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Developing a framework for Business Analytics: a structure for turning data into actionable insights

A case study at Volvo GTT PE

Master's thesis in Quality and Operations Management & Supply Chain Management

Adam Christoffersson
Chris Hunt Karlsson

Department of Technology Management and Economics
Division of Quality Sciences
CHALMERS UNIVERSITY OF TECHNOLOGY
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Adam Christoffersson & Chris Hunt Karlsson, 2015

Technical report no E2015:092
Department of Technology Management and Economics
Division of Quality Sciences
Division of Logistics and Transportation
Chalmers University of Technology
SE-412 96 Göteborg
Sweden
Telephone + 46 (0)31-772 1000

Abstract

At present, the available data in the world are continuously increasing from already unprecedented levels. The vast volumes, velocities, and varieties of data today, make the data harder to ingest, process, and visualize – a state that has been labeled "Big Data". This is one of recent trends which have led to the emergence of Business Analytics. As this trend shows no signs of slowing down, the need for Business Analytics will increase in the future as organizations attempt to obtain value from their data. This thesis is aimed to develop a Business Analytics framework for turning data into actionable insights using a case study at Volvo GTT PE. Through an abductive approach, where theory and the empirical world are systematically combined, it offers a number of contributions to the theory of Business Analytics and to the case company. First, this study recognizes the importance of including naturalistic concepts into Business Analytics, such as expertise-based intuition and the significance of experience and domain knowledge in data analyses. Second, it develops a new definition of Business Analytics to incorporate the findings of this research and to lay the foundation for further development of the subject. Third, it proposes a framework for Business Analytics and a step-by-step procedure for putting it into practice. How this framework can be used in practice is also exemplified using the empirical study as a base. In addition to these theoretical contributions, this study also analyzes and builds up support for improving the analytics structure at the case company – Volvo GTT PE in Gothenburg – and presents a number of improvement areas which the company should look further into.

Keywords: Business Analytics, evidence-based decision making, intuition, insights

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Adam Christoffersson

Chris Hunt Karlsson

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Abbreviations

Euro VI	European regulations for emission levels for heavy duty trucks, which were implemented in 2013
IUPR	In Use Performance Ratio: the ratio of the number of times that conditions have existed under which a monitor, or a group of monitors, in the engine should have detected a malfunction, to the number of driving cycles of relevance to that monitor or group of monitors
LAT	Logged vehicle data Analysis Tool: Volvo's internal database tool and platform for handling logged vehicle data
LVD	Logged Vehicle Data
NOx	Nitrogen oxides
OBD	On-Board Diagnostics: a system for detecting malfunctions in vehicles
SEWS 2	An internal support tool at Volvo, where log parameters are defined
Teamplace	Internal communication platform at Volvo
Tech Tool 2	An internal aftermarket platform at Volvo
Volvo GTT PE	Volvo Group Trucks Technology Powertrain Engineering

1. Introduction

In this chapter, the research area is outlined and the purpose and research questions of the study are provided.

1.1 Introduction

In recent years, there has been an explosion in the amount of available data in the world. The CEO of Google, Eric Schmitt, articulated in 2010 that as much data as were created in between the dawn of civilization and 2003, were then created every other day – with an increasing pace (Acito and Khatri, 2014); and currently, around 1.6 zetabytes of data are available in the world, which would be enough to watch high-definition TV for 47 000 years (Hoerl et al., 2014). Data are thereby becoming more and more available to businesses, which can obtain it from for example point-of-sale records, embedded systems, and social networking sites such as Facebook and Twitter (Saxena and Srinivasan, 2013). The high volume, velocity and variety of the data are changing the way in which we use it - a state that has been labeled "Big Data" (Saxena and Srinivasan, 2013). Lately, the concept of Big Data has come to revolutionize business, government, science, and essentially all parts of society (Hoerl et al., 2014). However, utilizing these vast amounts of data comes with a number of challenges (Kumar and Bhadani, 2014), and thereby often leads to failure and disappointments (Hoerl et al., 2014). The challenges of organizations today are therefore mainly not to obtain data, but to get the right data, and to turn it into information and knowledge (Dean, 2014).

The great increase in available data, in combination with the growing maturity of business performance management, increased focus on fact-based decisions, and the incorporation of analytics techniques into enterprise systems, have led to the emergence of Business Analytics (Acito and Khatri, 2014). Business Analytics assists an organization in obtaining insights (Stubbs, 2011) and value (Holsapple, 2014) from data. It has been defined as a way of "*delivering the right decision support to the right people at the right time*" (Laursen and Thorlund, 2010, p. XXI) and more recently as "*evidence-based problem recognition and solving that happen within the context of business situations"* (Holsapple et al., 2014, p.134). Even though analytics to some extent has a long history (Saxena and Srinivasan, 2013), it has more recently, as a concept, risen in popularity among scholars and practitioners (Holsapple et al., 2014). Recent studies have also shown that high-performing businesses utilize analytics to a greater extent than low-performing ones (LaValle et al., 2010). However, Holsapple et al. (2014) state that there has not been enough introspective investigation of Business Analytics as a field of study, wherefore they, through an extensive review of current literature on the topic, have developed a unified foundational framework of Business Analytics. In light of this unification of current literature, Holsapple et al. (2014) asked for empirical investigations of their conceptual framework through in-depth case studies.

This piece of research is a case study conducted at Volvo GTT PE in Gothenburg. Volvo GTT PE has recently started to investigate the possible value the organization may obtain from logged vehicle data (LVD) of their sold vehicles as they are operated by their customers. These data are currently coming in to, and are being stored in, various data systems at Volvo. At present, there are however not any clear structure nor any clear process in place for how to turn this data into business value. Therefore, this study will utilize Business Analytics theory to investigate how Volvo GTT PE can turn logged vehicle data into insights, which can subsequently be turned into value creating actions.

1.2 Purpose

The purpose of this thesis is to develop a Business Analytics framework for turning data into actionable insights using a case study at Volvo GTT PE.

1.3 Research questions

To obtain results that correspond to the stated purpose, the research questions for this study are formulated as:

1. How can theory from Business Analytics be used to analyze and improve an organization’s analytics structure?
2. In what ways can a practical application of Business Analytics contribute to development of its theory?

1.4 Delimitations

This study begins with a fairly wide scope, as it has all six perspectives of the Business Analytics Framework (Holsapple et al., 2014), which will be presented later in this report, as a base. However, as the study proceeds, the scope is narrowed down. First of all, three factors that are deemed more contextual will be analyzed, but no improvement suggestions concerning them will be generated, as that would require too extensive resources for this study. These factors are the decisional paradigm, the movement, and the capability set of Volvo GTT PE. Furthermore, the improvements that are implemented during this study are merely concentrated on one part of the transforming process, a process which in total ranges from the initial step of data creation to the resulting actionable insights. The process step in which the improvements are implemented, is in this study denoted “data to information”, and is essentially where the data are compiled and turned into information. Hence, no improvements are made concerning data creation and warehousing, or concerning decisions and actions taken based on the analytical findings.

As have been mentioned, the study is conducted at Volvo GTT PE in Gothenburg. The results are consequently based on findings from this site and this department. Whether this delimits the findings from being generalizable to other settings could be up for debate.

2. Research Methodology

In this chapter the methodology of this study is described, through explanations of its strategy, design, and methods. Reflections over the quality and ethics of research are also addressed.

2.1 Research strategy

This study is qualitative in nature. Qualitative strategies are commonly associated with inductive approaches to do research, whereas deductive approaches usually consist of more quantitative strategies (Bryman and Bell, 2011). Inductive and deductive approaches can be distinguished through their respective relationships between theory and research; in deductive approaches, theory is used to test a hypothesis, make observations and generate findings, and in inductive approaches, theory is the outcome of research. However, both approaches entail elements of each other (Bryman, 2012). Instead of choosing either an inductive or a deductive approach, however, this study has chosen an *abductive* approach based on systematic combining of theory, framework, and the empirical world. This means that an initial theoretical framework directs the empirical findings, and the empirical results generate a need to modify the theoretical model. Hence, the theoretical framework and the empirical study are developed and refined concurrently (Dubois and Gadde, 2002). The process of systematic combining is depicted in Figure 2.1.

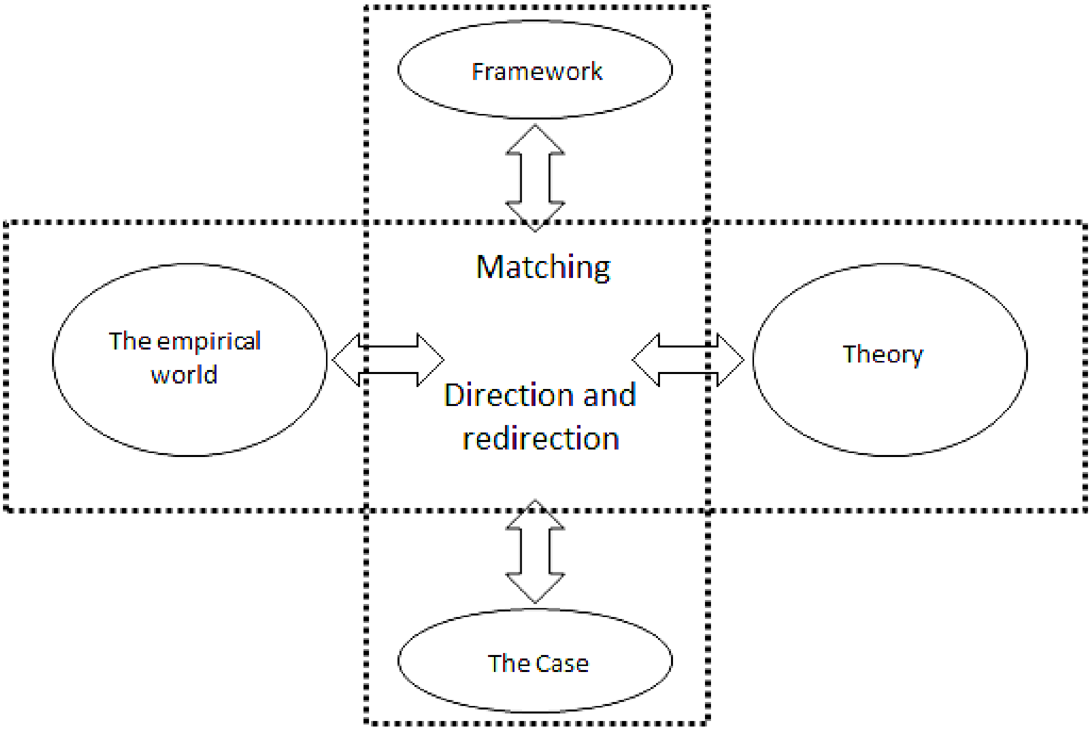

Figure 2.1 Systematic combining (Dubois and Gadde, 2002)

2.2 Research design

This research was conducted as a case study, which is an empirical investigation of a phenomenon within its real context, with the use of multiple sources of evidence (Yin, 1994). Bryman and Bell (2011) explain that it involves detailed and intensive analysis of a single case, in order to capture its complexity and particularities. Saunders et al. (2009) state that conducting a case study is a way to gain a rich understanding of a specific context, and case studies are preferable to use when questions such as why, what and how are to be answered, which is the case in this study. To perform empirical case studies of Business Analytics is in fact suggested by Holsapple et al. (2014), and the authors of this study also deem it as an appropriate method for investigating how Business Analytics works in, and how it can be developed through, practical applications.

2.3 Research method

A research method is a means of collecting data (Bryman and Bell, 2011). In this study, the means of collecting data is literature reviews, interviews, casual conversations, observations, and examinations of internal documents and reports at the case company. The two authors of this thesis spent, in total, 450 hours each at the site of the case company to collect data, with additional time being spent on reviewing literature, as well as summarizing and documenting findings.

2.3.1 Literature review

A literature review was conducted in order to develop a theoretical knowledge base and to direct the empirical study. The majority of information was collected from the websites http://www.sciencedirect.com, https://scholar.google.se, http://orm.sagepub.com, and https://webofknowledge.com/. Additional information was found in the libraries of the University of Borås and Chalmers University of Technology. The main keywords that were investigated were *Business Analytics*, *Big Data*, *decision making*, *evidence-based decision making,* and *intuition*.

2.3.2 Interviews

The three most common interview approaches are structured, semi-structured and unstructured interviews, where structured are more quantitative and the two latter more qualitative (Bryman and Bell, 2011). As qualitative interviews are utilized when there is a greater interest in the interviewees' point of view, and the aim is to attain more detailed answers (Bryman and Bell, 2011), they were the choice for this study. In addition, Bryman and Bell (2011) suggest using semi-structured interviews when the researchers have an idea of how to analyze the data, and if more than one person will conduct the interview, which was the case in this study as well.

Semi-structured interviews should be designed around pre-decided questions and topics that provide a guideline for the interview (Whiting, 2008). The interview guide used during the interviews is provided in Appendix A. As semi-structured interviews provide the possibility to add questions in line with the context and flow of the discussion, more and deeper knowledge about the research questions can be gained (Saunders et al. 2009). This was also utilized during the conducted interviews, where the interview guide was the base, but where the questions varied depending on the flow of the discussion. Moreover, Robson (2011) states that conducting interviews is a flexible way to receive responses and to identify underlying motives. However, as Robson (2011) and Saunders et al. (2009) mention, it should be noted that semi-structured interviews are time consuming, lack reliability, and that it is hard to protect the interview result from interviewer and interviewee bias. In addition, since the interviews during this study were affected by the flow of the conversations, they were not identical. Due to this, not all questions in Appendix A were asked to all interviewees, and some topics only came up during a few interviews, which may have had some effect on the results of the study.

Holsapple et al. (2014) suggest using their Business Analytics Framework (Section 3.3.5) as a guide to structure interviews and focus groups with practitioners. Interview questions for the semi-structured interviews were also brainstormed and created by the authors with the Business Analytics Framework (Holsapple et al., 2014) in mind, in order to capture views from interviewees on all its six perspectives. The interview questions were later structured in accordance with the laddered questions technique presented by Price (2002), which is built on the assumption that the interviewer knows which questions that will be perceived as most intrusive by the interviewee. This technique was assumed to build rapport between the interviewer and interviewee, which Duncan and Ryan (2010) explain will assist in generating richer data. Price (2002) proposes that laddered questions should be utilized in order to choose the most suitable level of questions, as the interview should involve three levels, seen in Figure 2.2, namely *action*, *knowledge* and *philosophy*. The questions should become more invasive as the interview proceeds and the interviewee becomes more comfortable. The first level is mostly used in the beginning and end of an interview, in which the questions mainly concern descriptions of actions. At the second level, questions are directed toward the knowledge of the interviewees, which they presumably are using to execute their actions. And lastly, the philosophical questions, at the third level, concern the motives and values of the interviewee. These types of questions are closest to the respondent's personal identity, and are therefore considered most invasive.

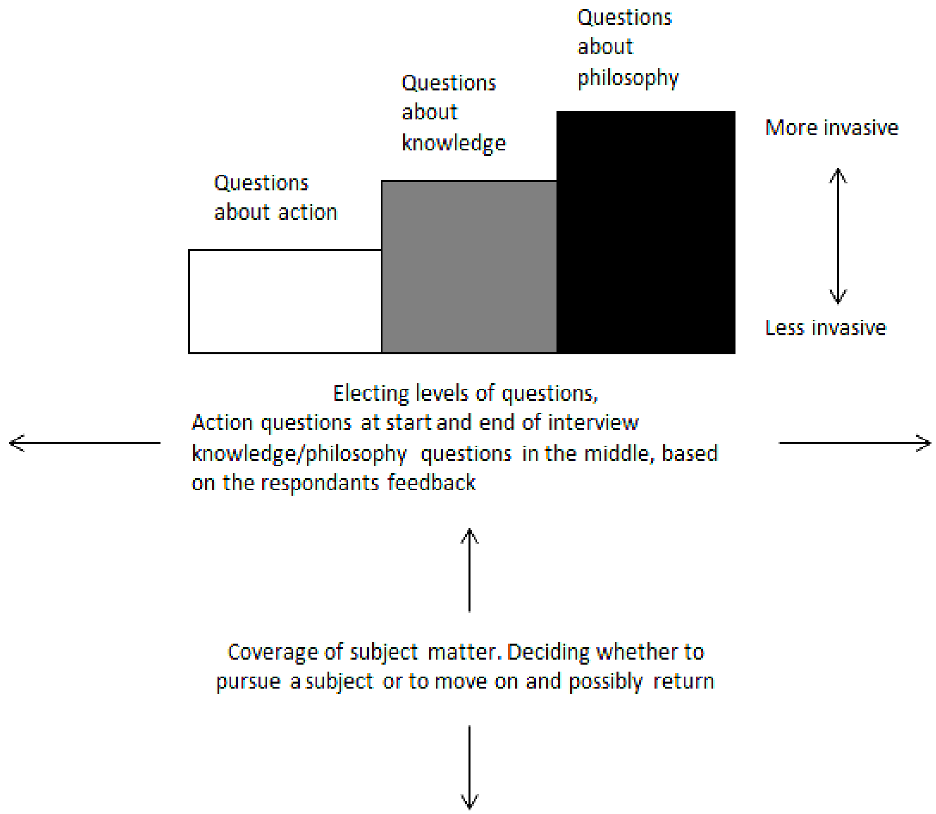

Figure 2.2 Laddered questions (Price, 2002)

Consequently, the whole process of creating and structuring the interview questions is visualized in Figure 2.3. In this picture, it is depicted how the six perspectives of the Business Analytics Framework (Holsapple et al., 2014) were used to generate questions, and how these questions were later sorted according to whether they were deemed to be related to action, knowledge, or philosophy (Price, 2002). This was how the interview guide for this study was developed.

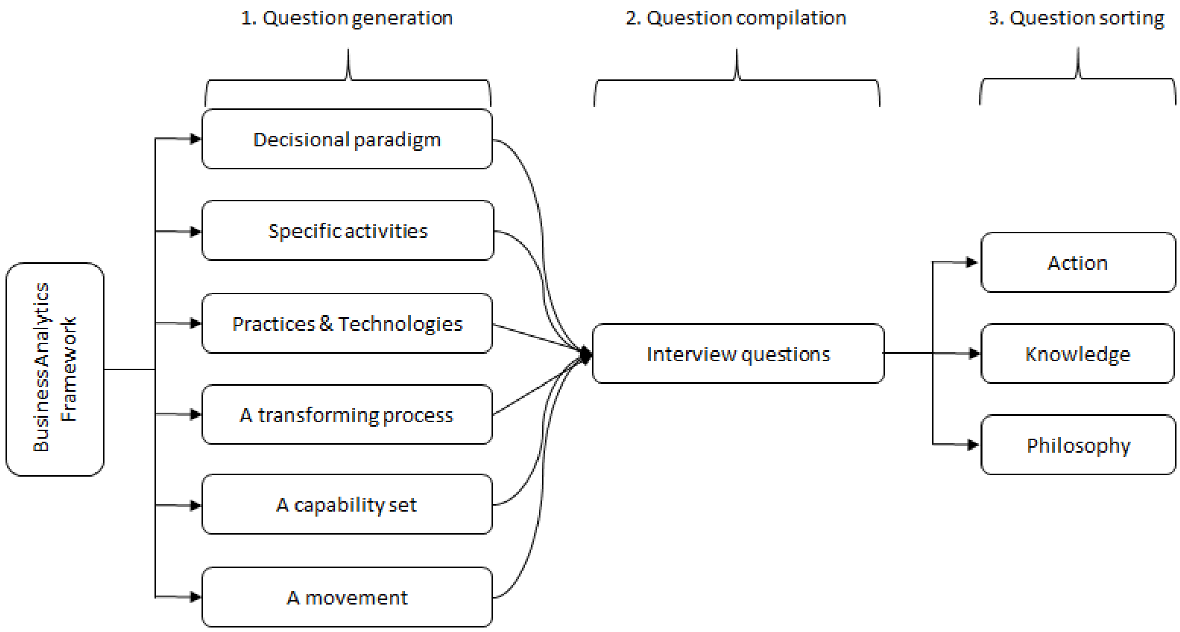

Figure 2.3 Process of generating interview questions

Interviewees were then selected based on a stakeholder analysis that was conducted during the initial stages of the study. Firstly, the transforming process was identified at Volvo GTT PE, which was determined to be the main steps of how data are created, turned into information, and how that information is used. Secondly, stakeholders in relation to the transforming process were identified. The stakeholder analysis is explained in more detail in the fourth chapter of this report, but it essentially involves identifying and defining internal team members, core externals, and "the rest of the world", as proposed by Maylor (2010). Internal team members were determined to be those directly affected by the transforming process, and all of these stakeholders, six in total, were interviewed. Subsequently, two "core externals", which were defined as other employees at Volvo, were included, based on suggestions from members of the internal team. In the "rest of the world" group, the stakeholders were defined as those being outside of Volvo. No stakeholder in this group was interviewed.

Prior to the interviews, the interviewees were given information about the purpose of them, and they were asked for permission to be recorded, which all interviewees agreed to. In addition, one of the authors took notes during the interviews that served as support for the transcription of them. The time of the interviews ranged from fifteen minutes up to one hour, depending on how much the interviewee had to say. The subsequent transcription process was conducted with help of the recordings and notes taken during the interviews. Thereafter, a transcribed version was sent out to the interviewees for validation; to remove any misunderstandings or misinterpretations, the interviewees were given one week to change or add something to their answers.

2.4 Data analysis

According to Saunders et al. (2009), qualitative data can be analyzed via for example summarization and categorization, and these methods can be used separately or in combination. In this study, a combination of summarization and categorization has been used, as is described below.

After the transcription and verification of the conducted interviews, the surfaced problems and stated stakeholder requirements were summarized. This essentially means that the meaning of long statements is expressed in fewer words to enable easier identification of themes and relationships (Saunders et al, 2009). An example of this is provided in Table 2.1, where it is demonstrated how a question raised by an interviewee was summarized into a requirement on the analytics structure at Volvo GTT PE. A more complete picture is provided in chapter four.

Table 2.1 Example of summarization technique

Voice of the interviewee	Summarized requirement on analytics structure
"If we have 10-30 readouts per vehicle in a couple of years… where are we supposed to store the data?"	Sustainable data storage

As stakeholders have different requirements and objectives, and as they differ in importance, they all should not be managed in the same way (Maylor, 2010). The stakeholders in this study were therefore evaluated based on whether they were deemed to have high or low levels of power and involvement in the transforming process. "Low Power" was defined as not having any authority to change the process, "High Power" was defined as being able to change the process immediately, "Low Involvement" was defined as not being directly involved in the process and "High Involvement" was defined as being directly involved in the process. The stakeholders that consequently were deemed more important to the project were managed closer than the others, as suggested by Maylor (2010). The stakeholder analysis is explained in further detail in Section 4.3 of this report.

A stakeholder that after the stakeholder analysis was deemed to be managed closely was thereafter asked to verify the results of the summarization of problems and requirements. These were subsequently categorized and divided into the classifications of the Business Analytics Framework (Holsapple et al., 2014) in order to enable an analysis of the analytical alignment of the organization. In addition, the problems and requirements were categorized into the Business Analytics Model (Laursen and Thorlund, 2010), to identify in which organizational level they were located and originated from.

Thereafter, as improvements were to be suggested and implemented, the stakeholder requirements were also ranked based on their estimated resource need. This ranking was performed by the authors of this thesis and it was later cross-checked with the case company to ensure its estimation accuracy. The requirements were subsequently categorized into whether they were estimated to require a high or low level of resources, which were defined as whether the available resources for this study would be enough to meet them (low resource need) or not (high resource need). The requirements that were deemed to be more contextual were however somewhat neglected in this step. Subsequently, those requirements that belonged to the analytics process, and which were deemed to require the least amount of resources, were implemented. The requirements that were estimated to need more resources to meet, but that were most important to stakeholders, were used as suggestions for further improvements at Volvo GTT PE. Some improvements were also followed up on to obtain some verification of their effects. The results and further explanations are provided in Sections 4.5 and 4.6.

