There is a high probability that this would be an investment that requires too much resources for the business, but despite this, it is a possible future development of their functions that can increase the company's profitability and further expose the brand.

Symbolic value

Asthe results chapter makes clear, the respondents say that the company strives for the symbolic value of customer satisfaction, which should give it a good reputation. The respondent says that the reason why the company wants to create a good customer experience and improved customer satisfaction is that the customer's sense of satisfaction should generate loyal and returning customers, which in the long run becomes a functional value because loyal and returning customers increase profitability - which the respondents agree is the company's primary objective.

It is also interesting that the symbolic value of customer satisfaction did not come up before we pointed out that there are studies that show that it is common for companies that strive for symbolic values in combination with functional values. We see this as an indication that the effect is of secondary interest. On the other hand, the respondents talk about how customer surveys and user-generated data are the basis for changes to the appearance of their interface.

In Grover et al. (2018) study, the authors conduct case studies at five different companies: UPS, Walmart, Deutsche Bank, E-bay, and ASCO Cancer LinQ. The symbolic value reputation was found in two of five businesses - E-bay and Walmart. These two companies have a common denominator with the business analysed in this study in that all three companies are active in the sales industry. This could of course be a coincidence, but otherwise an observation in how businesses in this industry can use big data to generate a symbolic value in a proven way.

In 2020, the company hired its own sustainability manager, which was also a position that the company previously outsourced to an external partner. One of the respondents explained how this was done because the business wanted to become independent, but one thought is that this outwardly gives the impression that the company protects the environment and works for a sustainable future. It can definitely be argued that this is positive in a reputational sense.

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4.6 Big Data Roadmap

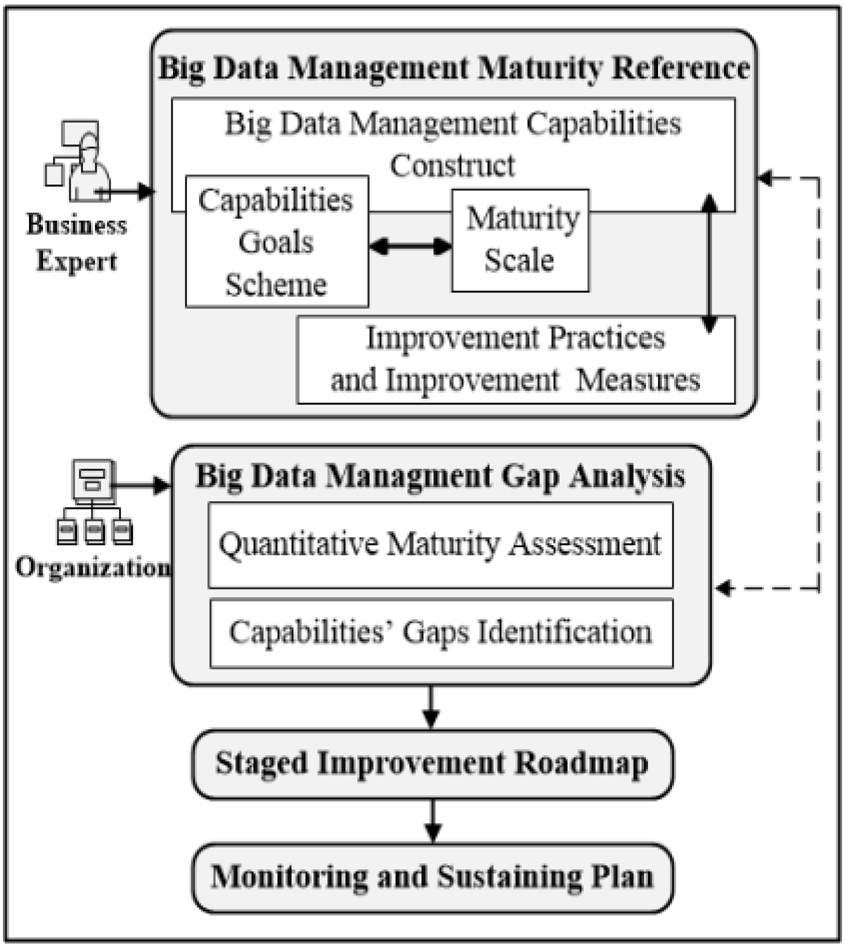

Figure 1: Big Data Management Maturity Roadmap (Self prepared)

Chapter 5: Conclusions and Recommendations

5.1 Conclusion

The company identifies that in order to enable value creation with the help of business analysis, it is of the utmost importance that the company invests in a solid infrastructure which enables the transformation of big data assets into valuable insights. With this as a basis, the company has inflows of external data from competing companies' range and pricing, external data from social media and user-generated data, which the company combines with internally generated data, which gives the company unique and inimitable insights. The company includes these insights in its strategy to enable increased profitability. (2). The company's data assets are sufficient to extract valuable insights that can contribute to increased profitability, which is proven by the fact that public figures regarding the company's turnover are increasing. (3) The company uses customer adaptation, prediction, targeting and availability as value-creating mechanisms to realize its value goals which subsequently lead to the company fulfilling the desired effect of increased profitability.

Furthermore, it was identified that the company also works for an additional functional value: increased market expansion as well as the symbolic value of improved customer experience. (4) The analysed business works with influencer collaborations and generates data as a result of a collaboration. This is a business analysis function not defined in previous studies.

5.2 Future Scope of Study

In the analysis and discussion chapter, there is a discussion linked to previous studies which conclude that companies need to invest in the infrastructure to enable value creation with the help of Big Data,

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however, there is no defined level that the companies need to achieve. A proposal for research is to try to clarify what level of infrastructural maturity a company needs to achieve in order to enable value creation with big data. Previous studies have, as explained in this study, established that increased big data assets are not synonymous with increased value creation. There is a possibility that this can be a basis for understanding the complexity and amount of analysis programs as well as the level of competence of a company's staff that is needed for a given number of big data assets to be processed optimally.

The second proposal we have for future research is also anchored in a company's big data assets. As previously mentioned, there is research that indicates that an increased amount of big data assets is not synonymous with increased profitability. It would have been interesting to test this theory on an individual big datafunction. For example, a study could explore whether the results from social media analysis for a SME would have generated more profitable insights if the company analysed data from several different social media sources.

It would also have been interesting to study in the SME's which external data a predictive analysis should use in order to generate the most precise insights into a customer's purchasing behaviour as many studies read are about predicting customers' future purchases and identifying upcoming trends.

Another suggestion for future research is to evaluate which factors are most decisive in the event of price optimization - and on the same topic: how can companies use big data to identify as early as possible which goods should be price adjusted in order to (1) free up inventory space if the item does not sell as expected, and (2) increase the price of items to as early as possible so as not to miss out on the increased margin for the products.

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