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EVALUATION OF BIG DATA MATURITY MODELS - A BENCHMARKING STUDY TO SUPPORT BIG DATA MATURITY ASSESSMENT IN ORGANIZATIONS

Master of Science thesis

Examiner: prof. Hannu Kärkkäinen
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ABSTRACT

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Big Data is defined as high volume, high velocity and high variety information assets, a result of the explosive growth of data facilitated by the digitization of our society. Data has always had strategic value, but with Big Data and the new data handling solutions even more value creation opportunities have emerged. Studies have shown that adopting Big Data initiatives in organizations enhance data management and analytical capabilities that ultimately improve competitiveness, productivity as well as financial and operational results. There are differences between organizations in terms of Big Data capabilities, performance and to what effect Big Data can be utilized. To create value from Big Data, organizations must first assess their current situation and find solutions to advance to a higher Big Data capability level, also known as Big Data maturity. Conceptual artefacts called Big Data maturity models have been developed to help in this endeavor. They allow organizations to have their Big Data methods and processes assessed according to best practices. However, it is a tough job for an organization to select the most useful and appropriate model, as there are many available and each one differ in terms of extensiveness, quality, ease of use, and content.

The objective of this research was to evaluate and compare available Big Data maturity models in terms of good practices of maturity modeling and Big Data value creation, ultimately supporting the organizational maturity assessment process. This was done by conducting a benchmarking study that quantitatively evaluated maturity model attributes against specific evaluation criteria. As a result, eight Big Data maturity models were chosen, evaluated and analyzed. The theoretical foundations and concepts of the research were identified through systematical literature reviews. The benchmarking scores suggest that there is great variance between models when examining the good practices of maturity modeling. The degree of addressing Big Data value creation opportunities is more balanced. However, total scores clearly lean towards a specific group of models, identified as top-performers. These top-performers score relatively high in all examined criteria groups and represent currently the most useful Big Data maturity models for organizational Big Data maturity assessment. They demonstrate high quality of model structure, extensiveness and detail level. Authors of these models use a consistent methodology and good practices for design and development activities, and engage in high quality documentation practices. The Big Data maturity models are easy to use, and provide an intuitive tool for assessment as well as sufficient supporting materials to the end user. Lastly, they address all important Big Data capabilities that contribute to the creation of business value.

TIIVISTELMÄ

HENRIK BRAUN: Big Data maturiteettimallien arviointi – Vertailututkimus Big Data maturiteetin arvioinnin tueksi organisaatioissa
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Avainsanat: big data, maturiteettimalli, arvonluonti, vertailu, arviointi

Big Data määritellään suureksi, nopeasti kerätyksi ja järjestelemättömäksi tietomassaksi, jonka syntyä on edistänyt tiedon räjähdysmäinen kasvu ja yhteiskuntamme digitalisaatio. Datalla on aina ollut liiketoiminnallinen arvo, mutta Big Datan myötä on ilmestynyt uusia arvonluontimahdollisuuksia. Tutkimusten mukaan Big Data valmiuksien käyttöönotto organisaatiossa parantaa organisaation tiedonhallintaa ja analyyttisiä ratkaisuja, mikä lopulta johtaa kilpailukyvyn ja tuottavuuden paranemiseen sekä taloudellisten ja toiminnallisten tulosten kohenemiseen. Organisaatioiden välillä on huomattavia eroja Big Data valmiuksien ja niiden hyödyntämisen suhteen. Jotta Big Datasta saataisiin luotua arvoa, organisaatioiden on arvioitava nykytilansa sekä löytää ratkaisuja Big Data valmiuksien eli maturiteettitason nostamiseen. Maturiteettimallit yrittävät tarjota tähän ongelmaan ratkaisun. Ne mahdollistavat organisaation Big Data menetelmien ja prosessien arvioimisen parhaita käytäntöjä vastaan. Organisaatiolla on kuitenkin vaikeaa valita kaikista hyödyllisin ja sopivin malli, sillä niitä on paljon ja jokainen niistä eroaa kattavuuden, laadun, käytettävyyden ja sisällön suhteen.

Tutkimuksen tavoite oli arvioida ja vertailla saatavilla olevia Big Data maturiteettimalleja hyvien maturiteettimallintamiskäytäntöjen ja Big Datan arvonluontimahdollisuuksien suhteen, ja tukea organisaatioiden Big Data maturiteettiarviointiprosessia. Tutkimus oli toteutettu vertailututkimuksena, missä maturiteettimallien ominaisuuksia arvioitiin kvantitatiivisesti tiettyjä kriteereitä vastaan. Tutkimuksen valinta kohdistui lopulta kahdeksaan Big Data maturiteettimalliin, jotka arvioitiin ja analysoitiin. Teoreettinen tausta ja tutkimuksessa käytetyt käsitteet tunnistettiin systemaattisten kirjallisuuskatsausten kautta. Vertailututkimuksen tulokset viittasivat siihen, että tarkasteltujen mallien välillä oli huomattavia eroja maturiteettimallintamisen hyvien käytäntöjen suhteen. Sen sijaan Big Data arvonluontimahdollisuuksia oli huomioitu tasapainoisesti. Kokonaistulokset kuitenkin viittaavat siihen, että eräät mallit suoriutuivat ja ryhmittyivät muita malleja paremmin. Tämän ryhmän mallit suoriutuivat suhteellisen korkeatasoisesti jokaisessa kriteeriryhmässä ja täten edustavat tällä hetkellä hyödyllisimpiä Big Data maturiteettimalleja organisaatioiden Big Data maturiteetin arvioinnin tueksi. Ne osoittavat, että malli on kattava, yksityiskohtainen ja rakennettu korkealaatuisesti. Mallien kehittäjät ovat käyttäneet yhdenmukaisia metodologisia ratkaisuja sekä hyviä kehityksen käytäntöjä, ja ovat dokumentoineet kehitysprosessiaan. Big Data mallit ovat helppokäyttöisiä ja tarjoavat intuitiivisen työkalun sekä ohjeistusta loppukäyttäjälle arviointia varten. Lisäksi, ne ottavat huomioon kaikki tärkeät Big Data ominaisuudet, jotka edistävät liiketoiminnan arvonluontimahdollisuuksia.

PREFACE

I began writing this thesis in September 2014. After nine months of hard work it is finally finished. This Master's thesis marks the end of my 19 year study journey which was overall very enjoyable. Now I can focus on utilizing all the new knowledge in the awaiting work environment.

I would like to thank my supervising professor Hannu Kärkkäinen for his valuable advice and guidance throughout the research process. His insights helped me outline the themes and topics of the research. I would also like to thank my friends and family for supporting me in all endeavors, both academic and personal.

Tampere, 11th of May 2015

Henrik Braun

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LIST OF SYMBOLS AND ABBREVIATIONS

ACID	Atomicity, Consistency, Isolation, Durability
BASE	Basically Available, Soft state, Eventual consistency
BDM	Big Data Management
BI	Business Intelligence
BI/DW	Business Intelligence and Data Warehousing
CAP	Consistency, Availability, Tolerance
CMM	Capability Maturity Model
DSR	Design Science Research
DW	Data Warehouse
GFS	Google File System
HDFS	Hadoop Distributed File System
ICT	Information and Communications Technology
IaaS	Infrastructure as a Service
IoT	Internet of Things
IT	Information Technology
KPA	Key Process Area
NoSQL	Not Only SQL
SaaS	Software as a Service
PaaS	Platform as a Service
RAM	Random Access Memory
QMMG	Quality Management Maturity Grid
SEI	Software Engineering Institute
TDWI	The Data Warehouse Institute

1. INTRODUCTION

Research in general is a "quest for knowledge through diligent search, investigation or experimentation" (WHO 2001, p. 1). Research involves systematic procedures and techniques for obtaining and interpreting new knowledge or resolving debatable existing knowledge (Moeen et al. 2008, p. 145). A thorough research process is delimited by philosophical and strategic assumption that guide in the selection of data collection methods and analysis techniques (Saunders et al. 2009).

The purpose of this Master's thesis is to conduct an academic research to identify the most suitable and useful maturity models for organizational Big Data maturity assessment in terms of extensiveness, quality, ease of use, and business value creation. In this chapter the background and motivation of the research is firstly introduced. Secondly, a look is taken into the research objectives, scope and limitations. Research objectives are transformed into a research problem, and ultimately to a set of research questions. The methodology of the research is also briefly discussed by introducing the research philosophy, approach, strategy, and techniques. This includes the introduction to all utilized frameworks, data collection methods and analysis methods. The last sub-chapter introduces the structure of this research.