2.5 Research quality

Typically, especially in quantitative research, the research quality is determined via its internal and external validity, reliability and objectivity. However, some argue that these are not applicable to qualitative research, and therefore the criterion of trustworthiness has emerged as a determinant of qualitative research quality (Bryman and Bell, 2011). Guba (1981) explains that the level of trustworthiness can be assessed via the credibility, transferability, dependability, and confirmability of research.

Bryman and Bell (2011) state that ensuring that research is carried out according to good practice, is what increases the credibility of it; therefore, this factor parallels internal validity. Two techniques that can be used to increase the credibility of research are respondent validation and triangulation (Bryman and Bell, 2011). In this study, both of these techniques were used. Transcripts of interviews were, as mentioned, sent to interviewees for validation. As the interview answers had been summarized, these summarizations were also verified by one of the more important stakeholders. Triangulation was used through spending plenty of time observing the process, the practices and technologies used, and the activities that were conducted. Casual conversations with stakeholders were also held to clarify any ambiguity, about for example interview answers or the way certain technologies and databases functioned. Internal documents and tools were reviewed as well, in order to ensure that the authors understood them and that issues raised during interviews could be verified. In addition, a literature review was performed which could reinforce many of the interviewees' statements; Section 4.6 provides examples of this.

The transferability of research corresponds to external validity, which is the degree to which research findings can be generalized to other settings. As qualitative research concerns more depth than breadth, findings tend to be based on unique contextual factors. Thick descriptions of the details of the context of the research could be used to enhance the transferability (Bryman and Bell, 2011). In this thesis the authors have tried to thoroughly explain the case and the research context in order to do this.

The reliability of qualitative research is designated dependability. This relates to the possibility of auditing the research process, which could be reached through clearly outlining the process and all steps belonging to it (Bryman and Bell, 2011). The authors of this thesis have tried to exhaustively describe the research process to satisfy this criterion.

And finally, Bryman and Bell (2011) state that the confirmability of research relates to the objectivity of the researchers; that they have acted in good faith and not allowed personal values to heavily affect the research findings. Guba (1981) explains that triangulation is one way of achieving confirmability, a method which, as previously explained, has been used in this study.

2.6 Ethics

There are mainly four ethical principles that should be considered when doing research, and these concern whether there is any harm to participants, lack of informed consent, invasion of privacy, or deception involved (Bryman and Bell, 2011). These principles have been carefully considered during this study. People who have been involved have received thorough and truthful explanations of the study and its objectives, in order to enable informed consent and avoid deception. Interviews have been voluntary, no private questions have been asked, and the interviewees have always had the possibility not to answer a question. The interviewees were asked in advance if the interviews could be recorded. Full anonymity has not been promised, but this has also been stated to all participants. In combination, these aspects cause the authors to believe that no invasions of privacy or harm to participants have been involved.

3. Theoretical framework

In this chapter the theoretical base of the study is described. Earlier literature on Business Analytics, expertise-based intuition, and the nature of insights are summarized, and a number of conceptual frameworks are reviewed.

3.1 Data, information, knowledge, and insights

As mentioned in the introduction, there has, in recent years, been an explosion in the amount of available data in the world, and the pace is continuously increasing (Acito and Khatri, 2014). Saxena and Srinivasan (2013) state that data are currently becoming more and more available to businesses and analysts, from for example credit card transactions, point-of-sale records, embedded systems (such as data loggers in trucks and airplanes, and radio frequency identification readers), and social networking sites such as Facebook and Twitter. The new state of how we use the high volume, velocity and variety of data has been labeled "Big Data" (Saxena and Srinivasan, 2013).

What constitutes "big" has been debated, but Minelli et al. (2013) suggest, similarly to Saxena and Srinivasan (2013), that it is data that extend beyond the traditional borders in terms of volume, variety, and velocity, and that these factors in combination make the data more complex to ingest, process, and visualize. Gandomi and Haider (2015) also mention that the "Three V's" of volume, variety, and velocity have emerged as the framework to describe Big Data, and in addition they state that it is impractical to determine any exact thresholds for when any of the Three V's become "big", as the defining limits depend on the size, sector, and location of the firm in question.

McKnight (2014) states that with the vast increase in available data, the nature of business judgment is changing; it must grow to utilize more information, and to utilize it in more depth. Silver (2012) mentions that we have more information today than we know what to do with, and relatively little of it is actually useful; what we actually want is knowledge, not information. Data, information, and knowledge may seem as terms and concepts that are used interchangeably, and their individual meanings can therefore be somewhat lost, so for clarification purposes it is suitable to make clear distinctions between them. Laursen and Thorlund (2010) explain that data are the carrier of information, and are commonly too specific to assist in decision making; information is data that is aggregated to such a degree that it is appropriate to use as decision support, and it could be materialized in for example tables and reports; and knowledge is what is attained after the information has been properly analyzed and interpreted. Nonaka (1994, p.15) defines knowledge as "justified true belief" and states that knowledge is created via information.

This study, however, aims to develop a structure for turning data into actionable insights; therefore, it is also in place to look deeper into the term "insights". Klein and Jarosz (2011, p.346) define insight as "*discontinuous discovery, a nonobvious revision to a person's mental model of a dynamic system, resulting in a new set of beliefs that are more accurate, comprehensive, and useful.*" Klein and Jarosz (2011, p.347) continue by explaining that when a person gains insights, his or her mental model shifts as "*either new data or a combination of data or a finding of a contradiction leads the person into a conceptual territory that was new in some aspects"*.

Klein and Jarosz (2011) subsequently present a framework, with three main pathways for an individual to gain insight: (a) through *contradiction*, where inconsistencies to the individual's mental model are detected, (b) through *desperation*, when there is a need to re-think the situation, and (c) through *connection*, when an implication is spotted. These three pathways eventually lead to a new understanding of a situation, which in turn may lead to a realization of how to act in accordance with the insight. The framework, as developed by Klein and Jarosz (2011), is presented in Figure 3.1.

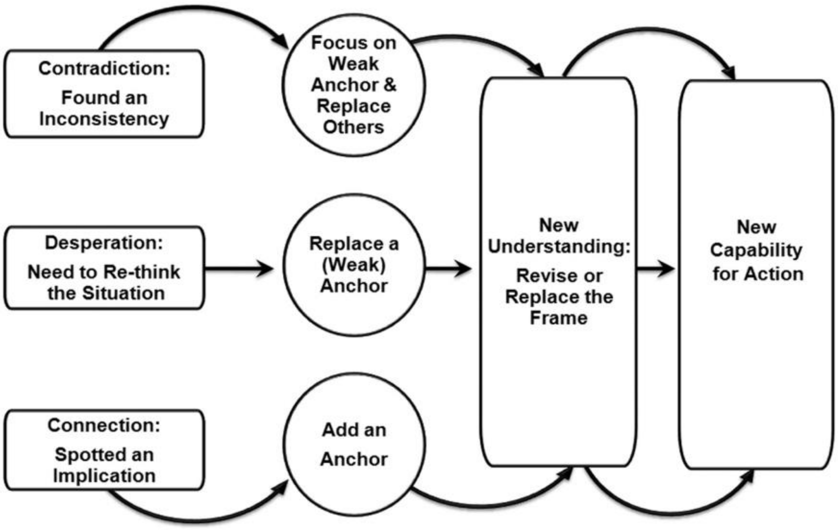

Figure 3.1 The anchor model of insight (Klein and Jarosz, 2011)

3.2 Business analytics

3.2.1 Emergence, characterizations, and definitions of Business Analytics

Saxena and Srinivasan (2013) believe that Business Analytics to some extent has a long history; they assert that it can be argued that it is the root of management theory itself, beginning with Frederick Taylor's use of analytics methods from observation to execution. After this initial phase, consultants commenced to provide analytics services, business analysts started to get hired as management assistance, and techniques from statistics, quality control, and operations research were developed and used by practitioners. With the developments in information technology, IT teams could start to provide managers with analytics dashboards and reports, and subsequently business intelligence and data warehousing teams in the IT departments continued on this path (Saxena and Srinivasan, 2013).

Acito and Khatri (2014), however, believe that Business Analytics in its current form is a fairly new concept. They state that the vast increase in the availability of data, which were discussed earlier, is one of several recent trends that have converged and led to the emergence of the concept of Business Analytics. A second, which has contributed to this development, is an increased maturity of business performance management, which has created a stronger connection between business strategy and data. A third reason is the increased realization that fact-based decisions are vital at all organizational levels. And lastly, a fourth trend is that advanced analytics techniques are more incorporated into enterprise systems.

Holsapple et al. (2014) propose that Business Analytics has three dimensions, which they call *domain*, *orientation*, and *technique*. These researchers explain that the domain dimension concerns the subject field of analytics, and could for example be knowledge analytics, marketing analytics, or supply chain analytics. The orientation dimension includes the analytics' direction of thought. The most frequently discussed orientation may be predictive analytics, while two others are descriptive and prescriptive analytics. The third dimension, technique, refers to how an analytics task is performed. This dimension has different perspectives, as techniques for example can be technology- or practice-based, and quantitative, qualitative, or hybrids. Techniques also encompass analytics mechanisms, such as data mining, text mining, and data warehousing.

Laursen and Thorlund (2010, p.XXI) define Business Analytics as: "*delivering the right decision support to the right people at the right time"*. These authors explain that this definition seeks to make the point that companies need the ability to control and monitor their processes, as well insights about how to improve them. Stubbs (2011) proposes that Business Analytics broadly is "*any data-driven process that provides insight*". Saxena and Srinivasan (2013) state that the main goal with analytics is to assist people in making rational decisions, and that analytics help in all four phases in the process of rational decision making: idea, analysis, decision, and execution. Holsapple et al. (2014, p.134) propose yet another definition of Business Analytics, as these authors state that it essentially is "*evidence-based problem recognition and solving that happen within the context of business situations*".

A concept which is related to Business Analytics is Business Intelligence; both Stubbs (2011) and Saxena and Srinivasan (2013) explain that Business Intelligence is a subset of Business Analytics, as Business Intelligence focuses on analyzing and presenting historical information - *what* happened (Stubbs, 2011). Advanced analytics, in turn, is a concept that tries to identify *why* things are happening, as well as predict what will happen next and which course of action that is recommended. Business Analytics, according to Stubbs (2011), encompasses all of these concepts and adds the requirements of actionable insights, business relevancy, and value and performance measurement.

Some reasons for pursuing Business Analytics are also given by Holsapple et al. (2014), and they include the possibilities to achieve a competitive advantage, support an organization's strategic objectives, improve the organizational performance, improve outcomes of decisions, improve decision processes, produce knowledge, and obtain value from data. Studies have also shown that high-performing businesses utilize analytics to a higher degree than low-performing ones (LaValle et al., 2010). As firms in several industries offer similar products with equivalent technologies, business processes are among the last differentiating factors - and organizations competing on analytics utilize every piece of value from those processes (Davenport, 2006). Therefore, high-performing companies are currently building their strategies around information-driven insights that enable great results, from the power of analytics (Maisel and Cokins, 2014).

3.3 Frameworks and models for business analytics

Throughout recent years, mainly from the millennium shift and onwards, a number of conceptual frameworks for Business Analytics have been developed by researchers. In one of the pioneering findings, Davenport et al. (2001) present a model for how to build an analytic capability within an organization.

3.3.1 A model for building analytic capability

Davenport et al. (2001) divide their model into three major elements: context, transformation and outcomes. The model is depicted in Figure 3.2.

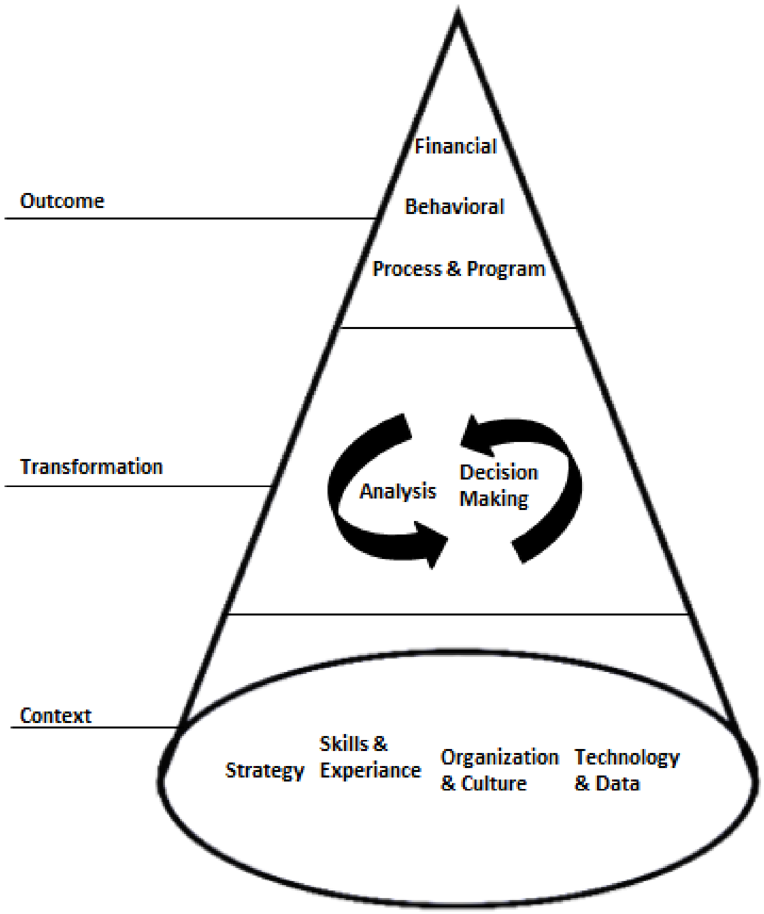

Figure 3.2 A model for building an analytic capability (Davenport et al., 2001)

The contextual factors can be viewed as prerequisites of success to creating an analytic capability. They include strategic, skill-related, organizational, cultural, technological, and data aspects. The data are analyzed and used as decision support in the *Transformation* element. The results from the analysis and decision-making are placed in the element of *Outcome*; unless something changes in the organization, the context and transformation are of little value. The three types of identified outcomes are behaviors, processes and programs, and financial results. The shape of a cone, which is used to visualize this model, is supposed to highlight the importance of the context that underlies the analytic transformation, which in turn is the base for creating better outcomes (Davenport et al., 2001).

Davenport et al. (2001) also propose some key actions and steps to consider as an organization starts building an analytic capability. First, they state that it should be ensured that the data to be used are of high quality. Second, that senior executives support the analytic capability building. Third, that the organization has a need for analytics. Fourth, that the analytical skills and culture exist in the organization. And fifth, the last step is to integrate analytics into the business.

3.3.2 The Business Analytics Model

Laursen and Thorlund (2010) present a different perspective of Business Analytics, as is depicted in Figure 3.3. These authors emphasize the layered and hierarchical nature of analytics, as information requirements flow in a top-down manner, from management in its mainly business-driven environment, and eventually down to IT professionals in the more technically oriented environment. Subsequently, the information supply flows in the opposite direction.

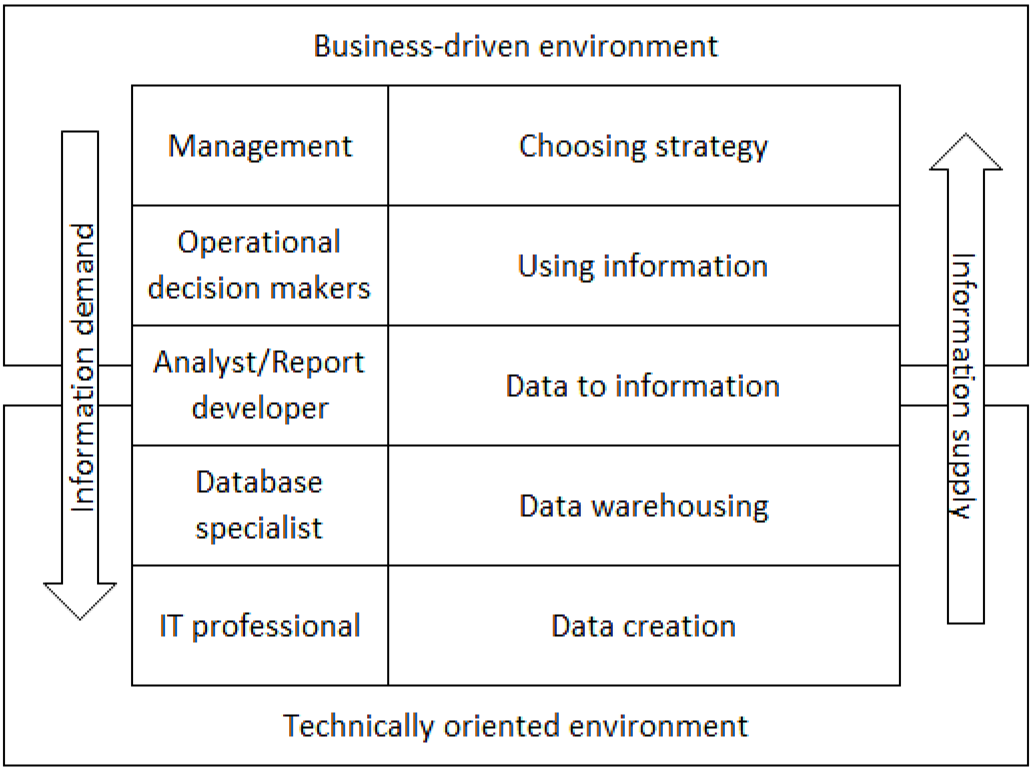

Figure 3.3 The Business Analytics Model (Laursen and Thorlund, 2010)

Laursen and Thorlund (2010) explain that in the business-driven environment, management creates and develops an information strategy, which is based on the entity's overall business strategy, such as its vision, mission and objectives. The overall business strategy is usually transformed into a set of key performance indicators, KPIs, which are put in place in order to measure and evaluate the degree of business performance. The strategy and the KPIs are subsequently translated into objectives and a framework for the operational level of the business. At this level, the desired behavior of the operational decision makers, and the requirements on information and knowledge to achieve it, are outlined. Business Analytics is, according to Laursen and Thorlund (2010), about aligning business processes and actions with the overall strategy and business objectives, and at this level, operational decision makers, in functions such as marketing, finance and production, can optimize their activities.

In the middle of the hierarchical structure, and in the borderline of the business-driven and technologically oriented environments, Laursen and Thorlund (2010) continue by explaining that analysts specify which data and information that are needed to achieve the desired behaviors of the operational managers. Information and knowledge are here generated through the use of statistics and data analysis. From the analysts in the middle layer, database specialists receive the requirements about data deliveries, and the data need to be retrieved and/or made accessible to the analysts at the higher level. Data can also be procured or obtained from an external supplier. Lastly, in the bottom of the figure, the development and operations of information technology must meet the requirements on data deliveries from the database specialists.

3.3.3 Levels of analytical sophistication in organizations

As Kiron et al. (2011) studied how organizations are using analytics, they identified three levels of analytical sophistication: aspirational, experienced, and transformed organizations. Longitudinal studies show that the two latter groups are expanding their analytical capabilities and expectations, whereas the aspirational organizations are falling behind. Organizations can be grouped in these levels based on their analytic use, reliance on analytics, information foundation, analytic tools, analytic skills, and culture. When Kiron et al. (2011) investigated what organizations at the most sophisticated analytical level, the transformed, did well, they found three key competencies: information management, analytics skills and tools, and data-oriented culture. The points of these competencies are, respectively, to manage the data, understand the data, and act on the data.

Kiron et al. (2011) also suggest that there are two paths to achieving an analytical capability. They choose to characterize these two alternatives as the specialized path and the collaborative path. In the specialized path, deep analytics expertise is developed in certain functions, whereas in the collaborative path, a cross-sectional information platform is created, but where the analytics expertise is not as developed.

3.3.4 A structural framework for business analytics

Another way to gain understanding and knowledge from data is presented by Acito and Khatri (2014) in their Business Analytics framework, as can be seen in Figure 3.4. The essence of the proposed framework is to, in a structured way, be able to derive value from data. The framework consists of six blocks: *Strategy, Desirable Behaviors, Business Performance Management, Tasks, Capabilities* and *Data*.

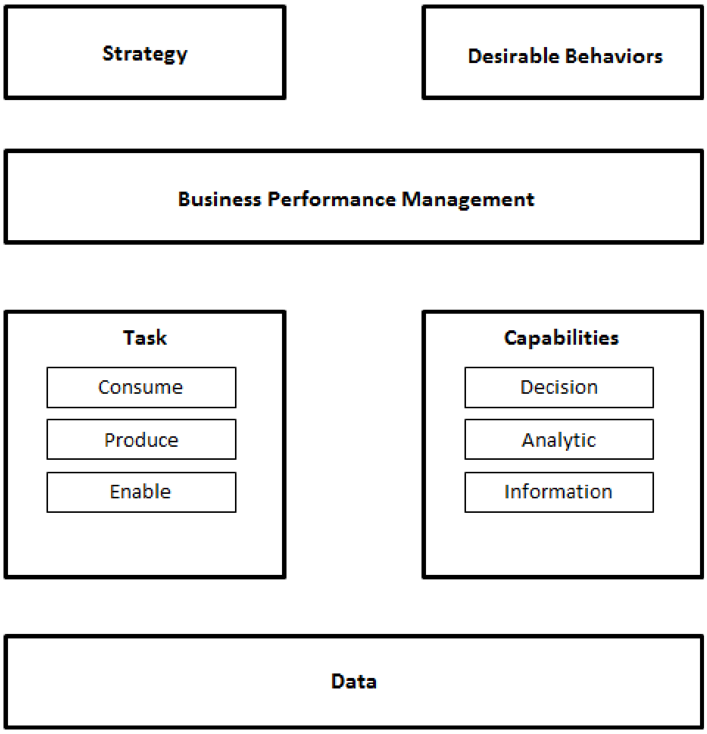

Figure 3.4 A structural framework for Business Analytics (Acito and Khatri, 2014)

The *Strategy* should be a plan of action describing how resources should be dedicated and used. Without a strategy it becomes difficult to identify the needed data and decide in which way it should be utilized. Acito and Khatri (2014) state that by constructing a plan, data can be found more easily and used in a meaningful way. *Desirable Behaviors* refers to the culture and beliefs within the organization and the way decisions are made. *Business Performance Management* works towards understanding how business performance can be measured and which drivers that are most important. It is used when hypotheses need to be tested and helps to decide how well systems work.

Acito and Khatri (2014) continue by explaining that *Tasks* refers to how insights should be handled by the organization and include the three parts *consume*, *produce* and *enable*. *Produce* means that data are being analyzed and defined. Later the data are *consumed*, which means that the insights are used in decision making. The information technology *enables* the organization to perform and evaluate the analysis of the insights. There are also three types of *Capabilities* used in this framework, namely *decision*, *analytic* and *information*. *Decision* capabilities are supporting tools that are used during decision making, such as dashboards which give visual support as well as enable higher collaboration. *Analytic* capabilities could be seen as a portfolio of tools, including simulations, predictive analytics etc., that support the analysis of information. The last, *information* capabilities, are technologies that help organizations to describe, share and arrange data.

3.3.5 The Business Analytics Framework

The last framework/model of Business Analytics to be presented in this literature review, is the framework that will be used as the initial base of this study, as it is the most recent, deemed to be the most encompassing, and as its developers ask for empirical tests of it. Through an extensive literature review, Holsapple et al. (2014) generated a framework which is composed by six classes of different perspectives of Business Analytics. The framework is presented in Figure 3.5.

The first perspective in the framework developed by Holsapple et al. (2014) is Business Analytics seen as a *Movement*. This involves a philosophy and culture where decisions are based on facts, and problems are solved with support from evidence. A mindset is in place, in which evidence-based problem recognition and solving direct an entity's strategies and operations. In the second class, Business Analytics is seen as a *Capability set*. The capabilities of a company determine how well problems can be identified and solved. This includes the competencies of the company and its workers, for instance their qualitative and quantitative techniques, their systematic reasoning, how they use descriptive, predictive, and prescriptive models, as well as how they work with evidence. However, even though the organization has access to capabilities, a structure and environment need to be in place in order for it to flourish.

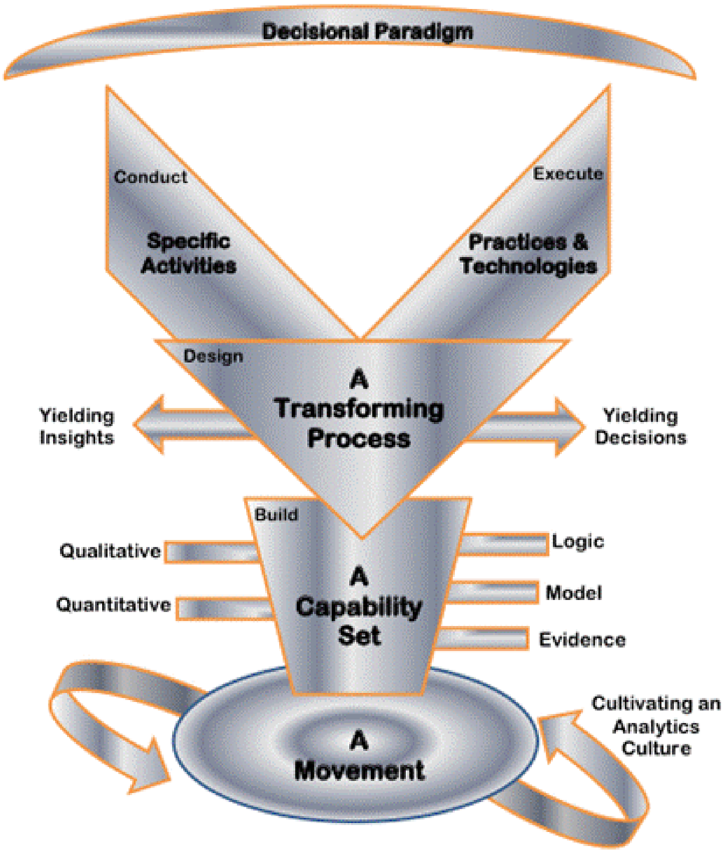

Figure 3.5 The Business Analytics Framework (Holsapple et al., 2014)

Business Analytics is, in this framework, also seen as *a Transforming process* where the collected evidence is transformed into decisions or insight. The transforming process presumably utilizes some practices and technologies, and is affected by the capability set and some cultural aspects. This perspective most heavily emphasizes the process that drives and coordinates the transformation, and the what, why, when, and how of the transformation are of interest. The *Practices and Technologies* refer to how things get done when working on evidence, such as to increase understanding, make predictions, generate knowledge etc.

Operations on evidence are also not only about crunching numbers; 80 percent of an organization's data or knowledge are not expressed in numbers. Therefore, both quantitative and qualitative, more practice based, techniques are needed within Business Analytics, and these two methods are often combined (Holsapple et al., 2014).

A fifth definition of Business Analytics is that it is a set of *Specific activities*. Together, these activities form a process to operate on evidence. The activities are, according to the definitions collected by Holsapple et al. (2014), accessing, examining, aggregating and analyzing evidence. Together with the practices and technologies, these specific activities enable the transforming process to transform the evidence into insights or decisions. The final perspective of Business Analytics, given by Holsapple et.al (2014), is of it as a *Decisional paradigm.* This implies that Business Analytics is a distinct approach to decision making, different than for example naturalistic decision making which involves basing decisions on experience and intuition. Business Analytics should at least be a part of the decision making process. The aim with the decisional paradigm is that decisions should be based on data and logical analysis.

3.4 Decisions not based on evidence

Due to the weight placed on evidence-based decision making and evidence-based problem recognition and solving in Business Analytics, it is of interest to investigate which contradictory paradigms that exist. A research field that has emerged fairly recently, and which provides a different view on decision making than Business Analytics, concerns decision making based on intuition. Salas et al. (2010) state, in a review of current literature on the topic, that intuitions play a major role in how people make decisions - and that conscious deliberation and reasoning are only at the tip of this process. These authors explain that there is much value for organizations to gain from using intuition, as experts that develop and use intuition effectively may have great influence on organizational practices and effectiveness. Decision makers that use expertise-based intuition make decisions rapidly and fairly automatically, through their extensive domain-specific knowledge that has been gained through experience. Through this expertise, patterns can quickly be recognized (Salas et al., 2010).

Klein (1999) has done a lot of research on firefighters and how they make their decisions. One story, which makes the case for intuition, has been cited by both Liebowitz (2014) and Gladwell (2005), who wrote a popularized book about the concept of intuition-based judgments. Klein (1999) interviews a fire ground commander, a lieutenant, who tells the story of when he and his men went into a house in a residential area to put out a fire in its kitchen. The firemen sprayed water on the fire, but it did not seem to help. Suddenly, the lieutenant feels that something is not right. He orders his men out of the building. Seconds later, the floor on which they had been standing on collapses. The fire had been in the basement, not the kitchen. Had the lieutenant not made his snap decision, the firefighters would have fallen into the fire. The lieutenant got this odd feeling, as he, with his experience, felt that the pattern was not right; the fire was not as noisy as it should have been if the fire would have been in the kitchen, the living room was hotter than he anticipated, and the fire did not react as he expected.

Some drawbacks of intuitive thinking have however been presented by for example Daniel Kahneman and Amos Tversky, two researchers who have demonstrated the flaws in human judgment through their studies of heuristics and biases. Their research is summarized by

Kahneman (2011). Kahneman (2011), Salas et al. (2010), and Liebowitz (2014) all describe the dual processing theory, as they separate between two cognitive processes of the human brain, System 1 and System 2, where System 1 is the intuitive, rapid, unconscious information processing system, and System 2 the analytical, slower, conscious system. Kahneman (2011) asserts that System 1 is more influential in choices and judgments than people believe. Examples of heuristics and biases that affect human judgment, especially in System 1, are representativeness, availability, and adjustment and anchoring, which are economical and effective heuristics, but lead to systematic and predictable errors (Tversky and Kahneman, 1974). Other biasing factors are for example the concept of risk aversion and effects of framing of outcomes (Kahneman and Tversky, 1984).

Pfeffer and Sutton (2006) describe how studies have shown that physicians only base around 15 percent of their decisions on evidence - instead they rely on obsolete knowledge from school, never proven traditions, patterns learned from experience, the methods they believe in and apply the most, and information from vendors. These authors state that the same holds true for managers in other types of organizations. Pfeffer and Sutton (2006) do believe that management is a craft that can be learned through practice and experience, but that the practice of the craft will be greatly improved if it is guided by logic and evidence. Some reasons why managers do not use evidence in making decisions, Pfeffer and Sutton (2006) claim to be that managers rely more on their own experience than they trust research and second-hand data, that managers prefer to use practices that they are most competent in, that hype and marketing distract managers from evidence, and that dogma and belief are used as base for decisions instead.

Gary Klein, one of the major proponents for intuition, and Daniel Kahneman, one of its major opponents, eventually joined forces and tried to work out their differences through writing an article together, with the objective of answering the question of when expert intuition can be trusted. Kahneman and Klein (2009) concluded that expert intuition can be trusted when the surrounding environment is sufficiently stable to be predictable, and when it provides experts with opportunities for prolonged practice, with rapid and unequivocal feedback. Salas et al. (2010) make similar points, as they state that factors that affect the use and effectiveness of intuition, are the level of expertise and processing style of the decision maker, the structure and availability of feedback of the decision task, and the decision environment (Salas et al., 2010).

Liebowitz (2015) has compiled a book with several authors, which also makes the case for intuition-based decision making, and especially in the era of Big Data. In the book, it is stated that no manager can make decisions based on analytics alone; there might not be enough time to gather and analyze all facts, there may be too much information, or the data may not be available. Liebowitz (2015) proposes that conditions which favor intuition are for example time-pressure, ill-defined goals, dynamic environments and experienced participants. Analytics is however preferred for conflict resolution, optimization, justification, and computational complexity. Liebowitz (2015) continues that data has value and a role in decision making, but that it is not the only factor to consider; relying solely on data can lead to missed opportunities or that mistakes are made, therefore it is important to use intuition to find other factors that can provide a more complete picture of the situation. Liebowitz (2015) further argues that logical reasoning works better in analyses of what Donald Rumsfeld, the former American secretary of defense, famously denoted “known-knowns” and “known-unknowns”, but that Rumsfeld has missed to mention the “unknown-knowns”, which are things that a person knows, without consciously knowing that he/she knows - and it is for these types of issues that intuition has an advantage over logical reasoning.

An interesting aspect is that Liebowitz (2015) refers to Gary Klein's research and findings when he summarizes these favorable conditions for intuition. However, the conditions Liebowitz (2015) propose are in some instances contradictory to Kahneman and Klein's (2009) conclusions: for instance, Liebowitz (2015) states that dynamic environments favor intuition based decisions, while Kahneman and Klein (2009) assert that intuition can be trusted in stable and predictable environments. It therefore seems as if conditions that favor intuition are not widely agreed upon among scholars.

4. Results

In this chapter, the empirical study of this research is explained through descriptions of the case and its results. In the end of this chapter, a number of possible future improvements at the case company are suggested.

4.1 The case - Volvo

The case study for this report was performed at Volvo Group Trucks Technology, and its department Powertrain Engineering, in Gothenburg. Volvo GTT PE (Group Trucks Technology Powertrain Engineering) is a part of the Volvo Group, which is one of the largest manufacturers when it comes to transportation, with around 100,000 employees, production in 19 countries, and with customers in over 190 markets (Volvo A, 2014). The Volvo Group has three main pillars: quality, safety and environmental care. The corresponding objectives are to focus on and exceed customer’s needs (Volvo C, 2014), to prevent accidents and continue being a world leader in safety innovation (Volvo D, 2014) and to reduce its environmental impact (Volvo E, 2014). These values shall permeate the organization and their way of working (Volvo F, 2014). Volvo Group's vision for the future is to become and remain one of the leaders in sustainable transportation (Volvo G, 2014).

Volvo GTT is one of eight business units in the Volvo Group, and GTT is where most research and development of technology, engines and trucks take place. The headquarters are located in Gothenburg, and Volvo GTT employs around 9000 people worldwide. The unit has eight main areas of responsibility: Product Planning, Project & Range Management, Complete Vehicle, Advanced Technology & Research, Vehicle Engineering and Powertrain Engineering (Volvo B, 2014).

Volvo GTT PE, where this study took place, engineers and designs engines, gearboxes, and axles for customers of the Volvo Group. It is a global organization with approximately 2000 employees in Sweden, France, USA, Brazil, Japan and India.

4.2 Logged vehicle data

Through a logged vehicle data (LVD) system, Volvo captures data on the actual performance of their products and components. LVD is Volvo’s internal database which gathers usage and ambient data from their vehicles, and these data are captured when the trucks are serviced at an authorized Volvo workshop or via diagnostics applications. Performance on emission levels and on-board diagnostics are examples of factors that can be evaluated and followed up. The data are transferred from the individual vehicle into an LVD database which authorized personnel at Volvo GTT PE can access.

The LVD contains a lot of different types of parameters and data, and therefore selections must be made on which data that are of interest before they are obtained. When the required data have been selected from the LVD database, the Volvo employee orders a report from the database with the readouts and parameters of interest. Afterwards, personnel responsible for the LVD database deliver these reports as data tables. There is also a company database and analysis platform called Logged Vehicle Data Analysis Tool (LAT) in place, where these reports can be extracted whenever an operator requires them.

In the process under study, the two main types of data that are extracted from vehicles, and subsequently analyzed, mainly concern In Use Performance Ratios (IUPR), belonging to the On-Board Diagnostics (OBD) system of vehicles, as well as the vehicles’ emission levels, especially of mono-nitrogen oxides (NOx). Volvo is obliged to report the performance of these parameters to authorities.

The United Nations has provided some definitions of the OBD system, which are stipulated in Regulation No. 49, Revision 6 (UN, 2013). These definitions are as follows: "The OBD system means a system on-board of a vehicle or engine which has the capability of:

1. Detecting malfunctions, affecting the emission performance of the engine;
2. Indicating their occurrence by means of an alert system; and
3. Identifying the likely area of the malfunction by means of information stored in computer memory and communicating that information off-board." (UN, 2013, p. 10).

"IUPR (In-Use Performance Ratio) is the ratio of the number of times that conditions have existed under which a monitor, or a group of monitors, should have detected a malfunction, to the number of driving cycles of relevance to that monitor or group of monitors." (UN, 2013, p.9).

The newest engine regulations in Europe are called Euro VI. In this version, the legal lower limit for IUPR is stipulated to be 0.1. The amount of legally acceptable NOx emissions is also postulated in regulations, and that limit is set to 0.69 g/kWh. In addition to these rules, Volvo has set some engineering targets with even higher demands on their vehicles and engines.

This is the type of data that was used in the analytics process investigated in this research, and which analytics framework that was evaluated in the case study. From this data, the objective is for Volvo GTT PE to obtain information about the performance of their trucks.

The studied analytics process had, at the time of this research, been in operation for around one year and the amount of vehicles that transfer data into the LVD system, is continuously increasing, as the first vehicles to do so were introduced to the market in the beginning of 2014.

4.3 Stakeholder identification and ranking

To recognize stakeholders and their needs are vital for the success of any project (Maylor, 2010), and therefore it is always recommended to conduct a stakeholder analysis, where stakeholders are mapped and it is evaluated how they should be managed (Tonnquist, 2008). This is just as true for analytics initiatives; Saxena and Srinivasan (2013) point to the importance of connecting stakeholders to Business Analytics, as it is vital to include the people who will be affected by decision making based on analytics. Otherwise, decisions or actions may not be possible to execute, since stakeholders may not act in alignment with decisions unless their interests are considered (Saxena and Srinivasan, 2013). Another reason for conducting stakeholder analyses in Business Analytics projects becomes evident when reviewing the framework proposed by Laursen and Thorlund (2010), which points to the importance of translating information requirements from organizational levels in the business-driven environment, down to the technically oriented environment, which is closer to the raw data. Hence, in order to know which data to create and supply, it is necessary to understand the information and knowledge needs from the interested parties: the stakeholders and the customers of the information.

A major challenge to achieve project success comes from the complexity of stakeholders' objectives and requirements, especially as they may be conflicting (Maylor, 2010). As different stakeholders have different levels of importance to a project, it is not required to manage them in the same way. Therefore they should be categorized into groups with varying importance; in this case, the categories of "internal team", "core externals", and "rest of the world", as proposed by Maylor (2010), were used. This categorization is visualized in Figure 4.1.

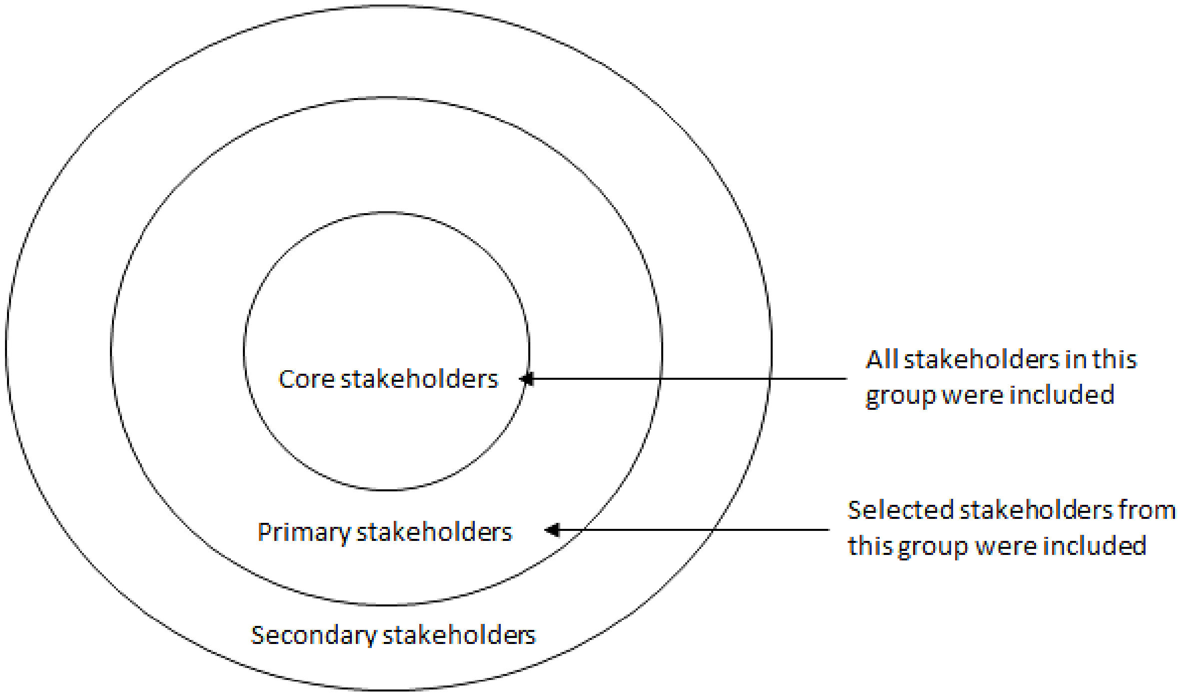

Figure 4.1 Stakeholder selection (Adapted from Maylor, 2010)

The stakeholder identification in this study commenced through identifying the stakeholders belonging to the internal team of the transforming process under study. These were determined to be those directly involved in the process; those who are directly affected if the process is changed. All stakeholders from this group, six in total, were included in the project. Subsequently, after advice and suggestions from members of the internal team, two core externals were included in the study as well. Core externals are, in this study, defined as other employees at Volvo. Stakeholders categorized as "rest of the world" are consequently stakeholders outside of Volvo. In total then, eight stakeholders were chosen to interview during this study, two of which were core externals and six of which were internal team members. In order to highlight in which organizational level the stakeholders were positioned, the Business Analytics Model (Laursen and Thorlund, 2010) is used in Table 4.1 to visualize this.

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Table 4.1 Stakeholder mapping over organizational levels

	Internal team	Core externals
Management	Stakeholder 7 & 8	
Operational decision makers	Stakeholder 4 &5	
Analyst/report developer	Stakeholder 3	Stakeholder 6
Database specialist	Stakeholder 2	
IT professional		Stakeholder 1

Subsequently, the selected stakeholders were interviewed and later categorized. Maylor (2010) proposes to categorize stakeholders based on the two dimensions "power" and "interest", where power can be exhibited through having direct or indirect authority, and the degree of interest can take the form of what knowledge a stakeholder possesses of a project. In this study, power is consequently defined as the stakeholders' authority to make changes to the transforming process, which ranges from "Low Power" where the stakeholder does not have any authority to make any changes in the process, to "High Power" where the stakeholder has the authority to instantly make changes to it. The term "interest" has, however, in this study been replaced by the term "involvement", as it was determined that the stakeholders who possess more knowledge of the analytics process are those who are most involved in it. In addition, a stakeholder could be interested in the analytics process without being directly involved in it. Therefore, for clarification purposes, the term "involvement" is used instead of "interest". In Table 4.2, these definitions of the different levels of power and interest are compiled

Table 4.2 Definition of stakeholder power and involvement levels

Level	Power	Involvement
Low	No authority to change process	Not directly involved in process
High	Authority to change process immediately	Directly involved in process

In order to visualize the different levels of importance of the stakeholders, a stakeholder mapping was done, based on each stakeholder's power and involvement levels. The internal team members were rated as being highly involved in the process and the core externals were denoted as having "Low involvement". In general, the higher the organizational level a stakeholder belonged to, the higher was also its power. In Figure 4.2 is this stakeholder mapping, which is adapted from Maylor (2010), depicted. The labels that are given to each stakeholder, which is "S" followed by a number, are included to easily identify which stakeholder that is represented by which point; stakeholder 1 is thereby, for example, denoted as “S1”.

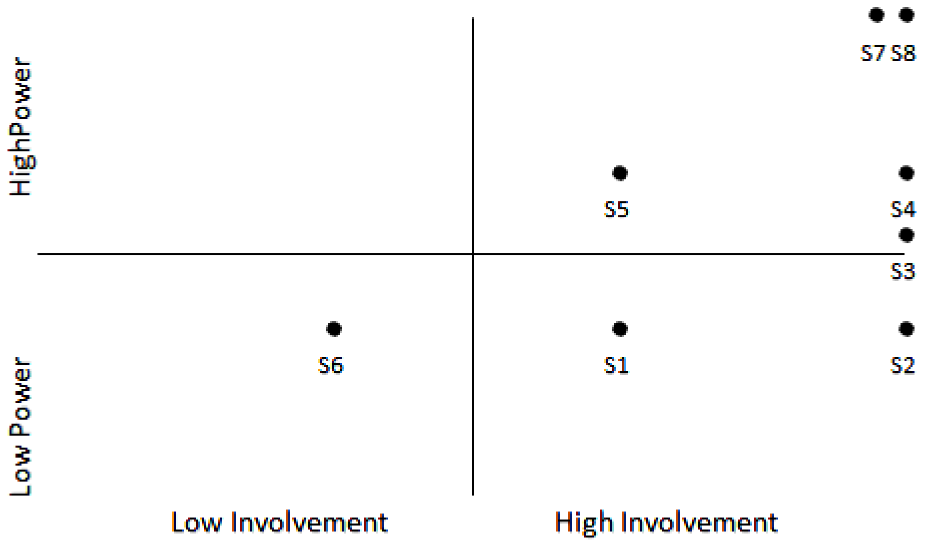

Figure 4.2 Stakeholder mapping

Following the suggestions by Maylor (2010), the stakeholders located in the four designated areas of the graph were managed in different ways: the stakeholders in the right upper corner were managed closely, stakeholder 6 in the bottom left corner had the least priority, and those in the bottom right corner were kept informed. Had there been any stakeholders in the upper left corner, they would have been attempted to keep satisfied, as Maylor (2010) proposes.

4.4 Analysis of current analytics situation at Volvo GTT PE

The Business Analytics Framework (Holsapple et al., 2014) was used as the initial conceptual framework for this case study. At the center of this framework is the *transforming process*, where data are turned into insights. Around the process, certain *practices and technologies* are used and some *specific activities* are conducted, and more contextual factors are in place, such as *the capability set*, the *decisional paradigm*, and *the movement*. Therefore, these six aspects were investigated at the case company, with the initial point of focus at the transforming process, and with a subsequent extension to the surrounding structure.

Through observations, reviewing internal documents, casual conversations, and the stakeholder interviews, the overall process was conceptualized and mapped out. It was determined to scope the investigation to start at the vehicles, when the data are created and transferred, and end when the data has been transformed into information and it can be turned into action. Thereafter, the identified stakeholders, at different stages of the transforming process, were asked about their roles, the specific activities they conduct, the practices and technologies they use, the analytical capabilities they possess, their view of the analytics culture at Volvo, and the way they make decisions, all in line with the Business Analytics Framework (Holsapple et al., 2014). In addition, their opinions about the current situation and their needs and wants were collected, in order to identify improvement opportunities.

4.4.1 The transforming process

From the mentioned investigations, the resulting, overall transforming process was mapped out. After going through all the steps in the transforming process, it was mapped into the Business Analytics Model (Laursen and Thorlund, 2010) to enable a greater understanding of where in the organization the different process steps take place. Therefore, the parts of the model that were used, were the five different organizational levels of “data creation”, “data warehousing”, “data information”, “using information”, and “choosing strategy”. The transforming process, merged into this model, is presented in Figure 4.4. The process map visualizes the process steps from the log parameter in the engine control unit of the vehicle, to when the data has been turned to usable information and can be acted upon. Firstly, however, the different shapes that are used in Figure 4.4 are explained via the legend below in Figure 4.3.