1.1 Research background and motivation

Today, organizations are collecting increasing amounts of disparate data. Companies push out a tremendous amount of transactional data, capturing trillions of bytes of information about their customers, suppliers, and operations. They are collecting more than they can manage or analyze, but they also realize that data and data analysis can provide important strategic and competitive advantage. (Manyika et al. 2011, p. 1; Halper & Krishnan 2013, p. 3.) There is a need for better infrastructure, data management, analytics, governance and organizational processes to handle this vast amount of data (Halper & Krishnan 2013, p. 6). These initiatives together are usually referred to as *Big Data*.

Big Data can be viewed as a phenomenon and a buzzword. There is no distinct definition of Big Data and the definition is usually intentionally subjective and incorporates moving elements. The definition can vary by sector, depending on "what kinds of software tools are commonly available and what sizes of datasets are common in a particular industry." (Manyika et al. 2011, p. 1.) According to Goss and Veeramuthu (2013, p. 220), Big Data is "the territory where our existing traditional relational database and file systems processing capacities are exceeded in high transactional volumes, velocity responsiveness, and the quantity and or variety of data." Halper and Krishnan (2013, p. 4) describe Big Data as not only a single technology, but "a combination of old and new technologies that help companies gain actionable insight while effectively managing data load and storage problems." According to Gartner (2014a), Big Data is "high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making."

The organization's Big Data program needs to meet the requirements of collecting, managing and analyzing potentially huge volumes of disparate data, at the right speed, and within the right time frame. Big Data is located in various internal and external sources, and can consist of structured data, unstructured data, streaming data, social media data, geospatial data, and so on. Leveraging all these data sources with success requires Big Data ready infrastructure, data, analytics, organizational structure, and governance. (Halper & Krishnan 2013, p. 4.)

The utilization of Big Data is becoming a key way for companies to outperform their peers (Halper & Krishnan 2013, p. 4). McAfee and Brynjolfsson (2012, p. 64) explored the impact of Big Data and corporate performance, and came to remarkable conclusion:

"The more companies characterized themselves as data-driven, the better they performed on objective measures of financial and operational results. In particular, companies in the top third of their industry in the use of data-driven decision-making were, on average, 5 percent more productive and 6 percent more profitable than their competitors."

Still, organizations confront differences in their ability to utilize Big Data effectively, as seen in their stages of Big Data maturity. These differences range from "adopting Big Data practices for operational improvement in selected functional areas or building or revamping an organization's value proposition to completely transforming their business model based on Big Data." (El-Darwiche et al. 2014, p. 50.) To keep up with the constantly changing business environment and good practices of Big Data, organizations require tools to assess their current state of Big Data adoption and guidelines on how to improve current Big Data capabilities.

Conceptual models called maturity models have been developed to assist organizations in this endeavor. Maturity models are used to "rate capabilities of maturing elements and select appropriate actions to take the elements to a higher level of maturity" (Kohlegger et al. 2009, p. 51). According to Halper and Krishnan (2013, pp. 5-6), maturity models that are designed for the Big Data domain help in creating structure around a Big Data program and determining where to start, identifying and defining the organization's goals around the program, and providing a methodology to measure and monitor the state of the program and the effort needed to complete the current stage, as well as steps to move to the next stage of maturity. However it is a tough job for the company to select the most appropriate maturity model, as there are a lot of options available and each one differ in terms of extensiveness, quality of development and testing, ease of use, and content. Maturity models are also often developed ad hoc without following a consistent development methodology, and may not provide a path way to further extend and update the model to encourage systematic enhancements and extensions (Proenca et al. 2013, p. 1474).

1.2 Research objectives, scope and limitations

The main objective of this research is *to support organizational Big Data maturity assessment by evaluating and comparing available Big Data maturity models in terms of usefulness, good practices of maturity modeling and business value creation*. First, systematical literature reviews are conducted to establish the theoretical foundations, concepts and themes of the research. This includes defining the different ways Big Data creates value as well as the good practices of maturity model development and classification. This information is then used to conduct a benchmarking study of available Big Data maturity models, where model attributes are evaluated quantitatively against predefined criteria. Instead of looking into a subject on too broad of a scale there is a need to narrow down and limit the subject to fit everything relevant into your research (Saaranen-Kauppinen & Puusniekka 2006, pp. 12-13). A Big Data ecosystem and organizational Big Data maturity in this research context is perceived as the collection of the internal Big Data capabilities of an organization, excluding all third party vendor capabilities. Also, the target of the latter systematic literature review is specifically the generic development and classification of maturity models. Here, “development” is referred to the complete lifecycle of a maturity model from early designing activities to the implementation and maintenance of the model. Special emphasis is put on identifying maturity model decision attributes since these are needed for constructing the classification system and benchmarking framework. Furthermore, when evaluating the Big Data maturity models on value creation, a commercial business scope is used shifting the focus off from public non-profit or governmental organizations. The benchmarking is done based on pre-defined criteria that contribute to the extensiveness, quality, and application of maturity model development as well as Big Data business value creation. The benchmarking is limited to only commercial-free available models.

A good research problem is unambiguous, clear and understandable (Saaranen-Kauppinen & Puusniekka 2006, p. 13). The research problem can be modified into the main research question:

> What maturity models are the most useful to organizations for determining and improving Big Data capabilities and ultimately creating business value?

Research questions that support the main question can be shaped into the following sub-questions:

- What is Big Data and what are the characteristics behind it?
- How can organizations utilize and create value from Big Data in their business?

- What are maturity models and the concepts behind them?
- What are the best practices for generic development and classification of maturity models?

- How can maturity models be evaluated and compared effectively?
- What kinds of existing models measure organizational Big Data maturity and what differences are there between them in terms of good practices of maturity modeling and Big Data business value creation?

The first three sub-questions help defining the basic concepts and terminology of the research, namely the concepts of Big Data and maturity models. This is done in the theoretical part of this research in chapters 2 and 3 through analysis of current literature. After establishing a theoretical background the fourth research sub-question, regarding the good practices of maturity modeling, is answered. This is done in a more systematic literature review in chapter 4 by comprehensively reviewing the literature on the topic of maturity model development and classification. Finally, in chapter 5 the last two sub-questions are answered by conducting a benchmarking analysis of available Big Data maturity models. Answering all the sub-questions will ultimately yield an answer to the main research question. Finally, all answers to the research questions are discussed and summarized in chapter 6.

1.3 Research methodology

The term “methodology” refers to the theory of how research should be undertaken (Saunders et al. 2009, p. 3), in other words, what the data consist of and how data was collected, organized, and analyzed (Berg 2004, p. 275). When conducting a research, the possibilities of choices are almost endless (Hirsjärvi et al. 2004). To answer the research questions described above, the ways in which research data is collected and analyzed must be first defined. Saunders et al. (2009, pp. 107-108) propose a metaphorical “research onion”, where the outer layers represent the context and boundaries within which the data collection techniques and analysis procedures (inner layers) will be selected. The research onion is illustrated in figure 1.1.

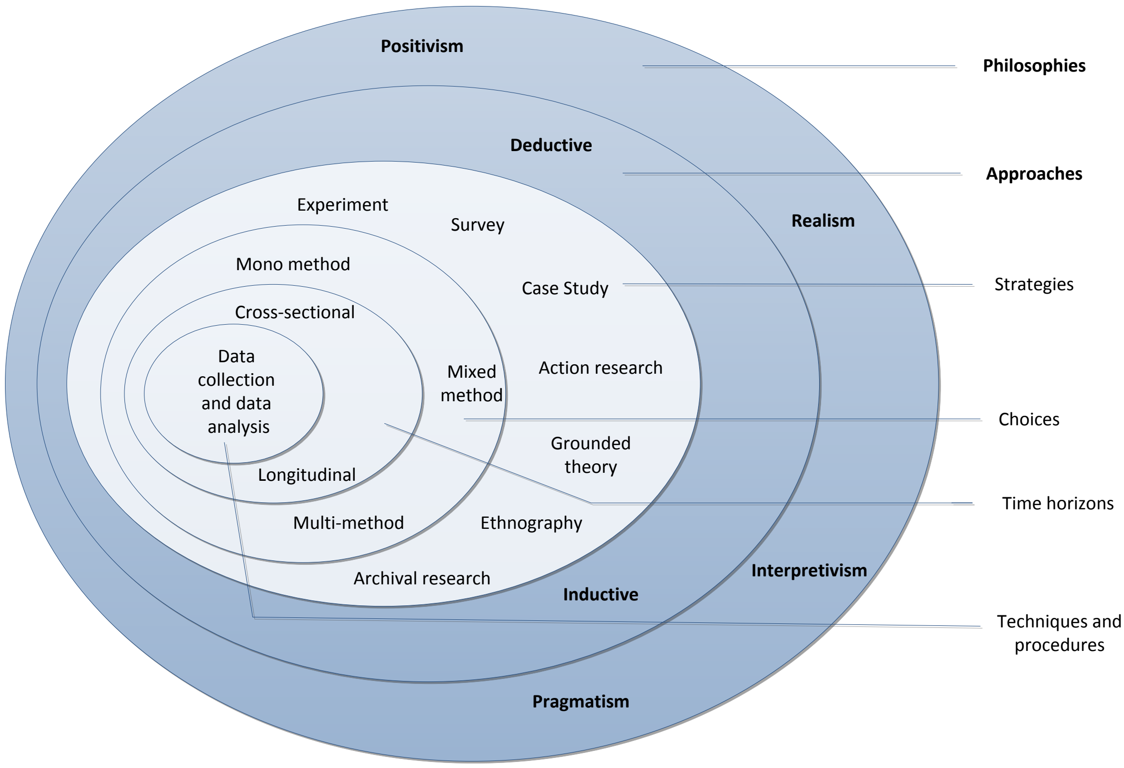

Figure 1.1. *The research onion (adapted from Saunders et al. 2009, p. 108)*

During this sub-chapter, the research onion is peeled open by first defining the research philosophy and approach. These act as a base for selecting the appropriate research strategy and other choices regarding the strategic process. The research strategy finally guides the selection of the data collection and analysis techniques.

1.3.1 Research philosophy and approach

Before a discussion about research philosophical approaches can be held, there is a need to define the conceptions of social reality, namely ontology and epistemology. Ontology is concerned with the nature of reality and existence, and introduces the terms “objectivism” and “subjectivism” (Saunders et al. 2009, p. 110). Objectivism portrays the position that all reality is objective and external to mind, while subjectivism suggest that all reality in the form of knowledge is subjective (Merriam-Webster 2015). Epistemology can be defined as the relationship between the researcher and reality, or how this reality is captured or known (Carson et al. 2001, p 6).

There are two ontological and epistemological ideologies that dominate the field. Based on the philosophical assumptions adopted, research can be classified as positivist and interpretive (Myers 1997). Positivist approaches assume that “reality is objectively given and can be described by measurable properties independent of the observer” (ibid). Positivistic research is likely to use existing theories to develop hypothesis, test, and ultimately confirm them. (Saunders et al. 2009, p. 113.) The positivist researcher will be likely to use a highly structured methodology in order to facilitate replication. Furthermore, the emphasis will be on quantifiable observations and statistical analysis. (Gill & Johnson 2002.) Interpretivism is highly subjective and advocates that there exist multiple instances of a reality. This is due to the assumption that people perceive the reality in different ways. Thus, the goal of interpretivistic research is to understand and interpret the meanings in human behavior rather than to generalize and predict causes and effects. (Carson et al. 2001, p. 6.) A general methodology for interpretation is hermeneutics (Gummesson 2003, p. 484). Ricoeur (1981, p. 43) defines hermeneutics as the theory of the operations of understanding their relation to the interpretation of texts. In other words, hermeneutics focuses on the meaning of qualitative textual data. Hermeneutics is often used in a business setting to understand the people and textual documents behind an organization (Myers 2008).

There are two main research approaches: deduction and induction. With deduction, a hypothesis (or hypotheses) is developed and a research strategy designed to test the hypothesis. With induction, empirical data is collected and a theory developed as a result of the data analysis. (Saunders et al. 2009, p. 129.) The purpose of the research approach is the overall plan for connecting the conceptual research problem to the relevant and practicable empirical research (Ghauri & Grønhaug 2005, p. 56). The classification of research purpose most often used in the research methods' literature is the threefold one of exploratory, descriptive and explanatory (Saunders et al. 2009, p. 139). An exploratory study is a valuable means of finding out "what is happening; to seek new insights; to ask questions and to assess phenomena in a new light" (Robson 2002, p. 59). It is particularly useful if one wishes "to clarify your understanding of a problem, such as if one is unsure of the precise nature of the problem" (Saunders et al. 2009, p. 139). The object of descriptive research is "to portray an accurate profile of persons, events or situations" (Robson 2002, p. 59). This means that the problem is well understood and highly structured. The term explanatory research advocates that "the research in questions is intended to explain, rather than simply to describe, the phenomena studied" (Maxwell & Mittapalli 2008).

This research is mainly defined as deductive-descriptive using hermeneutics as a philosophical approach. Maturity model development concepts and decisions, as well as benchmarking criteria are identified through the interpretation and description of academic research papers. The concepts found in the academic papers act as the theoretical foundation for the research, resulting in a deductive approach. Positivistic features are introduced in the research part when conducting the quantitative benchmarking process. The benchmarking process consists of assigning numeric values to different model attributes against pre-defined weighted criteria, and is thus highly replicable.

1.3.2 Research strategy

After defining the key concepts of the research onion's outer layer (figure 1.1), the process of choosing the appropriate research strategy can begin. There are many different ways to interpret the term "research strategy" (Lähdesmäki et al. 2014) and no research strategy is inherently superior or inferior to any other (Saunders et al. 2009, p. 141). A well balanced definition is proposed by The University of Reading (2006), defining it as "the activity that needs to be undertaken to ensure that there are adequate resources available to complete the study in the time available, to make sure that the approach to the design of the study is the appropriate one to achieve the study's objectives, that suitable software are available to manage and analyze the data, and that sensible sets of data are collected to ensure that analysis will allow the required information to be extracted."

It is common to divide research strategies into quantitative and qualitative. Quantitative research is an empirical research where the data is in the form of numbers (Punch 2004). Quantitative research methods employ statistical tools in the collection and interpretation of data. Their emphasis on systematic statistical analysis helps to ensure that findings and interpretations are healthy and robust (Devine 2002). Comparatively, qualitative research is a method of "a non-statistical form of inquiry, techniques and processes employed to gather data through the understanding of an event, circumstance, or phenomenon under study" (McNabb 2004, p. 104). In the qualitative perspective, "detailed knowledge of a given setting is sought through unstructured or semi structured data collection from a small number of sources" (Denzin & Lincoln 2011).

Kasanen et al. (1991, p. 317) propose a classification system for strategic research approaches, illustrated with a four by four matrix in figure 1.2. A research is often categorized into either a theoretical or an empirical research, based on ways information is being gathered. A distinction is also made between descriptive or normative approach, regarding the ways the collected data is used. These two categories act as the two axes of the research strategy matrix, in which Kasanen et al. introduce five distinct research approaches, namely the conceptual approach, decision-oriented approach, nomothetical (positivistic) approach, action-oriented (hermeneutic) approach and constructive approach.

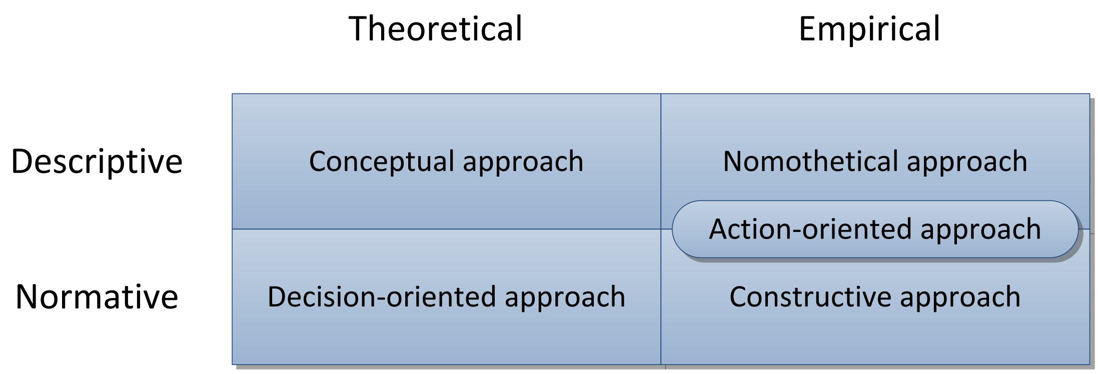

Figure 1.2. *Classifications of research strategies (adapted from Kasanen et al. 1991, p. 317)*

The data for this research is not intended to be collected by means of observation or experimentation, and thus empirical evidence is absent. Furthermore, a normative approach is eliminated since no practical improvement measures are being planned. In the light of these facts, this research can be classified as descriptive-theoretical with a conceptual approach. The purpose of the conceptual approach is to produce new knowledge through the method of reasoning, analysis, synthesis and comparison of data (Lukka 2001). The conceptual approach acts here as the qualitative research strategy, which guides in choosing the appropriate data collection and analysis methods, discussed next.