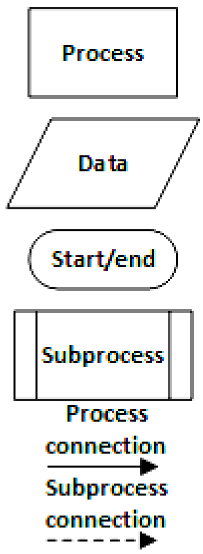

Figure 4.3 Legend of shapes in process map

The rectangle represents a process step where somebody conducts an activity; the parallelogram signifies a step where data are being moved from one place to another; the rounded rectangle shows the start and finish points of the process; and the last type of rectangle indicates when the process step is part of a sub process, and consequently is not directly involved in the LVD transforming process. The two different arrows indicates two various connection types, one for connections in the transforming process, and one for connections of sub processes. In Figure 4.4, then, the transforming process is mapped out.

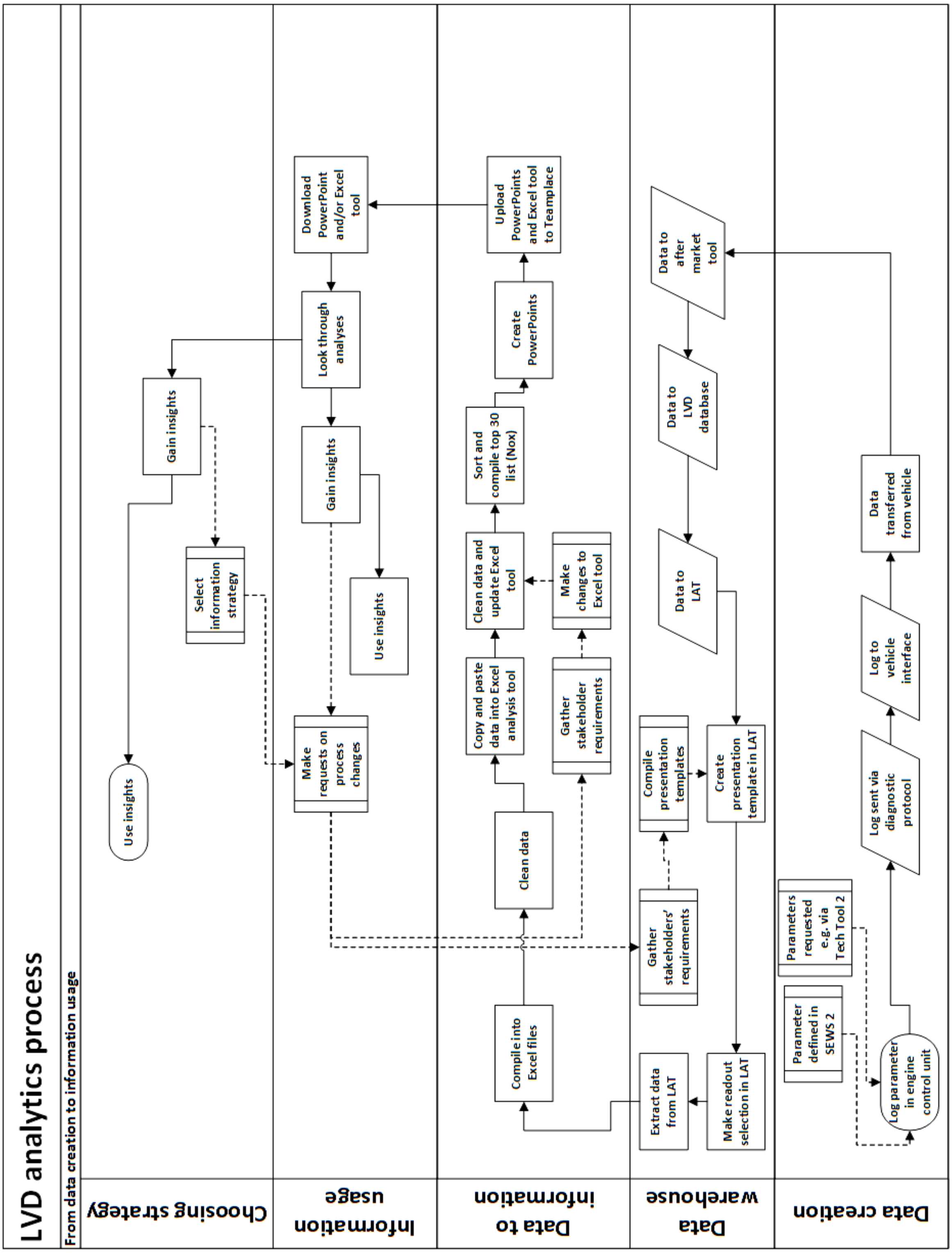

Figure 4.4 The transforming process of LVD at Volvo

The process begins at the engine control unit in the vehicle, where log parameters are data carriers. In an internal support tool, called Sews 2, the parameters are defined. In an internal aftermarket platform, for example one called Tech Tool 2, parameters from the engine control unit can be requested. These are subsequently sent via a diagnostic protocol to an interface in the vehicle. Then data are transferred, either via wire, wireless, or diagnostics, from the vehicle to an aftermarket tool. Tech Tool 2, which is connected to a central system, downloads the content. Subsequently the data are transported to an LVD database, and eventually the data arrive at the LVD Analysis Tool (LAT) database. Here the data are re-packaged to an xml format and given a data carrying identity, which is defined in Sews 2.

In order for analysts to obtain the data in a more manageable format, a database specialist gather requirements from stakeholders on data parameters and compile these into specifications for presentation templates; for the analytics process under study, which main goals are to provide information about emission and IUPR performance levels of engines, two presentation templates have been developed. Then, the data can be extracted from the LAT in these presentation templates, which for example can be an MS Excel file. The presentation templates need to be created, as too many parameters exist, and consequently it must be specified which that are of interest for each stakeholder; a stakeholder can for instance order a report with NOx emission levels, the distance driven by the vehicle, and the running hours of its engine.

In LAT, analysts go in and make their own selections of which readout data to attain; this could for example be which engine type and which time period of readout to include in the data set. The selected data can then be downloaded and extracted from LAT. Before these data are analyzed, however, they need to be manually cleaned. Subsequently, in the specific analytics process under investigation, two Excel files have been developed to function as analysis tools in order to transform the data into information; one tool is for analyzing emission data and one for IUPR data. These Excel analysis tools are based on Pivot tables, where the extracted LAT data can be copied into a table in one of its spreadsheets, and then graphs and tables can be updated in a fairly automatic way.

The most important graphs, and consequently the most important information, are later taken from the Excel analysis tool and compiled into two MS PowerPoint presentations on a monthly basis. These presentations, together with the Excel analysis tools, are then placed in an internal communication platform called Teamplace. Here, stakeholders and customers of the information can retrieve it, make some analyses themselves, and use it as decision support in their work. Currently, the information is mainly used to direct project groups and improvement initiatives, as well as to monitor and control engine performances. The users are, however, hoping to use information obtained from LVD more in the future, as some changes in the presentation templates from LAT have been made, and as the data set increases; the users would then get better use of the data in their quality work, and the analysis could be used for certification purposes to authorities.

4.4.1.1 Problems with the transforming process

During the interviews that were conducted, issues about the transforming process in general were raised; these are depicted in Figure 4.5.

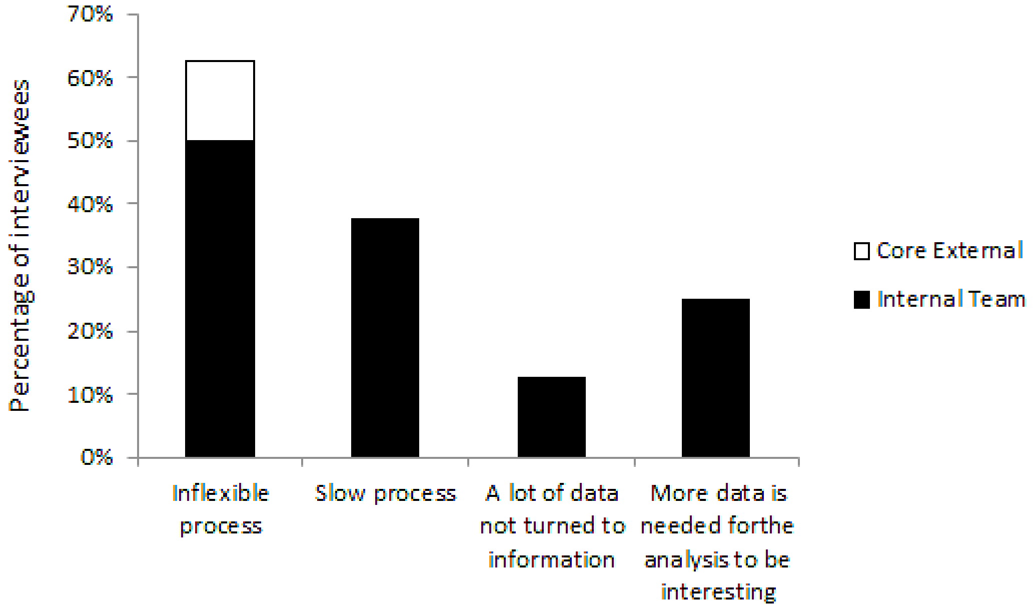

Figure 4.5 Issues raised about transforming process[1]

The issue raised by most interviewees was that the process is inflexible; it was for instance mentioned that:

"*when you want to add a new parameter from LAT, it does not exist. Then you need to order it from the responsible person from LAT, which takes a lot of time*".

"*something that is missing is the ability to easily change parameters in LAT*".

The process was also deemed to be slow, and one of the reasons was that it can take a couple of hours to extract data from LAT, which was explicitly stated by one internal team member:

"*extracting data from LAT is slow and takes a lot of time*".

It was mentioned by two internal team members that in order for the analytics process and its findings to become more interesting, more data would be desired. These interviewees said that:

"*a drawback is that we don't have too much history in the data yet. What we would like to do is investigate outliers more carefully. In the ideal world we would find these outliers and have more information about them*".

"*the analysis will be more interesting in a couple of years when it has more data*".

[1] The chart is a stacked bar chart. Hence, the total percentage value of a bar is the total numbers of interviewees who mentioned the issue it represents. This total percentage is then separated into how many of the interviewees, who mentioned the issue, that belong to the internal team and the core externals respectively. In Figure 4.5, "Inflexible process" has a total percentage value of 62.5%. This means that 5 out of 8 interviewees (5/8=62.5%) mentioned "inflexible process" as an issue. These 62.5% are then split into internal team members (50%) and core externals (12.5%). This means that 4 interviewees who were internal team members mentioned "inflexible process" (4/8=50%) and 1 core external did (1/8=12.5%). This stacked column chart will be used frequently throughout this report.

In addition, as evidence of the flaws in the process of transforming data to information, one interviewee expressed:

"*a lot of data are captured and saved in the company, but the data are not sufficiently well transformed into information*".

4.4.2 Specific activities and Practices and Technologies

Surrounding this transforming process are, in accordance with the Business Analytics Framework (Holsapple et al., 2014), some specific activities conducted and some practices and technologies executed and used. The ones deemed most important for this case, are depicted in Table 4.3. In this table, the steps from the Business Analytics Model (Laursen and Thorlund, 2010) are displayed, together with the activities that the stakeholder in that process step conducts, as well as the practices and technologies that he/she uses.

Table 4.3 Specific activities & Practices and Technologies in LVD transforming process

	Specific activities	Practices and Technologies
Choosing strategy	• Make strategic decisions • Allocate resources	
Using information	• Analyze data • Use the Tool & PowerPoint to discover internal improvements areas • Report to authorities • Monitor and control	• MS Excel (analysis tool) • MS PowerPoint • Teamplace • LAT
Data to information	• Make data selection in data warehouse • Extract data • Clean data • Put data in analysis tool • Create summary presentation of information • Upload information on communication platform	• MS Excel (analysis tool) • MS PowerPoint • Teamplace • LAT
Data warehouse	• Gather stakeholders´ requirements • Compile presentation templates • Order non-existing data from SEWS 2	• LAT • Tech-tool • SEWS 2 • Presentation templates (E.g. MS Excel)
Data creation	• Develop Logs • Test Logs • Calibrate Logs • Data created as truck is in operation • Data sent from truck • Data sent to LAT	• Programming software • Test and calibration tools • Engine control unit • Communication technologies (wire, wireless, telematics)

4.4.2.1 Problems with the specific activities and practices and technologies

Two concerns about the specific activities conducted in the process, which were surfaced by the interviewed stakeholders, are depicted in Figure 4.6. The principal issue, which was stated by three internal team members, was the amount of manual work - mainly included in obtaining data from LAT, creating PowerPoints, and distributing information - which have to be performed in order to transform data into valuable and accessible information. One of several related statements was the desire of a stakeholder to:

"*improve the tool… so that I do not need to do as much work as now*".

Another issue was that in order to transform the data into information, specific knowledge is required, which few persons possess. It was stated by one member of the internal team that:

"*users of data do not seem to have time to learn analysis tools, therefore a producer of information may be necessary in the future as well*".

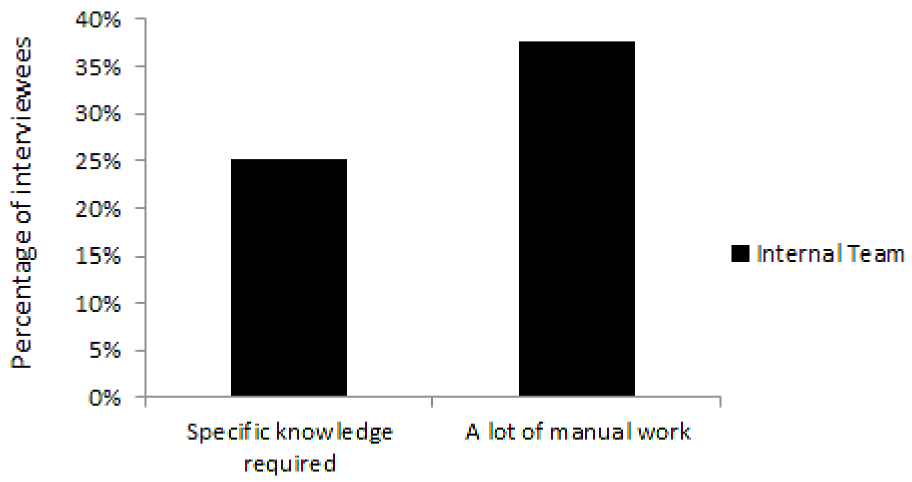

Figure 4.6 Issues raised about specific activities

The interviews also revealed issues concerning the current practices and technologies used in the LVD process, which are depicted in Figure 4.7.

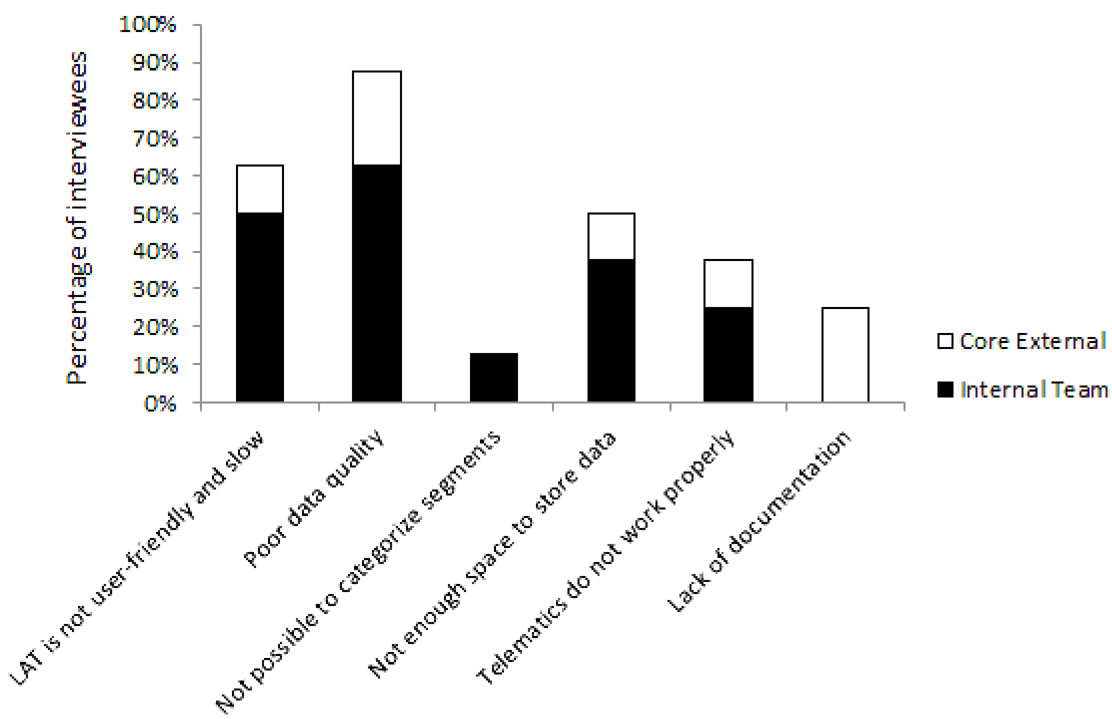

Figure 4.7 Issues raised about practices and technologies

The main point stated by the stakeholders was the lack of data quality assurance. However, the poor data quality meant different things for different interviewees, depending on where in the Business Analytics process they were positioned. The stakeholder mainly involved in the process step “data creation”, expressed:

“*that the data lacks quality is naturally very problematic ... it is a shame that we cannot control the data quality, because it feels as if more and more is built on information*”.

The analyst at the “data to information” stage mainly complained about the flawed and misplaced data that were extracted from LAT with comments such as:

"*when data are extracted, the data are lacking quality, the data are not clean and need to be filtered and some need to be deleted. Data in LAT may also not be reliable; when making selections in LAT… it has happened that data for another engine type have shown up. I would like to rely on statistics and data, but they need to be reliable. If I get a faulty statistic, I would not rely on it the next time*”.

In addition, four internal team members and one core external mentioned that the LAT tool is not very user-friendly and slow. Three quotes concerning this tool are provided below:

"*I have tried to export data from LAT, but I have not managed since it is not user friendly*".

"*LAT in itself is very problematic, as it is difficult to manage... LAT is so slow, that I have to limit the selection to around 100 vehicles in order for it to work*”.

"*LAT, the database, is not enough to handle this era of Big Data*”.

It was also expressed by fifty percent of the interviewees, that the way data are presently stored will not be sufficient in the future. One internal team member stated that:

“*the difficult part is to handle all the data; if we want to handle multiple readouts with the history of a vehicle, where are we supposed to save all the data? We have the tool to analyze the data, but where should we store it and how should we get or extract it?*”.

It was also stated by another internal team member that it is advisable to:

"*change from Excel as it is not sustainable, and as the amount of data is increasing*".

Lack of documentation was also a point that was expressed by two of the interviewees as an issue. A core external commented that:

“*nowadays people are switching between jobs more often, and then you lose the experience they had. What you did, the next person does not know about. Hence, documentation becomes much more important*”.

An internal team member, an information user, also expressed concerns that it was not possible to use analyses made in the Excel analysis tools for reporting to authorities, as different vehicle segments could not yet be categorized:

“*for the reporting, I have not used it since I have to categorize the segments, which we may be able to do in the future*.”

4.4.3 Decisional paradigm, movement, and capability set

According to the Business Analytics Framework (Holsapple et al., 2014), a decisional paradigm, which involves decision making based on logical analysis and evidence, and a movement, which involves a philosophy and culture that supports and aims optimize the analytical capability, as well as a capability set, which includes the competencies of the company and its workers, should be in place in an organization striving to make the best use of Business Analytics. Thinking about these three factors as more contextual, and as being the foundation of the transforming process, was by the authors deemed to simplify the conceptualization of the practical study.

4.4.3.1 Problems with the decisional paradigm, movement, and capability set

When interviewees were asked about the decisional paradigm at Volvo, as well as their personal approach to making decisions, the answers were somewhat unison; all stakeholders stated that they in some way use a mix of experience and data in their work. How and when they use their experience and/or intuition was however expressed in different ways, which is depicted in Figure 4.8.

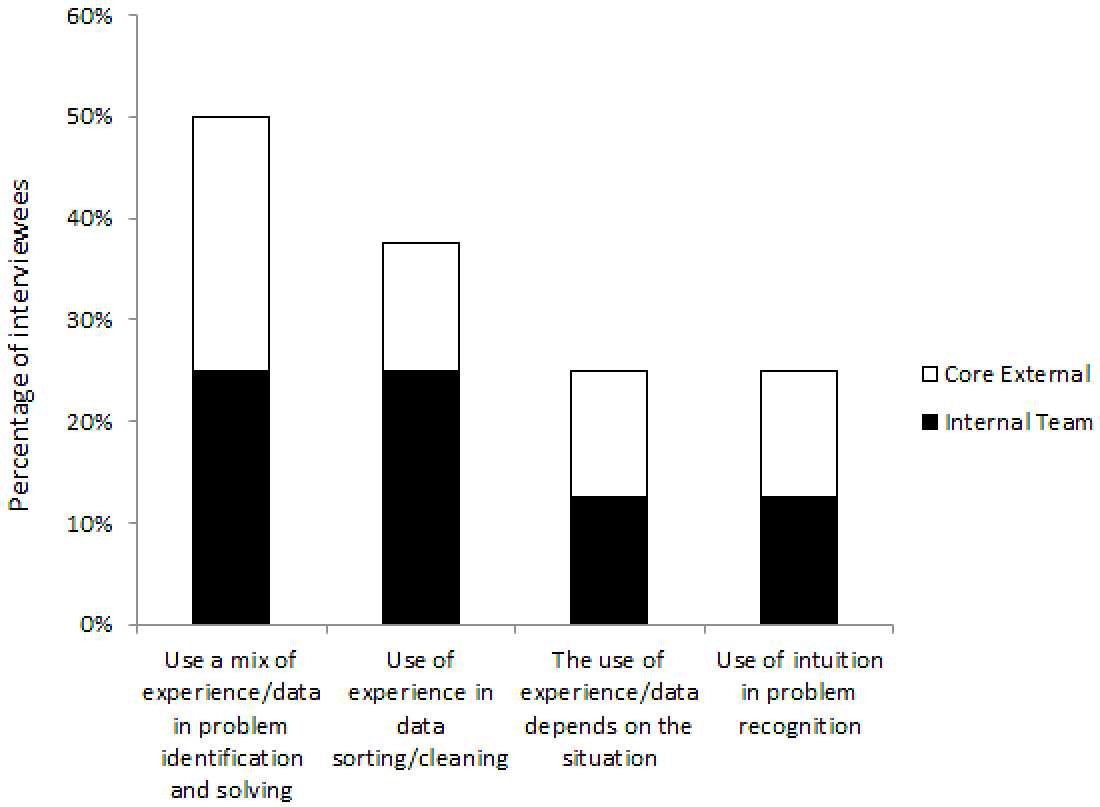

Figure 4.8 Decisional paradigm at Volvo

Two of the interviewees stated that experience and data have various importances depending on the situation; for example, experience and/or intuition could at times provide guidance to problem identification, and data could thereafter confirm that the problem exists. This was for instance expressed by one core external, who said that whether he/she uses data or experience in decision making:

"*depends on what type of decision I should make... but when you sort in the data you can use experience, to determine what is important and what is not... but the data is the foundation. You need to use both data and experience*."

That experience can be used to clean and sort data was also apparent from these statements:

"I have to use experience to understand when data are faulty, so that it can be cleaned".

"*When you sort in the data you can use experience, to determine what is important and what is not*."

Moreover, it was surfaced during some interviews that in order to arrive at a decision, a mix of data and experience was often used. Comments regarding this were for example:

"*I think that you should always know what you are talking about, which usually requires a mix of data and experience...usually my managers want my view on things, and it is not always based on data, but perhaps more on experience*".