1.3.3 Data collection and analysis techniques

For obtaining the right information, the ways data is being collected and analyzed must be first defined. It is necessary to develop a thorough understanding of previous research that relates to one's research questions and objectives. This can be achieved with a critical literature review, a process where literature sources are referenced, and key points are drawn out and presented to the reader in a logical manner (Saunders et al. 2009, p. 98). There is no one correct structure for a literature review and many approaches are available. However, Booth et al. (2012) argue that all literature reviews should be somewhat systematic. They mainly differ in "the degree to which they are systematic and how explicitly their methods are reported" (ibid). In a highly structured systematic literature review the processes of selecting the sources, constructing a search query, and applying screening criteria, are well documented. This results in an objective and transparent review which can be reproduced if necessary. (CRD 2009, p. 16.)

Literature reviews are common for a conceptual approach (Neilimo & Näsi 1980), and thus are used here in two different situations. Firstly, in defining the key concepts of this research including business value creation criteria for benchmarking, and secondly, in identifying the best practices of developing and classifying maturity models. The latter review is conducted more systematically and utilizes Fink's (2005) systematic literature review approach, discussed more specifically in chapter 4.1. After analysis and synthesis of the systematic review results, the data is used to construct a benchmarking framework for evaluating Big Data maturity models. The benchmarking framework is based on the proposal of Vezzetti et al. (2014), where maturity model attributes are evaluated quantitatively against pre-defined criteria. The numeric results can ultimately be presented visually by using radar charts. In order to control quality and maximize meaningfulness, only available and referenced models were used as input for the benchmarking process. The benchmarking process is discussed in more detail in chapter 5.2.

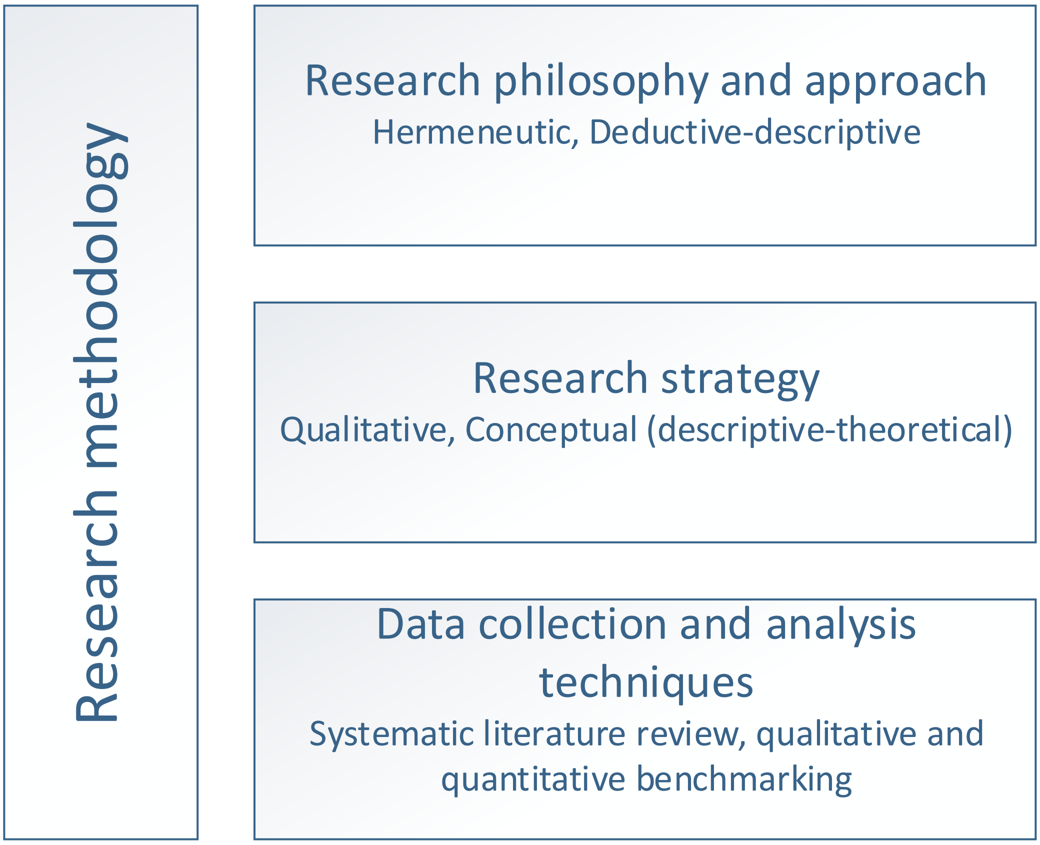

Figure 1.3. *Summary of the research methodology*

By combining several lines of sight, researchers obtain "a better, more substantive picture of reality; a richer, more complete array of symbols and theoretical concepts; and a means of verifying many of these elements" (Berg 2004, p. 4). The use of multiple lines of sight is frequently called triangulation (Tuomi & Sarajärvi 2002, p. 141). Triangulation is used in a few instances during this research, including in combining theoretical point of views in the systematic literature review, and in combining quantitative and qualitative techniques during the evaluation of Big Data maturity models. The overall research methodology for this research is summarized in figure 1.3.

1.4 Research structure

This research is conducted deductively by first establishing a theoretical background and then utilizing this information to collect and analyze data as well as form conclusions on the basis of the results. Thus, the research follows a chronological path starting with establishing a theoretical foundation through systematic literature views and then utilizing this information to collect and analyze Big Data maturity model data as well as form conclusions based on the results. The first literature review defines the general concepts of Big Data and maturity models while the second one defines maturity model development concepts in more detail. The latter one is also seen as more systematic.

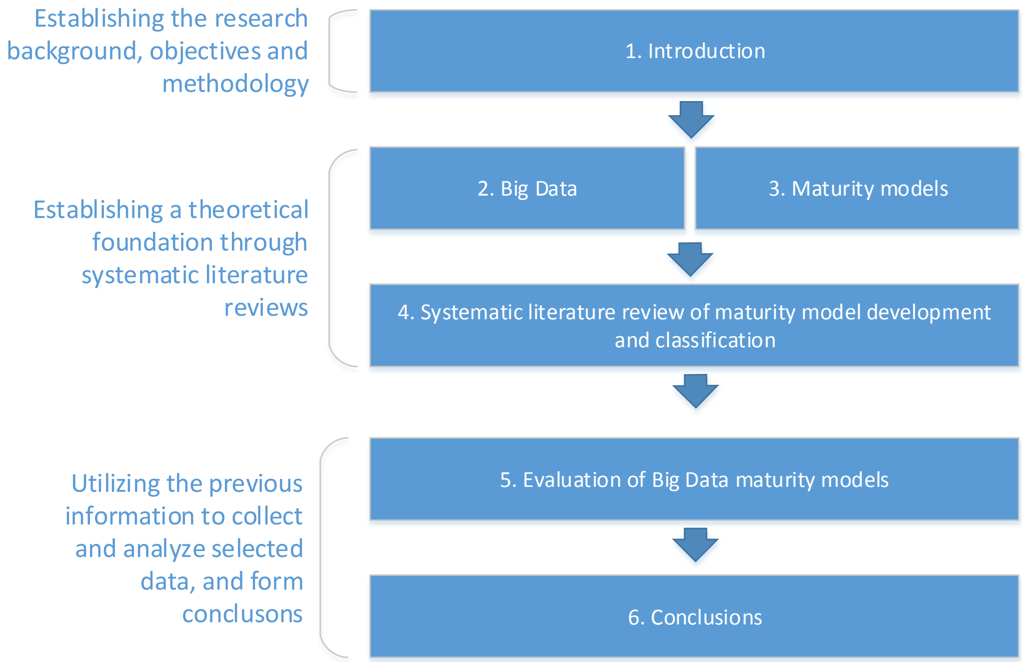

Figure 1.4. *The research structure*

As seen in the figure 1.4, the research is structured into six main chapters. The introduction chapter presents information related to the background and purpose of this research, summing up the research methodology. The second and third chapters act as the theoretical background and provide an overview of the concepts related to the research topic, namely concepts of Big Data and maturity models. Chapter 2 also identifies several Big Data domain capabilities, used later on as evaluation criteria for the evaluation process. In chapter 4, a systematic literature review is performed to identify best practices and decisions for developing and classifying maturity models. The data obtained from the systematic literature review is used for comparative purposes in chapter 5, where selected Big Data maturity models are evaluated through a benchmarking process. The evaluation consists of first selecting the Big Data maturity models, validating them through a benchmarking framework, and analyzing the results. The final chapter 6 concludes the research by summarizing all the key findings obtained during the whole research process and by answering the research questions.

2. BIG DATA

Big Data can be described as “high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making” (Gartner 2014a). The term Big Data emerged a few years ago and has since then gained a lot of attention and interest among the business community. Big Data has been called a phenomenon and even an ICT revolution. Manyika et al. (2011) approach Big Data by describing it as “the next frontier for innovation, competition, and productivity.” Big Data, as of July 2014, has passed the top peak of Gartner’s hype cycle meaning that markets are maturing, and implementing Big Data initiatives in organizations is becoming business as usual (DSSR 2014). The Big Data market has been claimed to exceed 7.9 billion euros in 2013 alone, growing on an annual rate of 30% (Alanko & Salo 2013, p. 4).

Devlin et al. (2012) argue that Big Data has evolved in two key directions: technology and business. First, due to the nature of Big Data being very complex and large in size, emphasis has to be put on new technological implications. These include improved processing speed, new ways of data structuring, and intelligent software applications. Second, the business perspective of Big Data is how it can support different business cases with well executed analytics, data management and data governance. To achieve a holistic view of Big Data, one must understand how business and technology issues interrelate. (Devlin et al. 2012, pp. 3-6.)

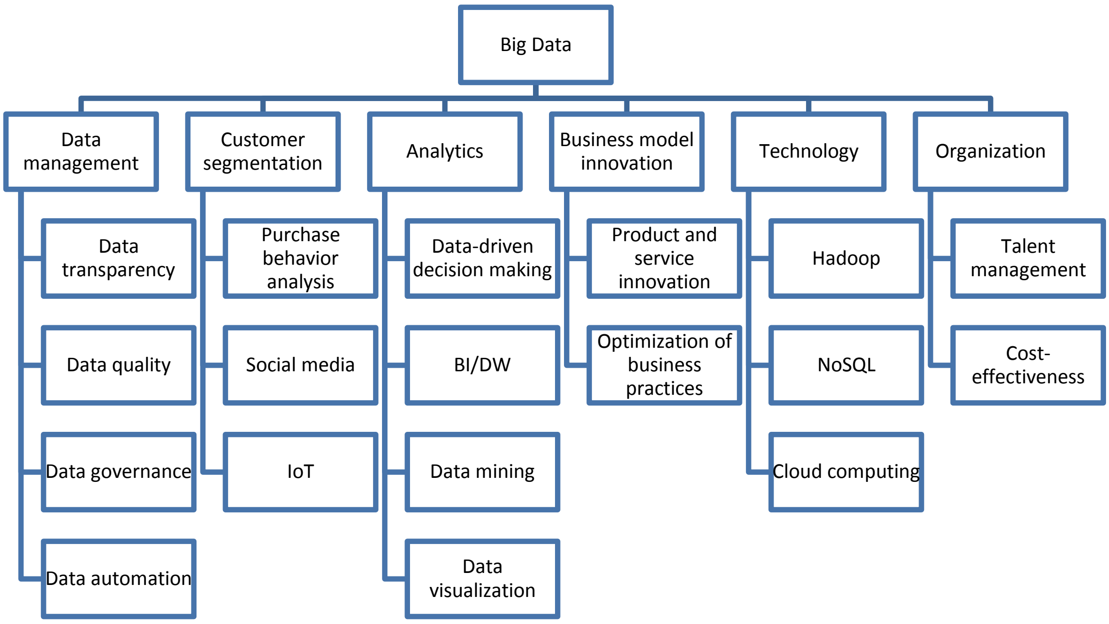

Figure 2.1. *Big Data domain capabilities*

In this chapter, a comprehensive examination of the Big Data concept is conducted. In chapter 2.1, Big Data is defined based on current literature and particularly on the attributes of the 3V framework, namely volume, velocity and variety. In chapter 2.2, a look is taken into the different technologies that have emerged alongside Big Data, in particular NoSQL databases, the Hadoop ecosystem and cloud applications. After clearing up the technical aspects of Big Data, a discussion is held in chapter 2.3 about how to capture value from it. This is done by investigating four key areas, including data transparency, customer segmentation, data-driven analytics, and business model innovation. Finally in chapter 2.4, after establishing a holistic view of Big Data and its benefits, a look is taken at the challenges that come with implementing Big Data initiatives. Big Data domain capabilities addressed during this chapter are summarized in figure 2.1.

2.1 The three V's of Big Data

The definition of data as a term is ambiguous and there are currently many definitions and interpretations available in literature. Webster's dictionary defines data as "facts or information used usually to calculate, analyze, or plan something" (Merriam-Webster.com 2015). The derivative of data, namely Big Data, is a concept arising from "the explosive growth in data led on by the continued digitization of society" (IRIS Group 2013, p. 2). Prescott (2014, p. 573) captures Big Data's main features by defining it as "the collection, storage, management, linkage, and analysis of very large and complex data sets." Davenport (2014, p. 45) adds to the definition by stating that Big Data requires vast computing power and smart algorithms to analyze the variety of digital streams. International management consultancies link the term specifically to automated processes like collection and analysis of data (Fox & Do 2013, p. 741). El-Darwiche et al. (2014, p. 3) go even further by arguing that Big Data represents the aspirations to establish and improve data-driven decision making in organizations.

A popular way is to characterize Big Data into three main aspects to distinguish it from traditional data processing and analytics. These aspects are called the three V's, volume, variety and velocity, first introduced by Laney (2001). The famous three V's of Big Data (illustrated in figure 2.2) have become ubiquitous and occur frequently in current Big Data literature (see McAfee & Brynjolfsson 2012, pp. 62-63; Alanko & Salo 2013, p. 3; Fox & Do 2013, p. 742; El-Darwiche et al. 2014, p. 43). Using the three 3V framework, Big Data can be defined as information management and processing activities involving data of high volume, high variety, and high velocity (Fox & Do 2013, p. 742).

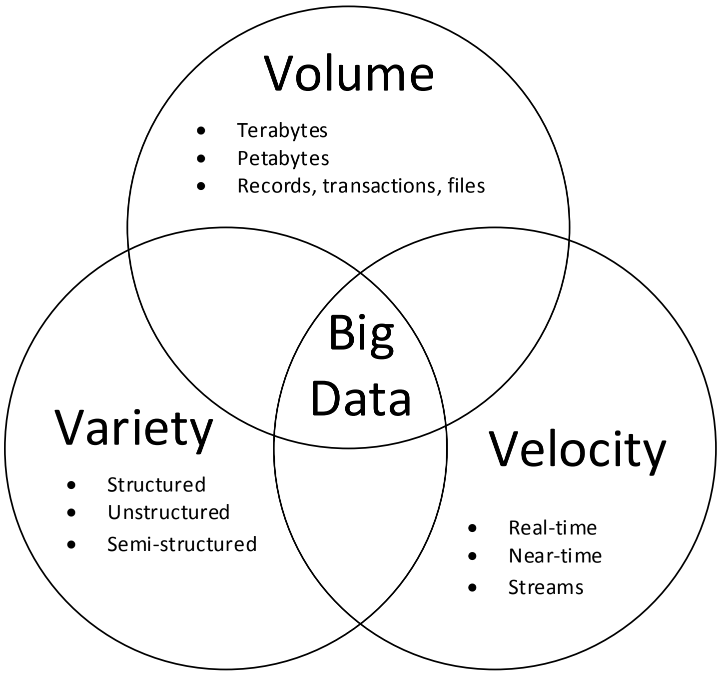

Figure 2.2. *The three V's of Big Data and their characteristics (adapted from Russom 2011, p. 7)*