"*I use a mix between experience and data when I make decisions".*

As for the capability set, all interviewed stakeholders stated that they have experience and knowledge in statistics and that they are used to reviewing analyses of data, even though not everyone is performing analyses themselves; statistical analysis is not a part of everyone's work tasks and everyone does not have sufficient time to perform analyses themselves. Especially in the upper organizational levels, managers do not have time to analyze data; they want the most important points and results from analyses presented to them quickly.

However, some issues around the capability set at Volvo, which were raised during interviews, are presented in Figure 4.9.

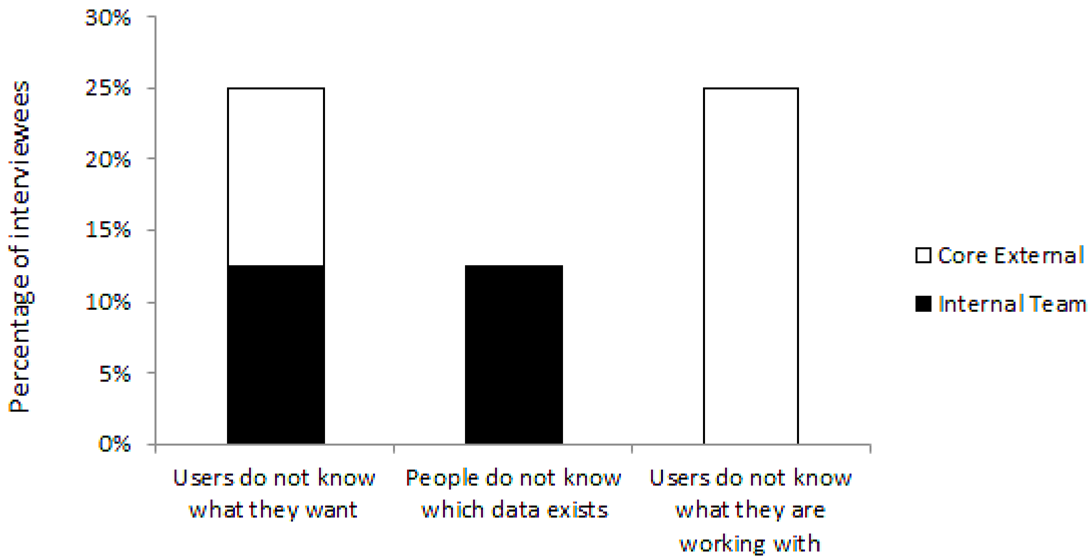

Figure 4.9 Issues raised about capability set

One aspect that was mentioned was the apparent lack of cross-functional knowledge transfer. The following were statements around this problem:

”*many people are involved, and not everyone knows what the data are for... people are just glad to find data that they can analyze*”.

”The message is that you need to know what you are dealing with - what the data represents. The source function is important; you need to know what the data show”.

Some concerns were also surfaced that users do not know what they want from LVD, or what data that actually exist in the organization. One internal team member said that:

“*many people are not aware of the data that exist... the users don't always know what information they need or want… I can show them a graph and then they realize that they wanted it*”.

As for the movement at Volvo, points that were brought up by stakeholders concerning this aspect are depicted in Figure 4.10.

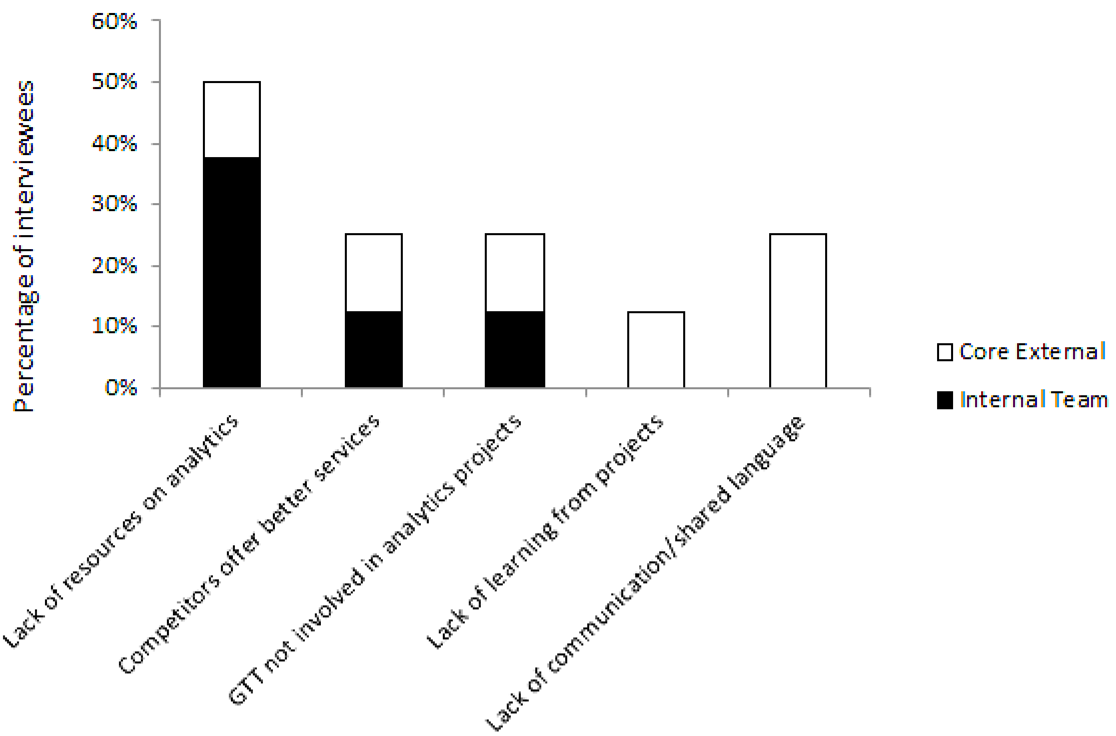

Figure 4.10 Issues raised about the movement at Volvo

Fifty percent of the stakeholders stated that more resources need to be spent on analytics initiatives at Volvo, as the current procedure suffers from lack of data quality, from slow lead times, and from outdated technologies for databases and analysis. For example, it was expressed that:

“*we have long lead-times due to limited budget and resources*”.

"*There is not enough focus on this… either we need to allocate more resources to it, or stop working with it… We know exactly what to do to solve this, but we do not have the resources – even though there are not a lot of resources that are required*".

Somewhat disturbingly, concerns were also raised by two interviewees that some main competitors to Volvo have put more focus and resources on using analytics:

"*I have heard that Volvo is lagging behind the competition … I don't know the reason behind this, but I believe that they are putting more money into this sort of projects*".

"*Volvo is lagging behind their competitors when it comes to offering data based services*".

Also, some statements from interviewees indicated a lack of learning from previous projects, inadequate communication within the organization, and that Volvo GTT does not participate in other analytics projects in other parts of the company. For example, it was stated that:

"*we are speaking different languages, and about different things. This is why definitions are vital - especially in cross-functional projects*".

"*GTT is not sufficiently on board with the analytics process in general and the GKO project in particular*".

"*We do not learn from finished projects and because of this we cannot bring the information and knowledge to new projects*".

4.5 Generating support for improving the analytics framework at Volvo

The collected data from the conducted research methods enabled an analysis of the nature of the current analytics situation at Volvo, while simultaneously highlighting some general problems concerning all the six perspectives of the Business Analytics Framework (Holsapple et al., 2014). The next step in this study, was to identify improvement opportunities to the analytics structure at Volvo GTT PE.

4.5.1 Problems and suggested improvements at different organizational levels

First, it was determined to highlight the main problems and suggested improvements that stakeholders raised at different organizational levels. This was done in order to clarify where in the analytics process the problems exist. Therefore, in Table 4.4, various problems and suggested improvements are presented, according to the different process phases that have been adapted from the Business Analytics Model (Laursen and Thorlund, 2010).

Table 4.4 Some suggested problems and improvements at different organizational levels

	Specific problem raised	Suggested improvements
Choosing strategy	• Have not been able to set correct system parameters for LVD	• Create action-oriented results, for instance the ability to track individual vehicles • Set up a central analytics department at Volvo GTT
Using information	• LAT: stops working constantly, does not have enough capacity • Quality of logs not followed up	• Take in vehicle samples from "real life" to check quality of sensors
Data to information	• LAT: slow, unreliable, not user friendly, parameters may not exist and takes time to order • Users do not know what they want, or which data that exist • Data requires a lot of cleaning • Excel may not be enough for handling Big Data	• Take a look into software alternatives for analysis tools, such as Qlikview
Data warehouse	• Long process lead times during updates of stakeholders´ requirements • Lack of quality assurance • GTT not on board with analytics projects at Volvo (e.g. the GKO project)	• Dedicate more resources to analytics • An OLAP cube solution, where stakeholders´ make their own adjustments
Data creation	• Lack of structure and order • Lack of common definitions • Quality of log parameters decreasing with time, and this is not tested • Product developers do not see the potential in information • Difficult to find root causes to problems	• Documentation about what is being done and where information comes from • Test and verify each software update (simulations, test rig or driving outdoors)

In the first level, "data creation", issues were raised concerning the IT infrastructure, as the structure and order of different modes and states of the data transfer from the vehicle to the data warehousing systems need improvement, in order to simplify the information therein and to make it easier to identify root causes to problems. Documentation also needs to be improved at this level, in order to enable people who are new to the organization to understand what has been done and what needs to be done in the future. At this stage, it was also sought after to perform more tests on software after updates, and of the log parameters after they have been used in real-life settings, as their quality may decrease during their product lifetime without anyone knowing by how much. These tests could be done through simulations in computers, through test rigs in laboratories, or through driving outdoors. The last alternative is the most expensive, but the more accurate one. Concerns were also brought up here, that product developers do not see the value of information, and consequently what can be done through integrating software to their hardware.

In the second level, “data warehouse”, the main problems seem to be the lack of resources. Updates of stakeholders’ requirements, on for instance parameters to analyze from LVD, can take months, which is a problem since flexibility and speed is requested from LVD users at higher levels. It was brought up, that the workers here know what needs to be done, but the resources do not exist to implement it. An example of this, was to create an OLAP cube solution in LAT, which would enable LVD users to make their own adjustments of for example parameters. Another thing that was brought up here, was that there are other analytics projects going on in other parts of the Volvo organization, and Volvo GTT is not sufficiently on board on these.

In the third level, “data to information”, the main issues were the data warehouse system, LAT, which is slow, unreliable, and not user friendly. There is a lot of manual work at this level, which could take hours and which could have to be done at multiple occasions as LAT does not work as it should, and shuts down at times. The data that is extracted is often flawed in a number of ways, and therefore it requires extensive cleaning before it can be used for statistical analysis. In addition, the analysis tools that are used, which currently are built up in MS Excel, are getting slower due to the increasing amount of data and therefore a sustainable solution for data storage and data handling must be developed.

At the two upper organizational levels, it was highlighted that LVD currently cannot be used for certification purposes. The hope is, however, that it will be possible in the future. Otherwise, a lot of the same issues that have already been mentioned were brought up, such as the need to follow up on the quality of sensors, the problems with LAT, and how to find a sustainable data storage solution.

4.5.2 Stakeholder needs determination and prioritization

In order to develop an analytics framework at Volvo GTT PE that corresponds to the needs and wants of its stakeholders, the collected data was also used to identify these needs and wants through translating the data into the “voice of the customer” (VoC), which Griffin and Hauser (1993) describe as a key criterion to collect and prioritize in quality management, as it is vital to satisfy customers. In this study, the terms “customers” and “stakeholders” are used interchangeably, as the stakeholders that are included in the study are the customers of it as well. Mitchell et al. (1997) also explain that customers are one form of stakeholders. In order to properly summarize and analyze the qualitative interview answers, they were codified and grouped. In Table 4.5, some examples of “voices of customers” are provided, as quotes from the conducted interviews, and subsequently how they were codified and summarized into groups which consequently were treated as the stakeholders’ requirements on the analytics framework at Volvo GTT PE.

Table 4.5 Translation procedure from VoC to framework requirements

Examples of voices of customers	Stakeholder requirements
“When you want to add a new parameter… it does not exist. Then you need to order it… which takes a lot of time”	Flexible selection making
"Long lead times… updates of stakeholders' requirements can take months"; "The process must be flexible and fast"	Fast analytic process
“If there are some vehicles with extreme values, it would be nice to be able to follow them more frequently to see what happens”	Ability to follow up on individual vehicles
"If I look at some average values, I want to know the confidence level of those numbers"	Analysis of variation and uncertainty
“I always highlight the importance of turning information into action”	Action-oriented results
"I would like a perfect… tool, where people could easily make analyses themselves"	Easy
“Improve the tool… so that I don´t need to do as much work as now”	Automatic
"LAT is not user-friendly"	User friendly interfaces
“The data are lacking quality”; “That the data lack quality is naturally very problematic”	High quality of data
"If we have 10-30 readouts per vehicle in a couple of years… where are we supposed to store the data?"	Sustainable data storage
“if they get fault codes, we could follow the vehicle with telematics to see how it is, and was, performing before and afterwards”	Ability to access real time data
"LAT stops working constantly - this is the biggest limitation for us"; "Excel is not appropriate for analyzing great amounts of data"	A new data warehouse/analysis tool
“There is no documentation, and therefore no structure”	Thorough documentation

"Users do not always know what they want or which data that exists"; "Product developers do not see the value in information"	Cross-functional knowledge transfer
“I use a mix between experience and data when I make decisions”; “intuition guides me… but when I make a decision I would like to have facts”	Decisions can be based in both data and experience
"Long lead times due to limited budget and resources"; "not enough resources are spent on achieving quality"	More resources to analytics
“We are missing that we can use the information to sell cars through providing services”	Offer better services based in information
"We talk about the same things but use different words"	Communication/Shared language
“GTT is not sufficient on board with the analytics process in general and the GKO project in particular”	GTT should be more involved in Volvo analytics projects.

After these stakeholder requirements on the analytics framework had been generated, they were compiled and analyzed. Due to the importance of sorting and clustering customer needs (Griffin and Hauser, 1993), the collected stakeholder requirements could be categorized into the six perspectives of the Business Analytics Framework (Holsapple et al., 2014). The resulting categorization, as well as the basis for categorizing requirements into each respective group, is presented in Table 4.6.

Table 4.6 Categorization of stakeholder requirements

Stakeholder requirement	Category	Basis for categorization
Flexible selection making Fast analytics process Ability to follow up on individual vehicles Analysis of variation and uncertainty Action-oriented results	Transforming process	Requirements that concern needs for insight from data, and how these insights are wished to be gained
Easy Automatic	Specific activities	Requirements that concern the nature of process activities
User friendly interfaces High quality of data Sustainable data storage Ability to access real time data A new data warehouse/analysis tool Thorough documentation	Practices and Technologies	Requirements that concern practices and technologies that are used in the process
Cross-functional knowledge transfer	Capability set	Requirements that concern organizational capabilities to work with analytics
Decisions can be based on both data and experience	Decisional paradigm	Requirements that concern how decisions are made in the organization
More resources to analytics Offer better services based on information GTT should be more involved in Volvo analytics projects	Movement	Requirements that concern the organization´s culture and efforts to develop an analytics capability

As has been mentioned earlier in this paper, it was determined during the study to categorize the six Business Analytics perspectives into those perspectives that are closer to the analytics process, which were deemed to be the transforming process, specific activities, and practices and technologies, and those that were determined to be more contextual, which were deemed to be the capability set, decisional paradigm, and movement. This categorization is visualized in Figure 4.11.

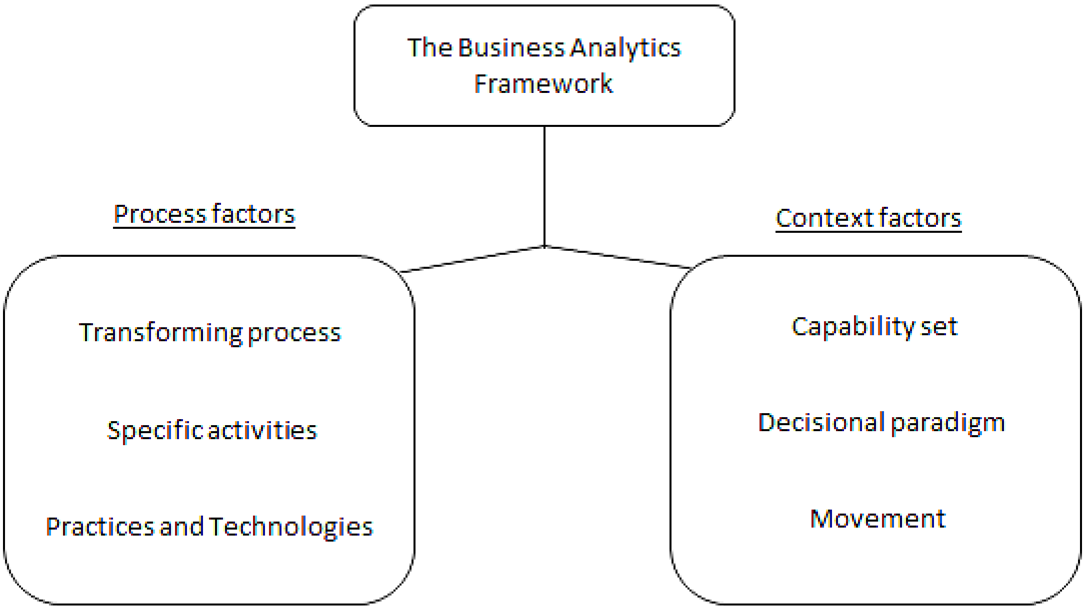

Figure 4.11 Categorization of Business Analytics perspectives

In order to make the stakeholders' requirements on the analytics framework at Volvo GTT PE more actionable, it was concluded that the requirements concerning the context factors would be neglected, as they would require too extensive resources for this study to change. Therefore, the stakeholder requirements that concerned the process factors were prioritized to improve in this study. Consequently, these requirements and their frequency of mention are depicted in Figure 4.12.

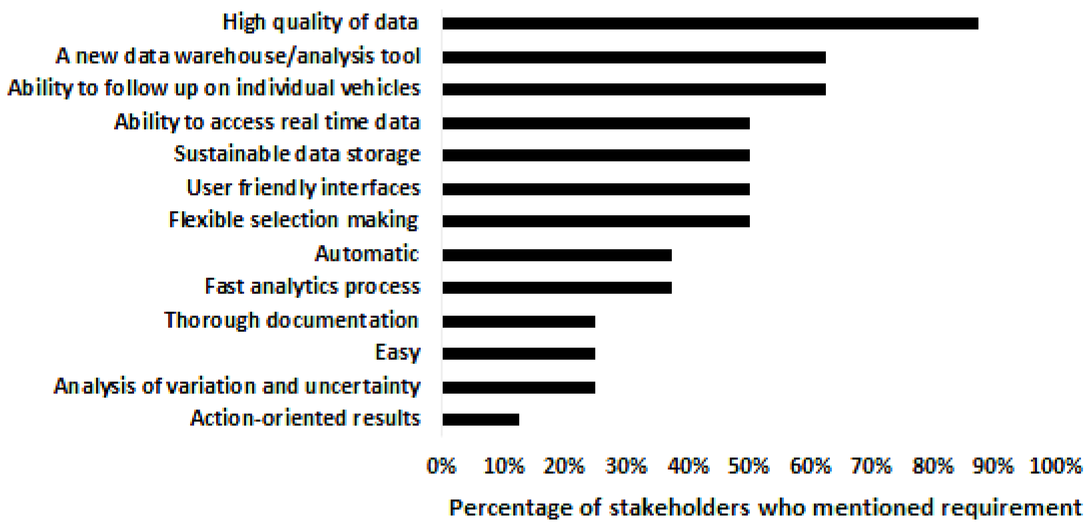

Figure 4.12 Stakeholder requirements on process factors

4.5.3 Translation of needs into improvement possibilities

The fact that Business Analytics must end up in actions is widely agreed upon amongst scholars. Stubbs (2011) asserts that insights do not create value, actions do; Kiron et al. (2001) point to the capability of putting insights into actions as a key differentiator between organizations with high and low analytical capabilities; Davenport et al. (2001) believe that if nothing changes in the organization, the context and transformation are of little value; Saxena and Srinivasan (2013) declare that the objective is that people in the organization should use the analytics, and therefore it must be actionable. Saxena and Srinivasan (2013) continue by mentioning that analytics can be actionable through suggesting actions to be taken, or to rank possible options. Hence, the importance of taking actions based on the findings from translating stakeholders' needs to process characteristics is evident.

In order to implement any improvements, the scope of this study had to be further narrowed, This was due to that the boundaries of this study to make any changes to the LVD analytics framework were limited; they were concentrated on the step "data to information". Moreover, changes could merely be implemented in a few of the practices and technologies used in this step; making changes in databases such as LAT was not feasible, but altering the MS Excel analysis tools and MS PowerPoints was.

Consequently, as is depicted in Figure 4.13, the translation of stakeholders' requirements to framework requirements will mainly be focused on how the step "data to information" can be improved, especially with respect to the MS Excel analysis tool and the MS PowerPoint reports.

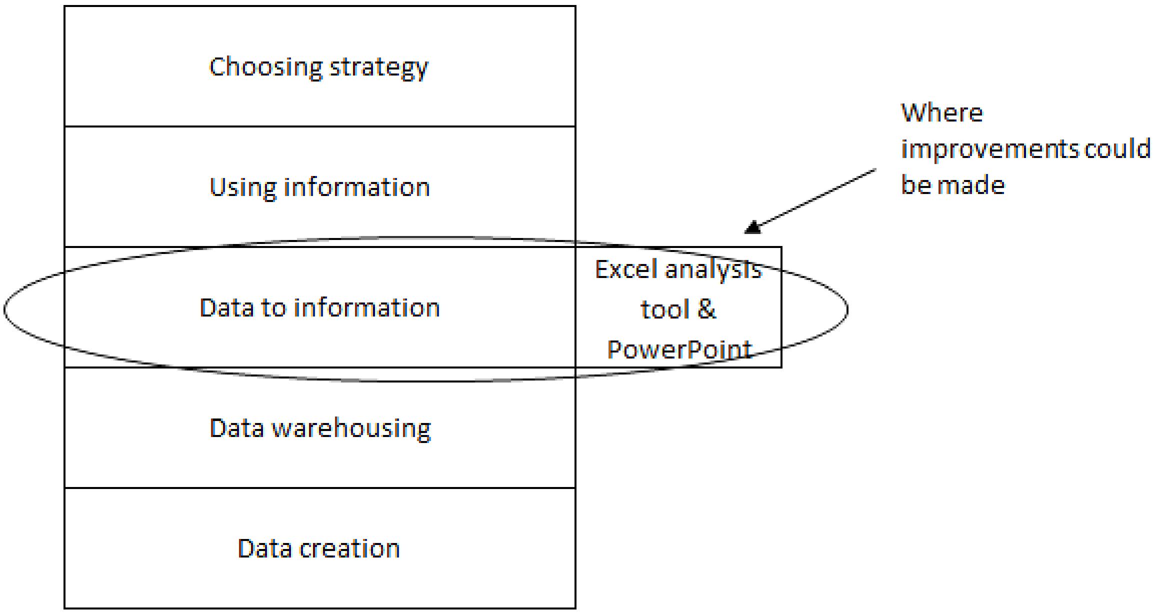

Figure 4.13 Boundaries of study to make changes

4.5.3.1 Evaluation of platform alternatives for analysis tools

The first attempt at trying to improve the analytics framework at Volvo GTT PE was to evaluate platform alternatives for analysis tools, as the analyst who is doing most of the work with the Excel analysis tool, asked for an investigation of platform alternatives to this software. The reasons for this were essentially that:

"*Excel is not good at handling a lot of data, for example since there is a limited number of available rows, and it becomes too slow when the data set is too big".*

The analyst also requested to:

"*improve the tool or use Qlikview so that I do not need to do as much work as now".*

Qlikview is a data discovery platform, developed by the company Qlik, which was founded in Lund, Sweden in 1993. Today, Qlik is headquartered USA and provides solutions for self-service visualization and guided analytics. The benefits with Qlikview are that it is built on associative data indexing which enables a deeper exploration of data and relationships, and that multiple data sources can be inserted and analyzed (Qlik, 2015).