The amount of data in the world estimated today has exceeded approximately five zettabytes (10^{21} bytes) (Alanko & Salo 2013, p. 3). As of 2012, 2.5 exabytes of data has been created daily and the number has been doubling every 40 months or so (McAfee & Brynjolfsson 2012, p. 62). The growth of data is illustrated in figure 2.3. The fast growth of the internet and rapid evolution of data capturing devices and sensors have contributed in the generation of a tremendous amount of digital data which can also contain excessive "exhaust data" (Manyika et al. 2011, p. 1). **Volume** refers to the large scale or amount of data which can enable the creation of new insights but requires infrastructure to manage it (Zikopoulos et al. 2011, pp. 5-6). Russom (2011, p. 6) argues that volume is the defining primary attribute of Big Data. Big Data is usually described in dozens of terabytes and multiple petabytes of data in an organization. However, Manyika et al. (2011, p. 1) think that Big Data can't be defined in terms of being larger than a certain number of bytes. Corporate analysts tend to describe their data warehouse not in bytes but in billions of records, transactions or files, and also take the time dimension into account (Russom 2011, p. 6).

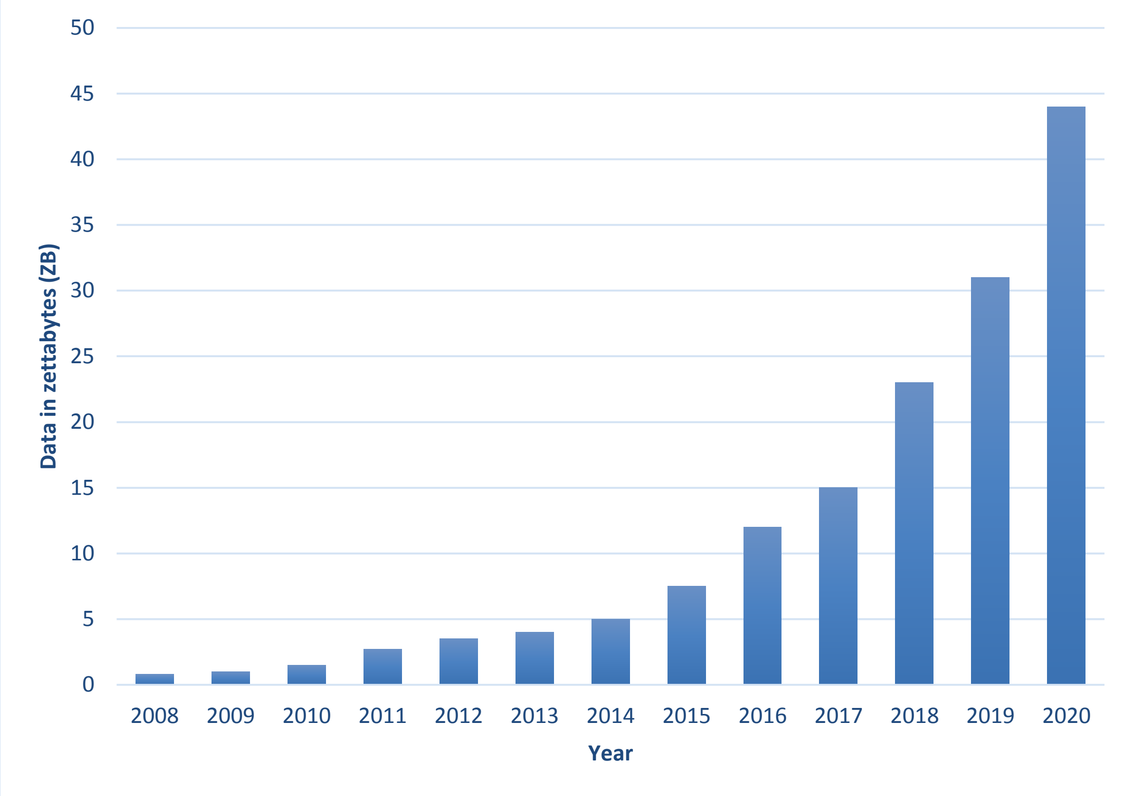

Figure 2.3. *Estimated annual growth of data (adapted from Ciobo et al. 2013, p. 2)*

Velocity refers to the rate at which data may enter the organization (Sagiroglu & Sinanc 2013, p. 43). As the amount of devices, sensors and digitizing interfaces for data increase, this data is now real time or near real time, requiring an increased rate of response (Williams et al. 2014, p. 312). In many cases applications can view the velocity or speed of data creation as more important than the volume of data (McAfee & Brynjolfsson 2012, p. 63). The velocity dimension shifts the data into a continuous flow of information rather than discrete packages of data (Williams et al. 2014, pp. 312-313). Big Data tries to overcome the major challenges of connecting fast flowing data streams, capturing and recording the valuable information, and analyzing it intelligently (Alanko & Salo 2013, p. 4).

Variety refers to "the heterogeneous nature of Big Data, with a mix of structured, quantified data and unstructured data that is difficult to incorporate into traditional organizational databases" (Chen et al. 2012 in Williams et al. 2014, p. 312). Devlin et al. (2012, p. 7) identify that there are three domains of information, namely human-sourced information, process-mediated data and machine-generated data. All three of these domains produce different forms of information from different types of sources. Human-sourced information can be gathered from people, it is highly subjective, and stored loosely structured in several of digitized formats. Process-mediated data is data collected from business processes events. Process-mediated data is highly structured and includes transactions, reference tables, relationships and metadata. Machine-generated data is structured data collected from different devices, sensors and computers. Machine-generated data is generated through a computational agent independently without human actions in between. (Devlin et al. 2012, pp. 6-7.) Many of the most important sources of Big Data are relatively new and produce human-sourced data in unstructured format. These sources include smartphones, sensors and social networks that collect social media data, mobile applications data and online gaming data. (McAfee & Brynjolfsson 2012, p. 63; Hashem et al. 2015, p. 100). In a 2012 Big Data survey, responses show that human-sourced information accounts for nearly half of the sources of Big Data (Devlin et al. 2012, p. 8). Unlike structured data, unstructured data is challenging to store in traditional data warehouses due to the nature of it not residing in fixed fields (Manyika et al. 2011, p. 33; El-Darwiche et al. 2014, p. 3).

Additional V's have been added by others to extend the definition of Big Data. Recently the popular candidates for the fourth V attribute have been both veracity and value. Veracity refers to the uncertainty of data, and value to the discovery of hidden insights in large datasets. (Alanko & Salo 2013, p. 4.) Other elements that have been recognized by companies are viability, variability, validity, virality, viscosity and vulnerability. There are frameworks that use up to 10 V-attributes in their definition of Big Data. Robinson (2012) finds that these additions are consequential and do not contribute to the fundamental definition. Grimes (2013) goes a step further by calling the additional elements misleading "wanna-V's" that just add to the confusion. Devlin et al. (2012, p. 4) also point out their skepticism by arguing that the additional dimensions are "qualitative in nature and limited only by the imagination of their promoters." Inconsistency between different vendor's definitions does not help understanding the main concept of the phenomenon. The essential part is that the original 3V framework represents the main challenges of Big Data the best. The additional V's are a reminder that when working to overcome Big Data challenges, many other aspects are present as well.

2.2 Big Data technologies

Big Data is in the territory where existing traditional storage systems start having difficulties storing and managing the data (Hashem et al. 2015, p. 106). The data is too big, moves too fast and doesn't fit the structures of the relational database management systems. To create value from this vast amount of complex data, technological solutions have been developed to address these data processing issues (Goss & Veeramuthu 2013, p. 220; Hashem et al. 2015, p. 106). McAfee & Brynjolfsson (2012, p. 66) conclude that technology is always a necessary component of a company's Big Data strategy.

There are a growing number of technologies used to aggregate, manipulate, manage and analyze Big Data (Manyika et al. 2011, p. 31). In this sub-chapter the most prominent technologies have been listed. Frist, NoSQL databases and the new ways of storing unstructured data are examined. Afterwards, a brief investigation is conducted about the Hadoop ecosystem and all the components associated with it. Finally, a discussion is held about the relation of Big Data to cloud computing.

2.2.1 NoSQL databases

Horizontal scalability is the ability to add multiple hardware and software resources, and making them work as a single unit (Banerjee et al. 2012, p. 3). Horizontal scalability is important because it provides high capacity for databases to perform their operations. However, traditional database systems, or relational systems, have little or no ability to scale well horizontally (Cattell 2010, p. 1). Padhy et al. (2011 in Moniruzzaman & Hossain 2013, p. 3) argue that the main limitations with relational systems are that they do not scale well with Data warehousing, Grid, Web 2.0 and Cloud application, all connected with Big Data. New database systems have been designed to address this scalability issue and to meet the heavy demands of Big Data. The high-scalable databases got quickly associated with a new term called **NoSQL**, or commonly referred to as "Not Only SQL" or “Not Relational” (Cattell 2010, p. 1). As illustrated in figure 2.4, NoSQL databases have the capabilities to maintain high performance when processing high volume data, while relational databases tend to fall off quickly.

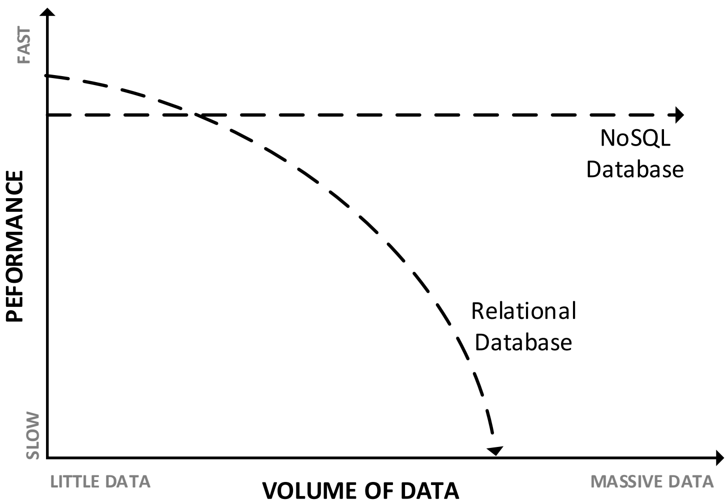

Figure 2.4. *Scalability of NoSQL databases vs. traditional relational databases (adapted from Lo 2014)*

NoSQL represents “a completely different framework of databases that allows for high-performance, agile processing of information at massive scale. The efficiency of

NoSQL can be achieved because NoSQL databases are unstructured in nature, trading off stringent consistency requirements for speed and agility.” (Lo 2014.) NoSQL systems use non-traditional storing mechanisms with each system having their own unique architecture and design. They usually operate with non-SQL languages (Moniruzzaman & Hossain 2013, p. 1). A NoSQL solution is attractive for organizations because they can handle huge quantities of data, relatively fast and across a high-scalable platform (Moniruzzaman & Hossain 2013, p. 8).

NoSQL store systems can be categorized according to the different functional and structural characteristics. A popular way is to classify NoSQL stores into key-value, wide-column, graph or document storage systems (Devlin et al. 2012, p. 11; Moniruzzaman & Hossain 2013, p. 4; Russom 2013, p. 30). These four NoSQL database type classifications are described in detail in Moniruzzaman and Hossain (2013) and summarized in table 2.1.

Table 2.1. *Classifications of NoSQL store system types (adapted from Moniruzzaman & Hossain 2013, pp. 4-8)*

Type	***Description***	***Examples***
Key-value	Key-value systems store values and an index to find them, based on a programmer defined key. Key-value systems are suitable for lightning-fast, highly-scalable retrieval of values needed for application tasks such as retrieving product names or managing profile data.	Dynamo, Voldemort, Riak
Document	Document store systems are able to store more complex data than key-value systems by supporting the management and storage of multiple types of object formats in a semi-structured manner. Primarily used for storing and managing Big Data-size collections of literal documents.	MongoDB, CouchDB
Wide-column	Wide-column stores use a distributed and column-oriented data structure mostly patterned after BigTable, Google’s high performance data storage system. These systems tend to build their platform by incorporating BigTable related mechanisms like a distributed file system and a parallel processing framework (see chapter 2.2.2). Useful for distributed data storage, large-scale data processing, and exploratory and predictive analytics.	BigTable, HBase, Hypertable, Cassandra, SimpleDB, DynamoDB
Graph	A graph database replaces relational tables with graphs, which are interconnected key-value pairings. Graph stores are human-friendly and focus on the visual representation of information. Valuable in identifying relationships between data and used in social networking or forensic investigation cases.	Neo4j, InfoGrid, Sones, GraphDB, AllegroGraph,

Major Internet companies like Google (BigTable), Amazon (Dynamo) and Facebook (Cassandra) contributed in the development of NoSQL systems by providing "proof of concept" systems that inspired many of the data stores described above (Cattell 2010, p. 1). Most of NoSQL systems are released as open-source and use cheap commodity servers, which give organizations a price advantage over commercial systems (Moniruzzaman & Hossain 2013, p. 8). A NoSQL system also does not require expensive database administrators for its design, installation and ongoing tuning since the system supports automatic repair and data distribution (Sekar & Elango 2014, p. 632).

According to Cattell (2010, p. 1), other key features of NoSQL systems are that they replicate and distribute data over a server cluster, they have a simple usable interface, they use efficient indexing and RAM for data storage and are not compatible with the integrity model ACID. ACID (Atomicity, Consistency, Isolation, Durability) refers to four properties that guarantee the reliability and integrity of database transactions (Sekar & Elango 2014, p. 631). The problem with ACID and NoSQL is that the systems have limited guarantees on the consistency of read operations while scaling across multiple servers (Cattell 2010, p. 1). Some authors have proposed an alternative to ACID and are using the acronym BASE, standing for Basically Available, Soft-state and Eventual consistency. BASE is often connected with Eric Brewer's CAP theorem. The CAP theorem states that from the three properties, namely consistency, availability and tolerance to network partitioning, database systems can only achieve two at the same time. Most NoSQL systems have loosened up the requirements on consistency in order to achieve better availability and partitioning. (Moniruzzaman & Hossain 2013, p. 4.)

Cattell (2010, p. 13) has predicted that NoSQL systems will maintain a strong niche position in the data storage domain and one or two systems will likely become the leaders of each NoSQL category. However, NoSQL databases are still far from advanced database technologies and they will not replace traditional relational DBMS (Pokorny 2013, p. 80). The NoSQL solutions are too undeveloped to be "enterprise ready" and they lack the robustness, functionality, familiarity, support and maturity of database products that have been around for decades (Cattell 2010, p. 13; Sekar & Elango 2014, p. 632). Sekar and Elango (2014, p. 632) add to this list of limitations by pointing out that installing and maintaining NoSQL systems require a lot of effort and a high expertise level.

There have also been the sightings of so called "NewSQL" systems. NewSQL systems support "scalability and flexibility promised by NoSQL while retaining the support for SQL queries and ACID" (Aslett 2011, p. 1). Systems that support SQL-like querying are already familiar to business users and thus do not require a steep learning curve. NewSQL systems handle data processing on multi-core multi-disk CPUs, in-memory databases, distributed databases and horizontally scaled databases (Cattell 2010, p. 13). The term in-memory database refers to a system where the data is queried from the computer's memory rather from physical disks (Russom 2011, p. 27). In-memory analytics allow for real-time responses from a database by eliminating the need for indexing and timely disk input/output actions (Goss & Veeramuthu 2013, p. 224). In-memory capabilities are used in the Business Intelligence domain for real-time reporting and dashboarding (Russom 2011, p. 27).