Another alternative to analysis platforms is provided by Microsoft, which from MS Excel 2010 and onwards provides an extension to Excel called Microsoft Power Pivot. This add-in to Excel has the capability of in-memory processing, as Qlikview has, and may therefore handle greater amounts of data, and process these amounts faster, than the usual Excel platform. In Power Pivot it is also, as in Qlikview, possible to import and analyze data from a multiple of sources (Microsoft, 2015).

These were the three analytics platforms that were determined to be compared and analyzed, in order to identify the best analysis tool option for Volvo GTT PE. Therefore, the authors of this study developed prototypes, similar to the existing Excel analysis tool, based on these platforms. The main comparable benefits of these platforms - to be able to handle greater amounts of data and the capability to insert data from multiple sources - were immediately evident. This would be advantageous directly for Volvo, as the analysis tools for IUPR and emissions' follow up could be merged into one tool, which is desired by some stakeholders as these two different data sets include different parameters that are of interest to connect and analyze together. To be able to handle greater amounts of data would also, for natural reasons, be very desirable.

Implementing any of these options would, however, not decrease the manual work and it would not directly make the analyst's work tasks easier, as the data coming in from LAT would still be in need for cleaning and as data needs to be inserted manually in these platforms as well. A benefit of Qlikview in comparison to the Excel platforms is nonetheless that Qlikview provides the possibility of drill-down analyses, where a user for example may click on a bar in a chart, and thereafter Qlikview lets the user see only data and information related to that bar (as unrelated data are thereby automatically filtered away). However, another issue is that there are not a lot of workers at Volvo which currently have Qlikview installed on their computer, and it makes Qlikview a fairly inflexible solution at the moment.

As Power Pivot is built on the usual Excel interface and software, it would however not be affected by this drawback to the same extent. Saxena and Srinivasan (2013) also state that as Microsoft Excel is the most popular and widely used platform for Business Intelligence, it is beneficial to base a platform on this interface, as it generates a higher degree of acceptance among users. Another point, as discovered by the authors, is that Qlikview at present does not include the possibility to create PowerPoints. As interviews with stakeholders at Volvo revealed, the PowerPoints with LVD findings are currently reviewed more often than the Excel analysis tool, which is why it was deemed to be unsuitable to move over to a Qlikview platform at present, at least until a new way of spreading the information generated from the analysis of LVD has been discovered.

In the future, it would nonetheless be of interest for Volvo to investigate how an analysis platform can be developed, preferably on an external server, and spread through the organization via Microsoft SharePoint applications or other communication portals, so that the analysis tool can be accessed directly and does not have to be downloaded to the computer of each user. To place the analysis tool on an external server is most likely necessary for the future, as the great amount of data must be stored somewhere, and storing them on personal computers is not a sustainable solution.

It would also be beneficial to integrate this developed platform with LAT, so that the steps of extracting data from LAT, clean it, and insert it into an analysis tool, could be abandoned. Whether a platform of this kind should be based on Qlikview or Power Pivot would need some further investigation; the benefits of using MS Excel interfaces have however been mentioned here. In addition, as Microsoft develops plenty of other software and solutions, such as SharePoint, and can provide maps and additional features which could be useful and added to a future analysis platform, it might be of interest to base the platform on Microsoft software.

Based on the preceding discussion, the authors of this study performed a rough selection analysis of these different platforms alternatives through a Pugh matrix, which is a useful technique for comparing and evaluating different ideas and design concepts (Silverstein et al., 2012). In this matrix, which is provided in Table 4.7, the baseline is the MS Excel tool that is currently used, while PowerPivot and Qlikview are compared to this baseline on the basis of whether they offer a better, worse, or indifferent solution to the criterion being compared. These ratings were subjectively determined by the authors, based on their experiences from developing the different platform prototypes.

Table 4.7 Pugh Matrix of analysis platform alternatives

	MS Excel (baseline for comparison	**MS Excel PowerPivot**	**Qlikview**
Data handling capacity	-	+1	+1
May use multiple sources of data	-	+1	+1
Amount of manual work	-	0	0
Drill-down analyses	-	0	+1
Flexibility	-	0	-1
Recognizable interface	-	0	-1
Possibility to create PowerPoints	-	0	-1
Sum:	**-**	**+2**	**0**

This matrix is merely provided to get an overview of the different options; to reach the "objectively best" platform solution, the different criteria should be more carefully weighted and deeper investigations of stakeholders' requirements should be performed. For the purpose of implementing improvements during this study, however, it was determined to focus on improving the Excel analysis tool that is currently being used, as developing other platform solutions would require some deeper investigations, more resources to develop a well-functioning alternative solution, as well as some relatively big changes to the current process. Thereby, it was determined to aim to optimize the current platform solution during this study, and to propose to Volvo to further examine how the analysis platform should take shape in the future; at this time and with the current conditions, this study does however suggest basing an analysis tool on Power Pivot in the future.

4.5.3.2 Generation of improvement possibilities

In order to carry out any improvements, some prioritization was required as the resources of the study were limited. Hence, following the recommendations by Saxena and Srinivasan (2013), the stakeholder requirements were ranked in order to focus the improvement efforts. The ranking was based on their estimated resource needs, which were subjectively assessed by the authors. The stakeholder requirements were assessed to either have a low or high demand for resources, if they were to be implemented. The basis for categorizing needs as having "low resource needs" was that it was possible to meet them, in some manner, during this study. The basis for categorizing needs as having "high resource needs" was consequently that it was not possible to meet them during this study. The results of this categorization are displayed in Figure 4.14.

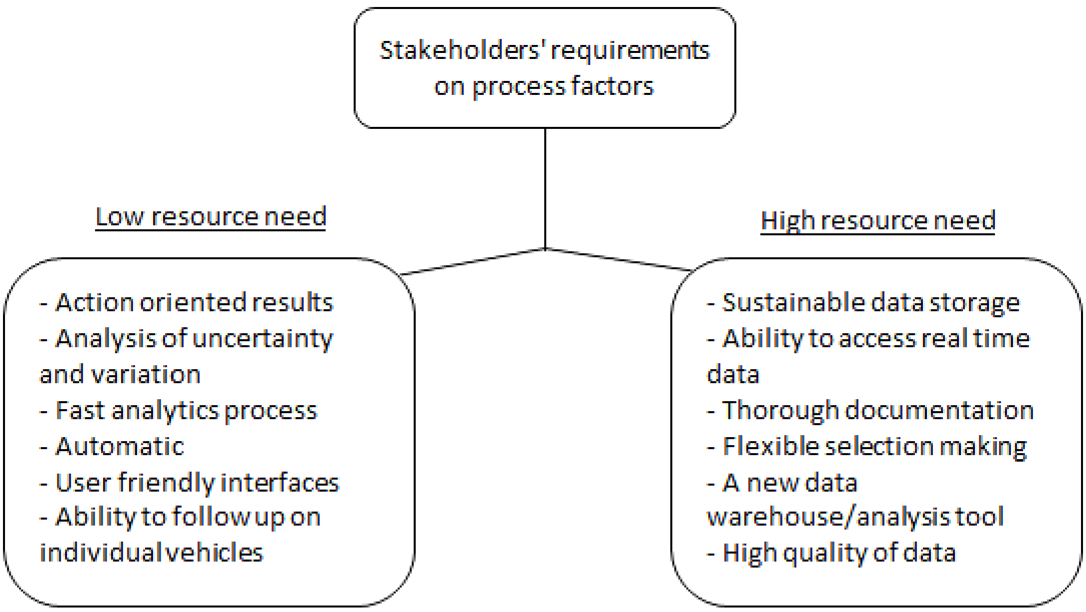

Figure 4.14 Stakeholder requirements categorized according to resource need

Subsequently, the requirements were analyzed based on both their estimated resource needs and their importance to stakeholder, in order to highlight which requirements that were most important, and which that were feasible for this study to improve. The requirements are therefore mapped in Figure 4.15, which highlights four different areas that require different approaches to improve.

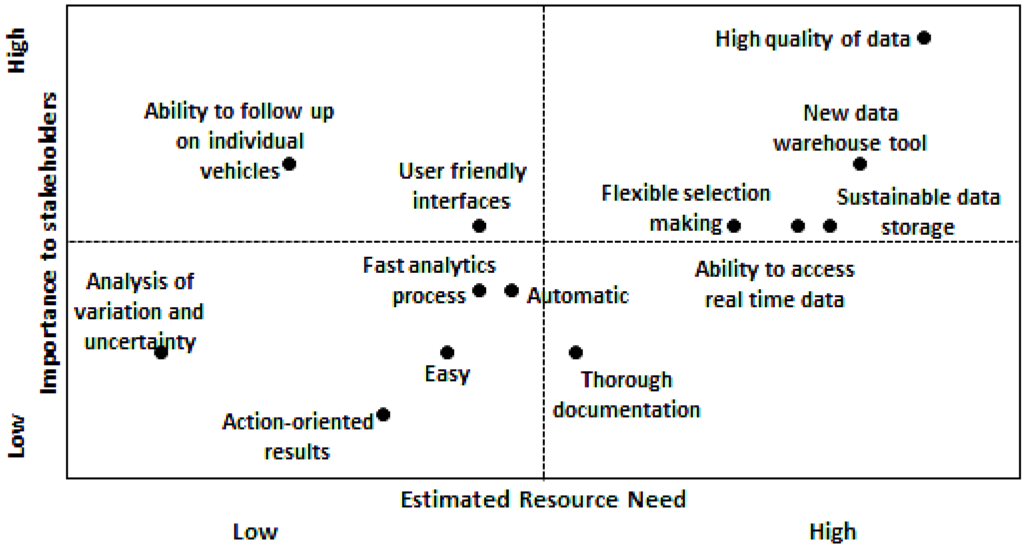

Figure 4.15 Different focus areas for stakeholder requirements

4.5.4 Improvements made

Following this ranking, the study continued with the stakeholder requirements that demanded the least estimated resources. Subsequently, a number of improvement alternatives were generated through brainstorming sessions among the authors, and through discussions with stakeholders. The improvements that were generated are presented in Table 4.8. As the processes for following up emission levels and IUPR data differ to some extent, for example through the use of two different Excel analysis tools, only the improvements that were made concerning the emissions' follow-up from LVD have been included here. Some of these improvements were made for the IUPR process as well, but the main focus of the improvement efforts was on the emissions' follow up.

Table 4.8 Implemented improvements

	Implemented improvements
A	Enable automatic creation of PowerPoint presentations from Excel analysis tools
B	Standardize layout in Excel tool
C	Automate creation of Top 30 list in Excel
D	Create Dashboard in Excel
E	Provide the ability to follow emission trends and fault codes of individual vehicles
F	Insert confidence intervals to average values and create boxplots of data

The first suggestion could be achieved through using visual basic in MS Excel, where macros can be programmed to automatically execute certain activities. In this case, macros were written to automatically create the PowerPoint presentations from the Excel tool, which are delivered monthly to information users and management after the analysis is made. Improvement B concerned the general layout of the Excel analysis tool, which was fairly unstructured in the beginning of the study. Now, the layout of different spreadsheets has been standardized to increase the user friendliness of the tool. Improvement C could be implemented through for example using Pivot tables in MS Excel, which generates an automatic update of the Top 30 list (of the highest measured NOx emissions in the data set), based on the data selections made by the users in the tool. Earlier, this was made manually.

Improvement D was the creation of a visual dashboard on a spreadsheet in the Excel tool, in order to easily get an overview of the data set. Improvement E was partly created through creating graphs in the Excel tool where a user can search for a specific vehicle, and subsequently see its trend over time and driven distance (when it for instance comes to emissions). A vehicle of interest could subsequently be investigated further in other databases to analyze its history of fault codes and repair reports. These individual analyses will however have to be further investigated at Volvo, as it is, in the long run, neither feasible nor practical to go between several different databases (of which access have to be requested) and manually carrying out these investigations. The last point, Improvement F, was made through creating box plot charts of the data, and through including confidence intervals to averages in the data set, in order to visualize the variation and uncertainty of the data.

How these improvements relate to the stakeholder requirements, in the process step “data to information”, are depicted in Table 4.9. Symbols are used to indicate whether the implemented improvements were deemed by the authors to have a low, medium, or strong relation to the requirements. A triangle (▲) indicates a low relation, a square indicates a medium (■) relation, and a circle indicates a strong (●) relation between improvement and requirement.

Table 4.9 Implemented improvements versus stakeholder requirements

Stakeholder requirements / **Implemented improvements**	Enable automatic creation of PowerPoint presentations from Excel	Standardize layout in Excel tool	Automate creation of Top 30 list in Excel	Create dashboard in Excel	Provide the ability to follow trends and fault codes of individual vehicles	Insert confidence intervals to averages and create box plots of data
User friendly interfaces		●		●		
Fast analytics process	■	▲	●	▲		
Automatic	●		●			
Analysis of variation and uncertainty						●
Easy	■	■	●	▲		
Ability to follow up on individual vehicles					●	

4.5.5 Measure of some implemented improvements

Saxena and Srinivasan (2013) highlight the significance of measuring the value of analytics, as it tests the value of the model and illuminates improvement opportunities. Stubbs (2011) mentions that measuring the value of analytics can for example help to optimize internal activities. Done et al. (2011) suggest that key performance indicators aligned to a change program should be developed, and that short term results subsequently should be recognized in order to obtain stakeholder motivation and commitment, and to thereby reach long-term results. In this study, improvement A and C were followed up on: the improvement to enable an automatic PowerPoint presentation from the Excel tool, as well as the automatic creation of a Top 30 list. How these improvements affect the stakeholders' requirements is evident through reviewing Table 4.9.

In Figure 4.16 it is depicted which activities that the analyst performs in order to transform the data into information; the two middle steps of the figure are those affected by the suggested improvements.

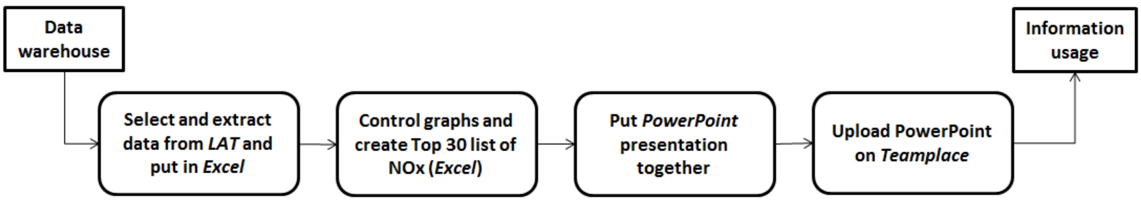

Figure 4.16 Map of activities for updating emissions results

In order to evaluate the effects of the implemented improvements, they were measured through their savings in process lead time. The cycle times of the activities from Figure 4-16 were consequently measured two times prior to, and two times after, the implementation of the improvements. The results are provided in Table 4.10, where the averages and standard deviations of these measurements are presented. For the first and last activity, no differences in cycle times are included as the implemented improvements did not affect these.

Table 4.10 Effects of implemented improvements

	Measured cycle times in minutes					
Activity	**$\bar{x}$ (old)**	**s (old)**	**$\bar{x}$ (new)**	**s (new)**	**$\bar{x}$ (difference)**	**p-value**
Select and extract data from LAT and put in Excel	169,5	10,5	-	-	-	-
Control graphs and create Top 30 list of NOx	76	44	6,5	1,5	-69,5	0,134
Put PowerPoint presentation together	65,5	24,5	26	4	-39,5	0,133
Upload PowerPoint on Teamplace	5	1	-	-	-	-
Sum:					**-109**	

As can be seen, the average saving in time for the monthly update of the emissions' results was 109 minutes. The p-values (based on a one-sided *t*-test, assuming unequal variances) are not low enough to show significant difference of the implemented improvements. This can be due to the small sample size (n1=n2=2) and the within-sample variation. Nonetheless, the analyst performing these activities was also asked about the experienced effects of the improvements, and the response was that the improvements did decrease the process time and the effort required to perform its activities, which create "*a possibility to spend the time saved on other work tasks*". The analyst continued by stating that it was "*nice to not have to perform this repetitive and uninspiring work*", as these activities had been automatized. Due to this, the analyst further explained that the number of "*human errors have been reduced*" which in turn have "*reduced the amount of re-work*". This can also be understood through reviewing the decrease in standard deviation of performing these tasks, as is evident in Table 4.10.

It should be noted, again, that these improvements merely affect a small part of the whole analytics framework at Volvo GTT PE. However, as Done et al. (2011) mention, short term results are important to highlight. In addition, the process of generating these improvements may function as an example of how to create actionable results from an investigation of an organizational structure for analytics, which is a highly significant contribution as well.

4.6 Proposed future improvements at Volvo GTT PE

As has been explained previously, this study was narrowed as it progressed from its initial wide scope, due to its limited resources and its boundaries in terms of where changes to the analytics framework at Volvo GTT PE could be made. The stakeholder requirements that were deemed feasible to try to improve, during this study, can be explained via Figure 4.15, as they are located in the two areas to the left. However, in the upper right corner of the graph, there are some needs that were frequently mentioned as important by stakeholders, but that this study was determined not to possess enough resources to satisfy. These points are therefore proposed as future areas for improvements for Volvo GTT PE. The points were, as Figure 4.15 shows:

a. A new data warehouse tool
b. Flexible selection making
c. High data quality
d. Sustainable data storage
e. Ability to access real time data

Points *a* and *b* are related, as investing and developing a new data warehouse tool, as a replacement to LAT, would ideally include a way for analysts and information users to flexibly make selections to parameters and type of data to include in the extracted data sets. One possible method to achieve flexible selection making is, according to the data warehouse specialist that was interviewed in this study, to create an OLAP cube solution, which would have an Excel interface and would enable analysts to make parameter selections themselves. This is an aspect that would have to be further investigated, especially if a new data warehouse tool is to be developed.

Point *e* relates to the telematics technology, which is used to transfer data from vehicles into aftermarket tools and LAT at Volvo. The desire here is to be able to use these telematics readouts in the analysis tools, in order to for example further investigate, in real time, vehicles with extreme values. At present, the telematics readouts do not work sufficiently well to accomplish this, but the hopes are that they will in the near future. Then it will have to be investigated how to incorporate this type of data transfer, and the real time data, into the analytics structure that is currently in place at Volvo GTT PE.

The points *a*, *c*, and *d* are requirements that are deemed fairly urgent for Volvo to find solutions to. The current data warehouse tool, LAT, does not seem to have sufficient capacity to meet the demands put upon it, and it is a vital part of the analytics process that cannot be circumvented. The data quality is also a severe issue, as it seems as if data users and analysts are not aware of it, and thereby what they are actually looking at. The lack of data quality also creates problems as it demands severe cleaning before the data can be used. Lastly, as the amount of logged vehicle data is increasing every month, and as the analysis tools currently in use are already at the top of their capacity, this is an issue that needs to be solved fairly quickly as well. Thereby, these points result in three suggestions for future improvements at Volvo GTT PE.

#1: *Change or improve data warehouse tool*.

LAT, the data warehouse tool for LVD, needs to be replaced or improved. It limits the ability to utilize LVD in an appropriate and desired way; all the interviewed stakeholders who actually use LAT stated that it needs to be changed or improved. A quantified testimonial of LAT's lack of capacity is the cycle time of extracting data from this database, as was measured when evaluating the effects of the implemented improvements in Section 4.5.5 of this report. It takes, on average, nearly three hours for the analyst to perform this monthly activity – and the measurements in this study were only performed for extracting emissions data. On top of this, the same procedure must be gone through when extracting IUPR data. Holsapple et al. (2014) state that misalignments of the elements of the Business Analytics Framework must be carefully considered, and at present the practices and technologies, especially LAT, at Volvo GTT PE are falling behind the other elements.

#2. Investigate how to achieve high data quality.

High data quality is wished for by more or less all stakeholders, but at present there seems to be a lack of data quality assurance. Some suggestions for how to do this were raised during interviews, and these are included in the Section 4.5 in this report. Three places in the process where the data quality hypothetically could mainly be affected are during the data creation in the log parameter, during the data transfer from the vehicle to the data systems at Volvo, or as data are extracted from LAT. Hoerl et al. (2014, p. 226) also highlight the importance of data quality when handling great amounts of data, as they write that "*data quality is often key to success*".

#3. Investigate how to store and manage data, and how to distribute findings.

Both LAT and the Excel analysis tools are becoming increasingly slower and ill-functioning as a result of the increased data amount, and therefore alternatives to these solutions should be generated. Issues have also been raised that there is no strategy in place for where to store the logged vehicle data, and as some stakeholders mentioned that the analysis from LVD will be more interesting when more data are available, this is a problem that needs to be dealt with. That the increasing volume, variety, and velocity of data make it harder to ingest, process, and visualize, is what defines "Big Data" according to various literature (Minelli et al., 2013; Saxena and Srinivasan, 2013; and Gandomi and Haider, 2015) and this is currently what

Volvo GTT PE has started to experience. To find sustainable solutions for data storage and handling is therefore necessary to make full use of LVD.

Options for analysis platforms, which currently the Excel analysis tools function as, should also be further investigated. To utilize an external server to store the logged vehicle data would probably be advantageous, as well as to develop an analysis tool which can be accessed via for instance Internet or SharePoint, so that these tools do not have to be downloaded to each individual computer. To start to use Power Pivot, the add-in to Excel, is advised by this study, as is explained in Section 4.5.3.1.

In addition to the three points that have already been mentioned, which mainly stem from the analysis of stakeholders and their expressed needs and wants, other suggestions were generated by the authors of this study. The first of these is to investigate how the value of analytics can be measured at Volvo GTT PE. This is suggested as there are some investments that are required to meet many of the other improvement possibilities, and as numerous stakeholders mentioned the lack of resources that are spent on analytics at Volvo. Therefore, in order to be able to build a business case for analytics and to create incentives for further investments, the benefits provided by analytics need to be measured and communicated within the organization. Hence, the fourth suggestion:

 # 4. Investigate which actions that can be taken based on LVD and how to measure the value of analytics.

Stubbs (2011) points to the importance of measuring the value of Business Analytics in organizations, in order to maintain the strategic focus, build trust and credibility, to be able to seek additional investments, and to optimize ongoing activities. As mentioned, currently this is not explicitly done at Volvo GTT PE. This could be because the value is not realized yet; interviews with stakeholders for example revealed that there may be a lack of awareness of what benefits information can yield. The LVD analytics process is also fairly new, and perhaps it has therefore not generated any significant value yet. Therefore, it should be investigated and more clearly outlined which type of actions that are taken based on LVD, and how their effects can be measured.

#5. Investigate how the databases of LVD, repair reports, and fault codes can be merged.

Late in this study, those stakeholders who were supposed to be managed closely, according to the stakeholder analysis, expressed interest in an examination of how LVD readouts could be cross-checked with other types of data from other systems and databases. Of special interest was data on registered fault codes in the vehicles and reports from repair shops. Some initial work on this was commenced during this study, but this is an area that needs further investigation if these different databases are to be used in combination on a larger scale in the future.

#6. *Set up a central analytics function in the organization.*

This was another question that was raised, fairly late in the study, by a stakeholder at the management level whom was managed closely in this project: to investigate the possibilities of setting up a central analytics function at Volvo GTT. Due to the issues that were raised by stakeholders concerning the capability set at Volvo GTT PE, such as that users do not know what they are working with or what they want, nor which data that exist, it could definitely be a good idea to set up a function where this type of knowledge is gathered. Morabito (2015) explains that to manage great amounts of data requires certain skill sets and technologies, and therefore organizations may need to make changes to their business processes and organizational structures in order to do so properly. Laursen and Thorlund (2010) discuss how barriers relating to competencies and organizational structures have been the most limiting factors for succeeding with Business Analytics initiatives; therefore they suggest creating a Business Intelligence Competence Center (BICC) which will work as an organizational entity of technical expertise, but still highly connected to business needs. The establishment of a BICC will provide the analytics function with a greater voice in the organization, and it will more efficiently link business strategies with analytics strategies (Laursen and Thorlund, 2010). Therefore, this could certainly be a good idea for Volvo GTT. It must, however, be ensured that this function also will possess appropriate domain knowledge (Hoerl et al., 2014), such as understanding of products, fault codes, and surrounding systems.

5. Analysis

In this chapter, the theoretical framework and the empirical findings are analyzed. A number of theoretical contributions to Business Analytics are provided, such as a developed framework and a step-by-step implementation methodology.

5.1 Theoretical contributions to Business Analytics

5.1.1 The role of intuition and experience in Business Analytics and the era of Big Data

A big part of Business Analytics, according to earlier literature, is about providing people with insights and decision support through data and evidence. Holsapple et al. (2014) for instance propose that a decisional paradigm, where decisions are based on evidence, should be a part of the Business Analytics structure in organizations. However, the authors of this study believe that it must be recognized by Business Analytics academia and practitioners that a lot of decisions, as well as recognition and solving of problems, in practice are based on experience and intuition, which both earlier research (Pfeffer and Sutton, 2006; Salas et al., 2010; Kahneman, 2011) and the results from this case study exemplify. Kahneman (2011) has through his research showed the flaws and biases in human judgment, which points to the importance of trying to fight and minimize the role of intuition in these processes. While this may still be true and important to recognize, it is in place to accept the reality of decision making processes, and look for ways to integrate Business Analytics with expertise-based intuition.

Klein (1999) has written extensively on intuition, and his example of the fireman saving lives due to his intuitive decision making, which is described in the literature review of this report, provides an example of its benefits in problem recognition and decision making. During the case study at Volvo GTT PE, it was also expressed by stakeholders how they often rely on experience and intuition to guide their work, for example through the statement of an internal team member that:

"*Intuition guides me in different directions... if I am out driving, I could feel if something is not right. And then we could look further into it. This is a lot based on earlier experiences...I can let the feeling guide me to where there can be problems and where and how to move on… or to not move on*".

This is in line with Liebowitz's (2015) argumentation that solely relying on data can lead to missed opportunities or mistakes. As this type of expertise-based intuition is vital for organizations to utilize (Salas et al., 2010), it should be ensured that a Business Analytics structure incorporates it. The types of insights that come from experience and intuition may provide significant information, and it is thereby a waste not to take advantage of them.

These points could be seen as arguments for utilizing experience and intuition "aside" from the process of turning data and evidence into insights. However, experience is also vital in the midst of the process of working on data and statistics. Hoerl et al. (2014) explain that "domain knowledge" is a principle of statistical thinking that is a must-have in Big Data analysis, but which have been somewhat neglected in the Big Data hype. This is due to that deeper understanding of the context and the system where the data operates is required, "*to properly analyze the data, in order to produce actionable conclusions* (Hoerl et al., 2014, p.227). This was also found during the case study; one stakeholder, for instance, mentioned that:

"*I have to use experience and intuition to understand when data are faulty, so that it can be cleaned*"

The same interviewee also explained that:

"*When you sort in the data you can use experience, to determine what is important and what is not*."

Hoerl et al. (2014, p.228) further explain that "*domain knowledge can be applied to include evaluation of data quality, identification of additional data needed, selection of variables and appropriate scales, selection of model form…, interpretation of results, ability to extrapolate findings, and determination of logical next steps".* Hence, the importance of including experience, domain knowledge, and intuition in the data analytics process is clear. And therefore, the need to incorporate these aspects into Business Analytics is also evident. A framework for Business Analytics that does this has been developed throughout this study and will be presented shortly.

5.1.2 A revised definition of Business Analytics

The contributions of this study to the theory of Business Analytics continue with proposing a new definition of it, which will serve as the base for the study´s other theoretical contributions. So far, there is no widely agreed-upon definition of the subject; earlier definitions of Business Analytics, that were presented in the literature review of this report, are "*delivering the right decision support to the right people at the right time*" (Laursen and Thorlund, 2010, p. XXI); "*evidence-based problem recognition and solving that happen within the context of business situations"* (Holsapple et al., 2014, p.134); and "*any data-driven process that provides insight*" (Stubbs (2011, beginning of chapter 2).

Bringing these earlier definitions together, and including the empirical experiences from this case study, the new proposed definition of Business Analytics is that it is:

A structure for providing actionable insights to the right people at the right time.

The authors of this study believe that the term "insights" encompasses both "decision support" and "problem recognition and solving" from other definitions, wherefore it is preferable. This is due to the definition of insight, which is formulated by Klein and Jarosz (2011, p.335) as "*discontinuous discoveries"*.

Klein and Jarosz (2011) also explain that insights mainly are reached through any of the three pathways of contradiction, desperation, or connection, and that new data, a combination of data, or finding a contradiction can change an individual's mental model. Thereby, the authors of this report believe that using the term "insights" in the proposed definition of this study, ensures that both evidence/data and experience/intuition is incorporated in it. This is a vital addition. Literature also states that in practice, people utilize experience and intuition in making decisions (e.g. Salas et al., 2010; Kahneman, 2011) and that expertise-based intuition has a place in the era of Big Data (Liebowitz, 2014). The empirical study confirms both of these points as well.

The importance of being able to act on insights generated by analytics has previously been described; it is supported by both literature (Kiron et al., 2001; Davenport et al., 2001; Stubbs, 2011; Saxena and Srinivasan, 2013) as well as the empirical experiences from the conducted case study. Therefore, the term "actionable" has been included in front of "insights" in the proposed definition.

5.1.3 A developed framework for Business Analytics

The earlier literature that was reviewed to support the empirical case study was useful in setting the theoretical context. However, the authors believe that no earlier theoretical model alone would have been sufficient to conceptualize the empirical study and its findings. Therefore, a developed conceptual framework for Business Analytics is presented in this section, which is meant to incorporate the most useful bits and pieces from earlier research.

The Business Analytics Framework (Holsapple et al., 2014), which was the initial theoretical base for the case study, provided a holistic and encompassing perspective of the Business Analytics structure at Volvo GTT PE as it incorporates a diverse set of factors through the inclusion of transforming process, specific activities, practices and technologies, capability set, movement, and decisional paradigm. It is therefore useful in analyzing the organization's analytical alignment, and it can be used to point out where the organization is falling behind and what it should focus on. Some questions may, however, be raised about the terms "movement" and "decisional paradigm" as they are quite ambiguous and may not be appropriate. To use the term "organization & culture", from the model presented by Davenport et al. (2001), was determined to be a more comprehensible alternative to the term "movement". Based on the analysis in preceding sections of this report, the term "decisional paradigm" will not be incorporated in the developed framework, as both literature and the empirical study highlight the importance of experience and intuition in decision making.

Subsequently, during the case study, it was deemed helpful to utilize the Business Analytics Model (Laursen and Thorlund, 2010) to conceptualize the transforming process via its steps of data creation, data warehouse, data to information, using information, and choosing strategy. Especially the three first steps were deemed useful to consider. Another theoretical piece, that enabled a greater understanding of the empirical study, was Davenport et al.'s (2001) categorization of Business Analytics into the three parts of context, transformation, and outcome, as it was deemed important to understand which parts that belong to the process and which parts that are more contextual, perhaps mainly as these categories of factors require different types of analyses and actions. Improving a process could be done during this study, with very limited resources, but to improve contextual factors such as the decisional paradigm, movement, or capability set of the organization, requires heavy investments and managerial involvement.

It is also deemed important to, for clarification and guidance purposes, in a framework for Business Analytics indicate where data comes into the picture (see Davenport et al., 2001; Laursen and Thorlund, 2010; Acito and Khatri, 2014), and to highlight the importance of turning information into action (see Davenport et al., 2001; Kiron et al., 2011; Saxena and Srinivasan, 2013). Another aspect that can be found in several earlier frameworks (Davenport et al., 2001; Laursen and Thorlund et al., 2010; Acito and Khatri, 2014) is the concept of "strategy", and which also can be deemed to be an important contextual factor for a successful analytics framework. Hoerl et al. (2014) also point to the significance of having data quality and strategies for data analysis, especially in the era of Big Data. Therefore, it is vital to include these points in a framework to highlight the significance of recognizing the quality and strategy of the data analysis.

The two preceding sections of this chapter have concerned the importance of recognizing experience and intuition in Business Analytics and the era of Big Data, as these concepts are a great part of people's actual decision making process, and as they are significant to generate value from data. Therefore, the term "insights" was used in the proposed definition of

Business Analytics, to incorporate both evidence/data and experience/intuition. In a framework for Business Analytics, the authors of this study therefore believe these concepts have a place as well. Insights can be gained through both evidence-based and expertise-based pathways, as is discussed in Section 4.8.2, and therefore both of these two paths should lead to insights in a conceptual framework.

Consequently, in order to incorporate all the points that have been brought up in this section, a framework for Business Analytics has been developed. It has been designated the ”House of Business Analytics” and is presented in Figure 5.1.

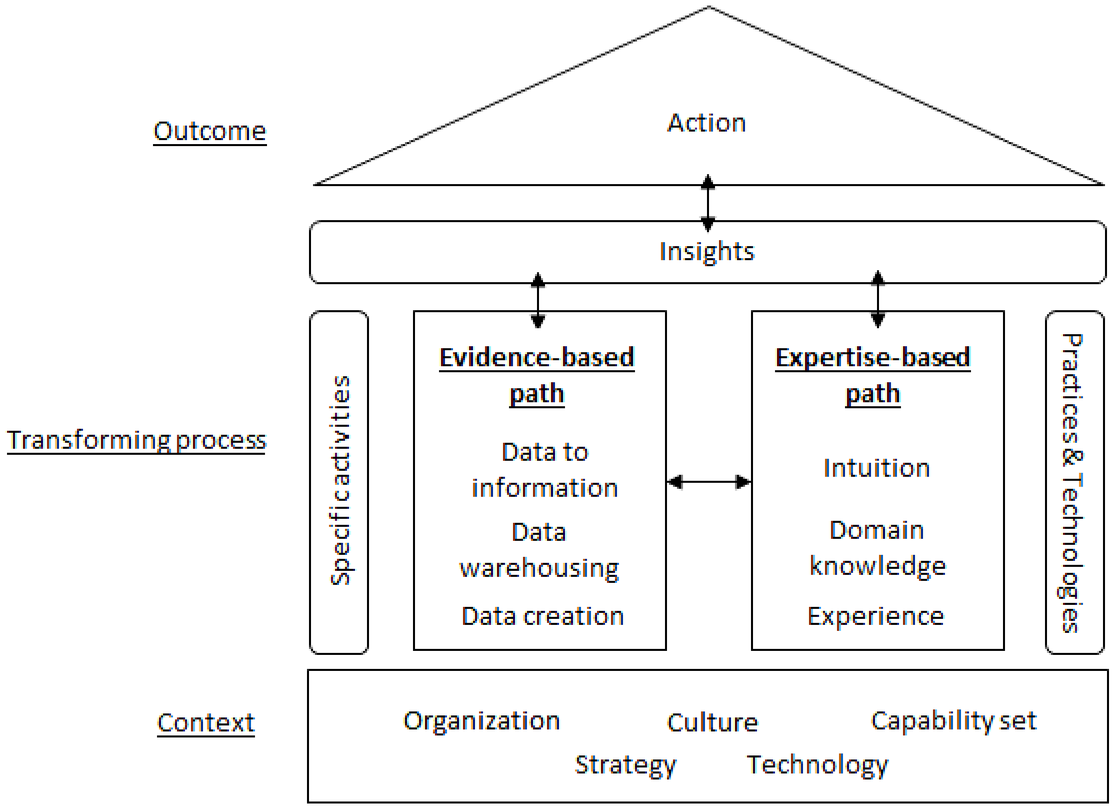

Figure 5.1 The House of Business Analytics

The foundation of the framework consists of the contextual factors; the prerequisites of the analytical capabilities of an organization (Davenport et al., 2001). The context of the proposed framework includes the factors of strategy, organization & culture, technology, and capability set. Business Analytics is about aligning the organization’s strategy and business objectives with its processes and actions (Laursen and Thorlund, 2010); therefore the strategy is an important contextual factor. The organization and culture must also promote and enable the analytics processes (Kiron et al., 2011). An appropriate technology level (Davenport et al., 2001) and capability set (Holsapple et al., 2014) must also be in place, in order to make the best use of analytics. In order to evaluate the analytical context in an organization, questions to answer could be:

1. Do the organization and its culture promote analytics and using evidence in gaining insights and taking decisions?
2. Does the organization’s overall strategy support the analytics initiative?
3. Is there a strategy for data analysis in place?

4. Is the available technology sufficient for being successful with analytics?
5. Does the organization possess the necessary capabilities to turn data into actionable insights?

Grounded in this context is the process of gaining insights. Insights can be gained via evidence and logical analysis, or via an individual's experience and intuition. Expertise is also utilized in the data analysis process, in order to for instance realize which data that needs cleaning, which findings that are interesting, etc. The "expertise-based path" may go fairly rapidly and without any structured process. The "evidence-based path", on the other hand, usually goes through the main steps of data creation, data warehousing, and turning data to information. To analyze the process of gaining insights in an organization, some questions to answer could be:

1. How is data created?
2. How is data stored?
3. How is data turned to information?
4. Which role does expertise and intuition have in this data analysis process?
5. How do workers obtain insights from their expertise and intuition?

Lastly, the outcome of the process and the gained insights should be actions, as it is through actions that value gets created from analytics (Stubbs, 2011). Some questions to answer at this part of the framework are:

1. Which actions can be taken based on the insights?
2. Who will execute the actions?
3. How will the effects of the actions be measured?

5.2 Proposed process for implementing the House of Business Analytics

With the empirical study and the developed framework for Business Analytics as a base, the authors determined to visualize a phase-based view for how an organization's analytics structure can be analyzed and improved. The importance of strategic thinking and disciplined phase-based approaches to produce solutions to Big Data problems is highlighted by Hoerl et al. (2014), and during the empirical study the authors felt that to have process for how to conduct a study of this nature would be beneficial to obtain structure and guidance in the project. In Figure 5.2, a developed phase-based process is therefore depicted. We believe that it is general enough to be transferable to other organizations and similar analytics projects.

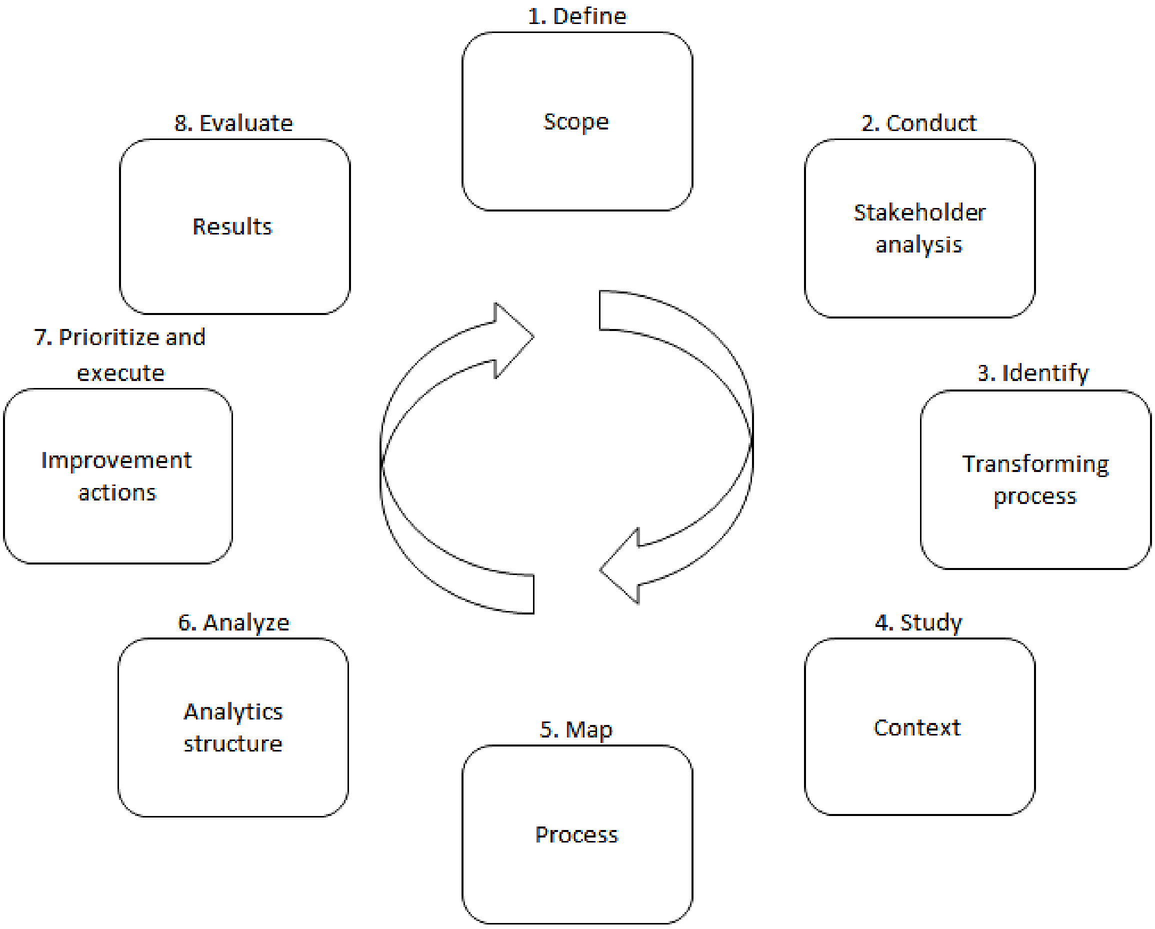

Figure 5.2 Proposed step-by-step procedure for implementing the House of Business Analytics

5.2.1 Step 1: Define scope

The proposed methodology commences with scoping the analytics study. The boundaries of the project should be determined and objectives should be set, and the business area of which the work will be focused should be decided. Holsapple et al. (2014) propose that Business Analytics has three dimensions; a domain, an orientation, and a technique. It could be of benefit to establish the nature of these in the beginning of an analytics project as well. Thereby, questions to answer in this initial step are for example:

1. What are the boundaries of the project?
2. What is the type of data that will be dealt with?
3. What is the objective of the analytics initiative?
4. How will the analytics tasks be performed?

During this study, the boundaries started with establishing the organizational unit which the study would take place in, Volvo GTT PE, and establishing that this study could make changes to the analytics process step where data are turned to information, and even more specifically that changes could be made to the Excel analysis tools and to the PowerPoints. The type of data to be dealt with in this study was explained to be LVD. The objective with analyzing LVD was for Volvo GTT PE to obtain information about the engine performances of their sold vehicles. Lastly, information was mainly to be gained from LVD via quantitative data mining.

5.2.2 Step 2: Conduct stakeholder analysis

Next, the proposed methodology suggests conducting an analysis of the stakeholders of the analytics project: the individuals or groups with interest in the process or its outcome (Maylor, 2010). Connecting stakeholders to Business Analytics is recommended by Saxena and Srinivasan (2013) to ensure that stakeholders act in alignment with decisions, so that decisions and actions can be properly executed. During the stakeholder analysis, the information needs from the business-driven organizational levels and the data supply from the technically oriented organizational levels (Laursen and Thorlund, 2010), can also be further investigated. Questions to answer in this step are for instance:

1. Who are the stakeholders of the analytics project?
2. Which stakeholders are the most important?
3. Which type of information is desired to obtain from the data?
4. What will the information be used for?
5. Which data can provide the desired information?
6. Which parameters and types of analyses are desired by these stakeholders?

In this study, the stakeholders were mainly users of the information or personnel conducting any activity in the transforming process. Some additional stakeholders were included as well, as they were deemed to possess supplementary knowledge about LVD and its analytics process, without being directly involved in it. The identified stakeholders were subsequently ranked based on their power and involvement in the process, and those who consequently were determined to be most important to the project, were managed closer and were given higher importance to the study.

The information obtained from the LVD analytics process was mainly used to understand the actual situation, the performance of Volvo's engines in real settings, and to thereafter guide improvement initiatives. In the future, the aim was also to use the transforming process for certification purposes.

Some parameters that were asked for by stakeholders were for example emission levels of NOx, regenerations of soot and sulfur, IUPR parameters, and fault codes. The types of analyses were for example engine family's average values, variation and uncertainty analysis in terms of for instance box plots and confidence intervals, as well as some trend analysis of both populations and individual vehicles. Consequently, the available logged vehicle data that could meet these needs were identified.

5.2.3 Step 3: Identify transforming process

Thereafter, the proposed methodology continues with identification of the transforming process; the main steps required to turn the data into information. The transforming process is at the center of the Business Analytics Framework (Holsapple et al., 2014), and during this study it was determined to be useful to put the process as the focal point of the investigation. The Business Analytics Model (Laursen and Thorlund, 2010) was also considered highly useful to conceptualize the process. Questions that may need answers at this step are:

1. How is the data created?
2. How is the data stored?
3. How is the data turned into information and insights?
4. How are the information and insights used?

The main process steps in the transforming process were determined to be (a) *data creation*, where data are created in a log parameter in the engine control unit of a vehicle, (b) *data warehousing*, where data are stored in different systems such as LAT, (c) *data to information*, where data are extracted from LAT, turned to information, and analyzed, (d) *information usage*, where the resulting information is used to drive improvement initiatives in the organization, and (e) *choosing strategy*, where management makes strategic choices for, and based on, analytics.

5.2.4 Step 4: Study context

After the process has been identified, it is suggested to collect data on the contextual factors, such as the strategy, technology level, culture and philosophy, as well as the capability set of the organization. Questions to ask in this step are for example:

1. Do the organizational culture and philosophy promote analytics initiatives?
2. Does the organization have the technology required for Business Analytics initiatives?
3. Does the organization have the capabilities to turn the data into information, and to use that information?
4. Does the analytics initiative support the overall strategy of the organization?
5. Does the organization have a strategy for analytics – for instance how to get data, how to transform it to information, and how to use the information?

To investigate these factors during this study, the included stakeholders were asked about them. From the answers it seems as if not enough resources are spent on analytics within Volvo GTT, and as if there are analytics projects going on in other parts of Volvo, which GTT does not sufficiently take part in. Volvo is a big organization and has a high technology level, but the technologies used during the LVD analytics process under study are however somewhat outdated. The company also has a lot of capabilities in their workforce and organization, but it seems as if these capabilities are not sufficiently spread between different departments and projects. More cross-functional cooperation and knowledge transfer could be necessary. As for the aspect of strategy, making full use of the LVD analytics process does correspond well to Volvo's overall strategy with the key pillars of quality, safety, and environmental care. There is, however, currently a lack of strategic thinking for how to make the best use of LVD, such as what to do, in more detail, with the generated information and how to build up a well-functioning structure with adequate technologies around the process.

5.2.5 Step 5: Map process

Subsequently, the factors of the Business Analytics Framework (Holsapple et al., 2014) which are deemed to be more process related, such as the practices and technologies that are used and the specific activities that are conducted, can be mapped out and studied more carefully. During this study, it was deemed useful to investigate these factors in relation to each main process step. In addition, as expertise and intuition have been found to be important factors of the analytics structure of an organization, these should also be studied in relation to the process steps – how does, for instance, a worker use intuition to analyze data? As the House of Business Analytics contains two paths to insights, one evidence-based and one expertise-based, it is also of interest to investigate how workers can gain insights via their expertise and intuition. Questions that may need answer in this phase are:

1. Which activities are conducted at each process step?
2. Which practices and technologies are used at each process step?
3. How do workers utilize their expertise and intuition during these process steps?
    a. Which type of expertise do they use? Can it be transferred to others?
4. How do workers utilize their expertise and intuition to gain insights?
5. Which actions are taken based on the gained insights?

During this study, each process step was here evaluated in more depth to understand each activity carried out and the technologies used to do them. Problems with these aspects were also highlighted by the identified stakeholders. This part of the study can be further reviewed in Section 4.4.2.

Here, it was also attempted to understand how for example the analyst uses its expertise and intuition when turning the logged vehicle data into information, which for example materializes through quickly identifying faulty data, or understanding which data patterns that are of interest. Stakeholders were also asked about how and in which situations they can obtain insights, which do not come from evidence, and which can guide them in their work. An information user then explained how he can feel when something is not right as he is test driving a truck, and subsequently may initiate an investigation to look further into it.

5.2.6 Step 6: Analyze analytics structure

In the sixth step of the proposed methodology, the investigations of the process and context related factors can be analyzed to identify problems, performance gaps, and improvement possibilities. Improvements of factors related to the process are hypothesized to require fewer resources than those related to context. However, it must naturally be prioritized which aspects that are most urgent to improve to achieve the desired result.

1. Are the main problems, or gaps between current and desired performance, located among the process factors or the context factors?
2. Which problems or performance gaps are most urgent to fix or improve?
3. Which are the causes of these problems?
4. Which resources are available?

During this study, it was quite quickly established that the available resources for the project would not be sufficient to make any changes to any contextual factors. Therefore, it was determined to proceed with improvement efforts on process factors during the study. Furthermore, improvement efforts were determined to be concentrated on the step “data to information” in the transforming process.

5.2.7 Step 7: Prioritize and execute improvement actions

Analytics can, as stated by Saxena and Srinivasan (2013), be made actionable through ranking possible options and/or to propose suggestions to take, and Kiron et al. (2001) state that turning insights into actions is vital for organizations to achieve high analytical capabilities. The proposed methodology therefore includes this step where actions are taken and improvements are made. Examples of questions that may need to be answered in this step are therefore:

1. How could the analytics structure be improved?
2. Which improvements are most critical to implement?
3. Which improvements can be implemented directly?
4. Which improvements should be implemented and when?

This study utilized a two-by-two matrix, with one axis representing the estimated resource need for the generated stakeholders' requirements, and the other axis representing their importance to stakeholders. Through this graph it became evident which requirements that could be met immediately, and which that would require more resources than this project possessed. Thereafter, the requirements that were deemed to require the least resources were chosen to satisfy directly, and improvement actions were generated to do so. These were subsequently implemented in the transforming process.

5.2.8 Step 8: Evaluate results

In the last step, results from the implemented improvements should be evaluated. Saxena and Srinivasan (2013), for example, explain the importance of measuring the value of analytics. As everything always can be improved, since it is always possible to improve quality while decreasing resource usage (Bergman and Klefsjö, 2010), the evaluation should preferably end up in what should be done next. This is also in line with other improvement methodologies, such as the PDCA cycle (Bergman and Klefsjö, 2010) and DMAIC from Six Sigma (Schroeder et al., 2008). As Business Analytics as a subject is broad and encompassing, the authors of this report believe that there will always be room for improvements within an organization. For example, the different domains, orientations, and techniques of Business Analytics (Holsapple et al., 2014) will most likely always be possible to vary, and thereby new improvement possibilities may be discovered. Questions to be answered here are:

1. How can the implemented improvements be measured?
2. Are the improvements validated?
3. What should be done next?

In this study, it was determined to measure the implemented improvements that could generate the most rapid feedback, which was those related to the decrease in manual work and savings in time for the analyst turning the data into information. The average savings in lead time were measured to be 109 minutes and the measured standard deviation decreased by 63. These results were further verified as the analyst was asked about the effects of the improvements, and expressed satisfaction over the decrease in repetitive and uninspiring work, the ability to spend time on other tasks, and the decrease in errors caused by the human factor. The study also ended up in some proposals for future improvements and areas for further investigation of Volvo, in order to keep improving the analytics structure. These points were determined to demand more resources than the project possessed if they were to be met.

5.3 The House of Business Analytics used in practice at Volvo GTT PE

In order to further explain the findings of the study, the developed House of Business Analytics is, in this section, used to describe the current analytics structure of LVD at Volvo GTT PE. The proposed phase-based process, which was explained in the preceding section, was used to generate the empirical findings of the study, and these findings are, in Figure 5.3, therefore inserted into the House of Business Analytics.

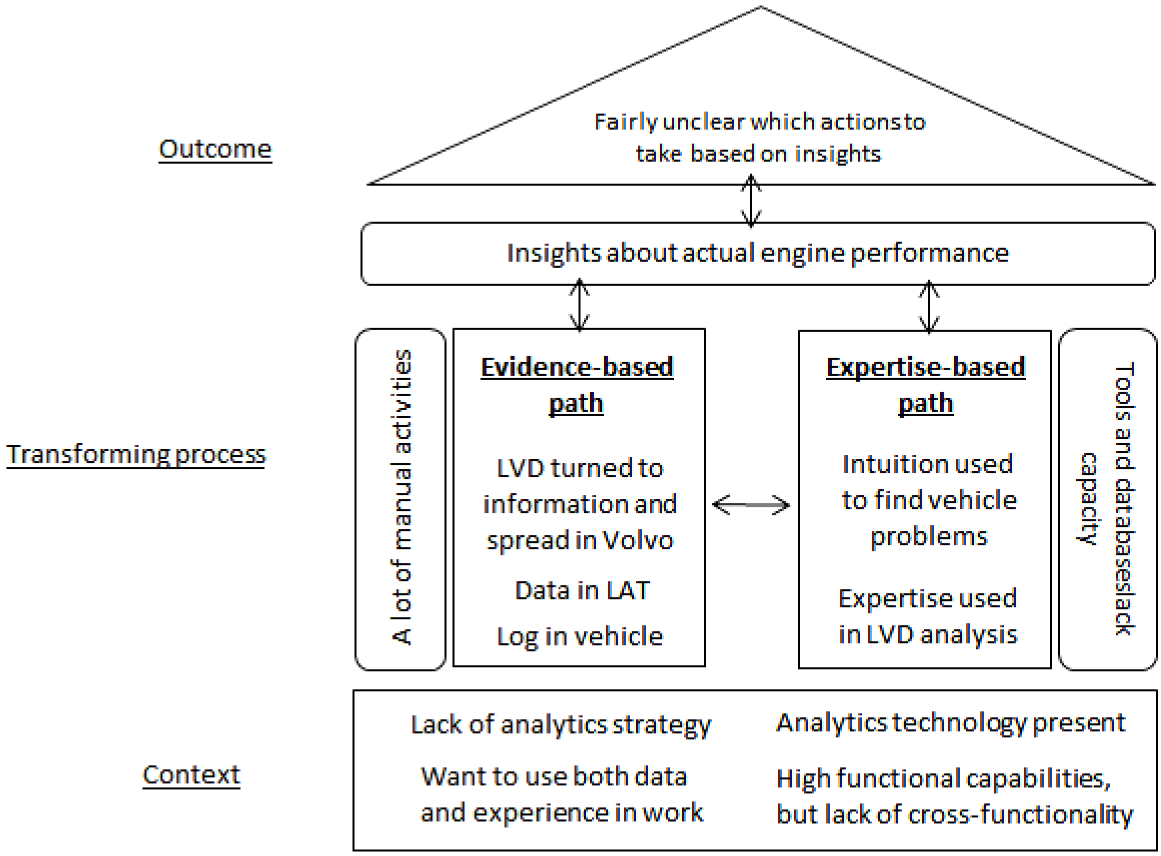

Figure 5.3 The House of Business Analytics used in practice

Starting with the contextual factors, the Volvo Group is a big organization, and does have the technology level to produce data and distribute it, as well as the information it provides, to different databases and functions of the Group. It should, however, be noted that some issues have been surfaced about for example the quality of the produced data. The organization does possess the capabilities required to turn data into insights as well; there are several skilled workers at different functions of the organization. However, Volvo seems to somewhat be on the specialized path to an analytical capability (Kiron et al., 2011), as deep expertise is developed in certain functions but not sufficiently spread across functions; interviews with stakeholders for example revealed that information users do not always seem to know what they want or what type of data they are working with.

The overall strategy of the Volvo Group, which is based on the three pillars of quality, safety, and environmental care, is in line with working towards analytics of LVD to evaluate and ensure the quality and sustainability of their products. However, strategies for data analysis of LVD, which Hoerl et al. (2014) deem to be significant, are still somewhat missing; it is not clear which insights and actions that are wished to gain and be able to take from LVD, or which form the structure and process of data analysis is supposed to take. Within the organization, the culture seems to be in place to use data and evidence to guide operations and decisions, but experience and intuition are a big part of these aspects as well. However, the apparent lack of resources spent on analytics could indicate that the organization currently has other main focus areas.

Grounded in this context, the process of turning the LVD to insights goes from the creation of the data in the vehicles to the data being stored in LAT and then extracted and converted to usable information, all in line with the three lower steps of the Business Analytics Model (Laursen and Thorlund, 2010). During these steps, analysts and users utilize their experience and domain specific knowledge to understand which data, information, and analyses that are of interest. The data and experience/intuition are thereby used in combination to conduct activities and use practices and technologies in the transforming process. In addition, some employees can come to new insights solely based on intuition, such as when one interviewee stated that he can feel when something is not right with a vehicle during test drives. Of special concern in this part of the framework is, at Volvo GTT PE today, the technologies used, as they seem to lack capacity to deal with the increasing amounts of data coming in from the vehicles. The two streams in the transforming process, the evidence-based and the expertise-based, eventually lead to gained insights about the performance of Volvo GTT PE's products and components.

And lastly, the outcome of the process and the gained insights should be actions; if Volvo GTT PE for instance learns something new about one of their engine models, how should it be handled? In order to get actionable insights from data, domain knowledge is required (Hoerl et al., 2014). At Volvo, it could be more clearly outlined how to respond to insights that are gained from analyses of LVD; for example which actions that should be taken, and whose responsibility it is to take them. Therefore, this is something to investigate more thoroughly for the organization, as it is through actions that value gets created from analytics (Stubbs, 2011). After actions have been taken, they also need to be measured to identify the value of analytics (Saxena and Srinivasan, 2013) and LVD.

5.3.1 Proposed future and implemented improvements at Volvo GTT in the House of Business Analytics

This study has proposed a number of suggestions for future improvements to the analytics structure at Volvo GTT PE. Some improvements have also been implemented. This section aims to explain these proposed future and implemented improvements in relation to the House of Business Analytics.

The first, third, and fifth points in the list of suggested future improvements in Section 4.6 mainly belong to the practices and technologies of the transforming process to the right in the House of Business Analytics. These are to change or improve LAT, investigate how to merge databases, and investigate how to store, manage and distribute data. The second point, to investigate how to ensure high data quality, is deemed to mainly belong to the initial phases of the evidence-based path in the transforming process, when data are created, transferred to data warehouses from the vehicle, and extracted from LAT. The fourth suggestion belongs to the roof of the House of Business Analytics, as it concerns which actions that can be taken based on insights gained from LVD and how the value of these actions can be measured. The sixth and last suggestion, to set up a central analytics function at Volvo, is more contextual and aimed towards the organization.

6. Discussion

In this chapter, the findings and contributions of the study are discussed, and possible concerns are addressed.

6.1 The empirical study and Business Analytics frameworks

The results and analysis of the case study conducted during this research have resulted in one framework and one step-by-step implementation procedure. The reviewed and utilized earlier conceptual frameworks do not present any process for how to practically implement and use them, and therefore it can be questioned if the process during this case study has been in line with what Davenport et al. (2001), Laursen and Thorlund (2010) and Holsapple et al. (2014) had in mind for their models. The authors of this study designed a process with the structure of these frameworks as a basis, and whether the proposed process makes the best use of these conceptual models, and whether this process is generalizable to other settings and organizations, is up for debate. Perhaps additional empirical case studies can provide some guidance on this matter.

In addition, the research methods used to investigate and analyze the six perspectives of the Business Analytics Framework (Holsapple et al., 2014) at Volvo GTT PE were qualitative and mainly carried out via interviewing stakeholders. It could be interesting to see a quantitative study of these perspectives, for example via conducting a survey, to minimize the risk of interviewer and interviewee bias that are present during qualitative interviews (Saunders et al., 2009; Robson, 2011). These possible biases could also have affected the end result of this study. The contents discussed during the qualitative interviews somewhat differed from occasion to occasion, as the flows of the discussions differed, which greatly helped the authors in for example identifying new aspects to investigate and to obtain a clearer and more complete picture of the situation for each interviewee. However, this also led to some aspects solely being discussed at a few interviews, and some aspects not being brought up during others. This could, naturally, have had an effect on the end result as well. A quantitative approach would not obtain the benefits from the chosen qualitative one, but it would probably not have these disadvantages. Quantitative methods could also, perhaps, better highlight performance gaps and thereby enable a quantitative analysis of the alignment of the analytics framework. This could be interesting for further research, and perhaps it would also be of interest to quantify the current and desired state of some analytics perspectives at Volvo GTT PE.

Quite a great part of this study has been dedicated to discussing around the concept of Big Data. Whether the logged vehicle data at Volvo GTT PE, which was the data set used in this study, actually is “big” could definitely be debated. According to definitions provided by Minelli et al. (2013) and Saxena and Srinivasan (2013), data are “big” when it extends traditional borders of volume, variety, and velocity, which makes it more complex to process and visualize. Following these definitions, the LVD is just on the verge of becoming big, at least for Volvo GTT PE; the current analytics framework is quickly becoming insufficient to handle the amount of data that is being processed. However, in intra-organizational comparisons where petabytes of data could be handled (Hoerl et al., 2014), the data volume, variety, and velocity of the LVD would, so far, be considered fairly “small”. Nonetheless, in the near future, as more vehicles transfer data to the LVD system, it will become more suitable to denote this “big” data. Therefore it is also vital for Volvo GTT PE to ensure that a structure is in place to deal with this increasing volume, variety, and velocity of LVD.

The proposed phase-based methodology for analyzing and improving analytics structures in organizations, could be said to have several similarities to the DMAIC cycle, which is often used in the Six Sigma improvement methodology (Schroeder et al., 2008); step one to three could be said to be included in the “Define” phase of DMAIC, whereas step four and five are similar to the “Measure” phase, and the steps six, seven, and eight bear similarities to “Analyze”, “Improve”, and “Control”. However, the methodology proposed in this report did help the authors to structure the empirical study, and the denotations of the steps were also chosen to highlight where and how the different Business Analytics models, from earlier literature, were used during the empirical study. Nonetheless, just having a phase-based approach to solving Big Data problems is important (Hoerl et al., 2014). Which methodology to choose, or how to denote the different phases is, of course, up to each individual. Important to highlight is also the significance of phases similar to “Define” in the Big Data era. “Define” has been recognized as critically important for the success of Six Sigma projects (Hoerl et al., 2014). In Big Data projects, this phase may be more important than ever, which could be why Hoerl et al. (2014) separate it into two phases for their proposed methodology of Big Data projects, and why this study in turn has divided it into three phases.

The framework for the structure of Business Analytics, which was developed in this study and has been designated the “House of Business Analytics”, has incorporated a multitude of conceptual frameworks and included the bits and pieces that were deemed most useful during the practical study. This approach can be questioned, as different frameworks provide different pictures of real-life situations, and it could be discussed whether it is possible to merge them in this manner. The authors do however believe that the resulting framework provides a clearer and more encompassing picture of the structure of Business Analytics than preceding conceptual models. Nonetheless, the House of Business Analytics is merely based on one setting and has therefore not been widely proven to work well. Therefore its generalizability may be further examined. For example, there could be contextual factors that have not been recognized during this study but which other may find significant. Likewise, some factors that have been found during this study may be deemed insignificant by others. Further exploration and additional applications of the House of Business Analytics would therefore be beneficial to refine and validate the framework.

6.2 Evidence- and intuition-based decision making

This study has claimed that it is of significance for Business Analytics to incorporate naturalistic aspects in its field of study. It could, however, be argued that decisions based on evidence and intuition represent two different dimensions of decision making; that intuition can be the base when there is a need for rapid decisions and evidence for when there is time to collect and analyze data (Liebowitz, 2015). Most researchers do, however, seem to believe that there is a time and a place for both. Kahneman and Klein (2009), for example, assert that expert intuition can be trusted during certain preconditions, and Liebowitz (2015) state that intuition is necessary, even in the era of Big Data, as analytics cannot provide all the answers alone due to limited available time, the presence of too much information, or the fact that data may not be available. These conditions were also encountered during the case study as well. Intuition and experience (Liebowitz, 2015), as well as domain knowledge (Hoerl et al., 2014), seem to be necessary to be able to make the best use of Big Data; for example when it comes to identify and sort out important information - to know what to look for in the great amounts of available data - and to realize which data that is flawed and should not be used, as well as to know what to do when data do not exist on a certain matter. However, it would be interesting with further studies about how to integrate evidence-based and naturalistic approaches to make decisions and gain insights.

7. Conclusion

In this chapter, the conclusions from the study are presented and areas for future research are proposed.

7.1 Conclusion

The purpose of this thesis was to develop a Business Analytics framework for turning data into actionable insights using a case study at Volvo GTT PE. This study has achieved the stated purpose through answering its two research questions, and the answers are summarized below.

Research question 1. How can theory from Business Analytics be used to analyze and improve an organization's analytics structure?

The process for how the theory from Business Analytics was used to analyze, and eventually improve, the analytics framework at Volvo GTT PE is summarized and visualized in Section 5.2 and Figure 5.2 of this report. We believe that this phased-based methodology is generalizable to other organizations and settings as well, and this framework functions as an answer to the first research question. Regardless of the theory and structural framework chosen to conduct an empirical project that concerns Big Data and Business Analytics, both this study and other literature recommend using a phased-based approach, which in this thesis is concretized via this step-by-step procedure for implementing the House of Business Analytics.

Research question 2. In what ways can a practical application of Business Analytics contribute to development of its theory?

During this study, a framework for the structure of Business Analytics has been developed and is presented in Section 5.1.3 and Figure 5.1. This framework has been designated the House of Business Analytics. It incorporates parts from other conceptual models, which were deemed useful during this study. In addition, the developed framework recognizes the significance of experience, intuition, and domain knowledge in generating actionable insights. This is an important contribution to earlier literature on Business Analytics, which mainly focus on the importance of evidence-based decision making and problem recognition and solving.

Another contribution of this study is the basis for categorizing stakeholders' analytics requirements into the six perspectives on Business Analytics, as proposed by Holsapple et al. (2014). This categorization can be found in Section 4.5.2 and Table 4.6 of this report.

In addition, a new definition of Business Analytics is proposed in Section 5.2.2. The new definition is the result of reviewing literature and analyzing empirical results, and was deemed necessary in order to set a suitable base for the developed structural framework of Business Analytics. The proposed new definition is that Business Analytics is:

A structure for providing actionable insights to the right people at the right time.

Lastly, the answer to the first research question can also be viewed as a part of the answer to the second, as it provides a phase-based view of how to practically analyze and improve the analytics structure in organizations, via its step-by-step procedure for implementing the House of Business Analytics.

7.2 Future research

First and foremost, it will be interesting to see how Business Analytics as a field of study will develop in the near future, as it is a relatively new subject with a steadily increasing interest among scholars and practitioners. It would, of course, be interesting to see other research based on the findings of this study, to further develop and refine its contributions. The developed framework and its step-by-step implementation procedure could for example be the basis for further empirical case studies to validate their usefulness.

In addition, it would be interesting to see quantitative studies of for example the six perspectives of Business Analytics, as proposed by Holsapple et al. (2014), and perhaps see it implemented on a larger scale. Firstly, it would be interesting to see how the six perspectives could be quantified, and which possibilities a quantification would generate, in terms of for example highlighting performance gaps and analyzing their alignment. Secondly, this research was focused on a small part of the Volvo Group, with the focus on one specific transforming process; if the scope was to include the entire Group, there would for example be a lot of processes to investigate. Thereby, perhaps, other results would be discovered than this study generated.

Another part of Business Analytics, which would benefit from further research, is how to measure the value of it. Preferably, conceptual models and roadmaps would be developed to work as bases for how to identify and measure the value of analytics. Among other things, this would enable organizations to build business cases for allocating resources to analytics initiatives.

Last, but not least, this study merely provided the beginning of an integration of naturalistic approaches and thinking to Business Analytics. Future studies on the roles of intuition and expertise in Business Analytics, and in evidence-based management in general, will be highly interesting to follow.

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Appendix

Appendix A - Interview guide

Background

This interview will be a part of our thesis work, which goal is to design a business analytics process for LVD here at Volvo. Business analytics is essentially about how to efficiently turn great amounts of data into information and knowledge, that can be used as support for solving and recognizing business problems.

LVD

If you do not know what LVD is - it is Volvo's internal database which gather usage and ambient data from vehicles, and this data are captured when the trucks are serviced at an authorized Volvo workshop. Performance on emission levels and on-board diagnostics are examples of factors that can be evaluated. Hence, this is a way to analyze and follow-up the actual performance of developed and produced engines and other products.

Purpose

The purpose of this interview is to gather information about your current usage and knowledge of LVD data, as well as your ability to use the analysis tool and interpret the information therein. We would also like to collect views and ideas for how you would like this analytics process to work in the future, and hence what possibilities there are in the LVD.

Ethics

If you allow, this interview will be recorded. We cannot promise any anonymity regarding the questions, but you have the opportunity to change any answer in the interview by contacting us within one week after the interview. If anything during the interview seems unclear or needs to be further explained, just let us know.

Interview questions

<u>Action</u>

- Please describe your section
- Please describe your role - what are your main responsibilities?

A movement

- Could you describe how you usually encounter, or are presented with, problems in your work?
    - What role does data and statistics play when you recognize problems?
- Could you describe how you usually solve problems in your work?
    - What role does data and statistics play in your problem-solving process?

<u>Knowledge</u>

A capability set

- How do you use data in your work?
    - Do you have to understand data to perform your work?
    - Do you analyze data yourself?
        - **If yes:**
            - Which sort of infrastructure do you use?
            - Which programs, software etc.
        - **If no:**
            - How comfortable are you with analyzing data?
            - How comfortable are you with working in Excel?

Practices and technologies

- How do you obtain and spread understanding and knowledge from data, in your work and in your department?

A transforming process

- Do you currently use LVD in your work?
    - **If yes:**
        - How do you use it?
        - What do you use it for?
    - **If no**:
        - Why don't you use it?
        - Could you benefit from using it? How?

Specific activities

- How do you *access* (LVD) data today?
    - How would you like to *access* it?
- How do you *analyze* (LVD) data today?
    - How would you like to *analyze* (LVD) data?
- How do you *distribute* your analytical (LVD) data findings to co-workers, managers and/or other departments?
    - How would you like to *distribute* them?

A transforming process

- Which type of **information** (charts, averages etc.) and/or **knowledge** (gained when information is understood) would you like to get from LVD?
    - Which LVD **parameters** are you interested in?
        - Are there any missing, that you would like to access?
    - Which **type of analyses** are you interested in?
        - E.g. longitudinal, which type of stratification etc.
- Which type of decisions would you make based on LVD?

When would you like to receive LVD analysis updates?

- How often?

- At any specific occasions?

Practices and technologies

- Do you trust the LVD?
    - What do you think about the quality of the data?

How do you feel about the current LVD databases used (e.g. MS Excel)?

- Will they suffice in the future?
    - **If no**, what do you suggest for the future?
        - Which sort of infrastructure (such as software) would you like to have for using and analyzing LVD?

Philosophy

Decisional paradigm

- How do you use **evidence** when making decisions in your work?
- How do you use your **experience and/or intuition** when making decisions in your work?

What do you consider most important of these in making decisions and guiding your work?

A movement

- How do you perceive the culture of recognizing and solving problems around you, at Volvo?
    - Is data required by co-workers and managers etc.?
    - If there is a contradiction between a worker's experience and data, how is that handled?

A transforming process

- Going back to LVD, could you summarize how you would like the future LVD process to work?