2.2.2 Hadoop and MapReduce

Hadoop is an open-source software project that "allows for the distributed processing of large data sets across clusters of computers using simple programming models" (Hadoop 2014). Developed by Apache, a decentralized community of developers supporting open software, it got its inspiration from Google's distributed file system GFS and MapReduce (Alanko & Salo 2013, p. 7). The computer clusters in Hadoop are a group of inexpensive commodity servers that allow the Hadoop library to detect and handle failures at the application layer, rather than relying on high-availability delivery through expensive hardware (McAfee & Brynjolfsson 2012, p. 64). It must be understood that Hadoop is not a type of database, but rather a software ecosystem that supports parallel computing (Lo 2014). In addition to the distributed file system, Hadoop also provides tools for analyzing the data. The original Hadoop consisted of the primary components Hadoop Distributed File System and Hadoop MapReduce. New iterations of Hadoop have since emerged, opening up a wealth of new possibilities. An improved version MapReduce, MR2, is now running on top of Hadoop YARN, a framework for job scheduling and cluster resource management (Cloudera 2014; Hadoop 2014).

Hadoop Distributed File System (HDFS) is "a file system that spans all the nodes in a Hadoop cluster for data storage. It links together the file systems on many local nodes to make them into one big file system" (IBM 2014). In other words, it provides fast high performance access to application data (Hadoop 2014). HDFS differs from other file systems by storing metadata and application data separately (Shvachko et al. 2010, p. 1). Metadata, containing attributes such as access time, modification and permissions, is stored in a node called a namenode or "master." The content of the namenode is split into large blocks that are independently replicated across nodes called datanodes or "slaves" containing application data. The namenode actively monitors the numbers of replicas and makes sure that information isn't lost due to a datanode failure. (Hashem et al. 2015, p. 107).

MapReduce is "a system for easily writing applications which process vast amounts of data (multi-terabyte datasets) in-parallel on large clusters (thousands of nodes) of commodity hardware in a reliable, fault-tolerant manner" (Hadoop 2014). In other words, the main task of MapReduce is to take intensive data processes and spread the computational load across the Hadoop cluster (Lo 2014). The MapReduce functionality has been credited for changing the game in supporting the enormous processing needs of Big Data (ibid). MapReduce in actuality contains two separate and distinct procedures that Hadoop performs, namely Map() and Reduce(). The Map() tasks allow different points of the distributed cluster to distribute their work and Reduce() tasks are designed to reduce the final from of the cluster's results into one output (Janssen 2014). MapReduce tasks are governed by the Hadoop framework that takes care of all the scheduling, monitoring and machine failure related tasks (Hadoop 2014). The following have been presented as advantages of using MapReduce functionality: simplicity, scalability, speed, built-in recovery, minimal data motion, and freedom to focus on the business logic (Lee et al. 2012, p. 13; Hortonworks 2014). However, based on the research of Lee et al. (2012, p. 11), MapReduce has inherent limitations on its performance and efficiency. Lee et al. argue that MapReduce is unlikely to substitute database management systems for data warehousing, but it can complement the existing solutions with scalable and flexible parallel processing.

A variety of related open source projects have emerged around Hadoop to support the activities of systems management, analysis and query function (Devlin et al. 2012, p. 4). Cloudera (Awadallah 2009), one of the leading Hadoop providers and supporters, describes the Hadoop ecosystem and the relations of the components as illustrated in figure 2.5. The ecosystem, in addition to the core components HDFS and MapReduce, consists of the following:

- **Avro** serializes data, conducts remote procedure calls, and passes data from one program or language to another.
- **HBase** is a columnar NoSQL store and a management system providing fast read/ write access.
- **Hive** is a data warehouse system built on top of HDFS that provides support for SQL. Hive uses its own query language called HiveQL.
- The **Pig** framework generates a high-level scripting language called Pig Latin and operates a run-time platform that enables users to execute MapReduce on Hadoop.
- **Sqoop** is a tool designed for efficiently transferring bulk data between Hadoop and structured data stores such as relational databases.
- **ZooKeeper** maintains, configures, and names large amounts of data. It also provides distributed synchronization across a cluster.

(Khan et al. 2014, pp. 5-6)

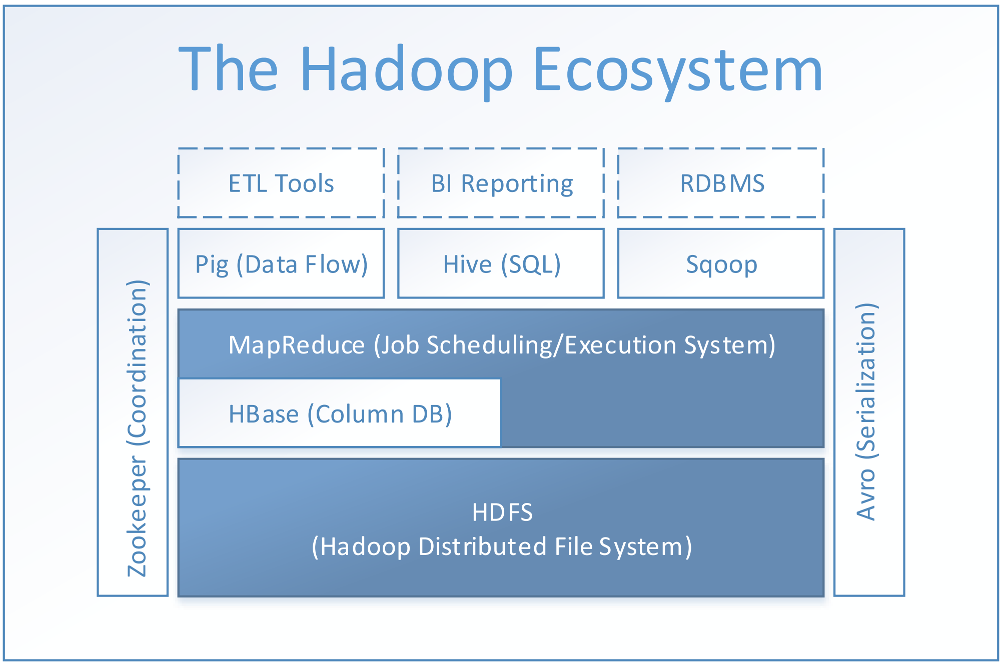

Figure 2.5. *The Hadoop ecosystem (adapted from Awadallah 2009)*

Hadoop has become synonymous with Big Data (Devlin et al. 2012, p. 4) and is the commonly known Big Data technology (Alanko & Salo 2013, p. 7; McAfee & Brynjolfsson 2012, p. 66). According to the Big Data survey of Russom (2011, p. 16), Hadoop has a respectable presence in companies and is already in use by 24% of the survey respondents. However, it is suspected that these are mostly experimental use cases and thus it's difficult to say whether Hadoop usage will evolve into a permanent presence in IT (ibid). In the Big Data study of Devlin et al. (2012, p. 38) Hadoop like programmatic data environments existed in 22% of the organizations. Hadoop is widely used in industrial applications including spam filtering, network searching, click-stream analysis, and social recommendation (Khan et al. 2014, p. 6).

Despite the hype about Hadoop, relational systems are still the most popular Big Data stores among organizations according to Devlin et al. (2012, p. 38). Hadoop and MapReduce have their own limitations and according to Hashem et al. (2015, p. 112), they lack query processing strategies, and have low-level infrastructures with respect to data processing and management. Big Data environments in organizations are thus usually built on top of hybrid solutions that make use of both traditional SQL-based environments and new Big Data technologies (Rastas & Asp 2014, p. 27; Russom 2014, p. 34). A Hadoop centric architecture is not likely to benefit an organization, since it requires too much of calibration, integration with existing systems, and massive testing. A more probable alternative is to use Hadoop as part of an existing architecture. (Alanko & Salo 2013, p. 7.) This has been backed up by studies of Russom (2014). Russom's findings indicate, that DW teams implement Hadoop solutions to improve their enterprise DW in data staging, data archiving, handling multi-structured data and flexible processing.

2.2.3 Big Data in the cloud

Cloud computing is a successful paradigm of service oriented computing and has revolutionized the way computing infrastructure is used today (Agrawal et al. 2011). The National Institute of Standards and Technology NIST defines cloud computing as “a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction” (Mell & Grance 2011, p. 2). In other words, cloud computing allows organizations to access reliable software, hardware and infrastructure delivered over the Internet and remote data centers (Armbrust et al. 2010 in Hashem et al. 2015, p. 101). The cloud architecture can perform very large-scale data storing, processing and analyzing tasks which have led to a wide adaptation in organizations (Huan 2013 in Hashem et al. 2015, p. 101).

Mell and Grance (2011, p. 2) suggest that the cloud model is composed of five essential characteristics, three service models, and four deployment models. These are illustrated in figure 2.6 below.

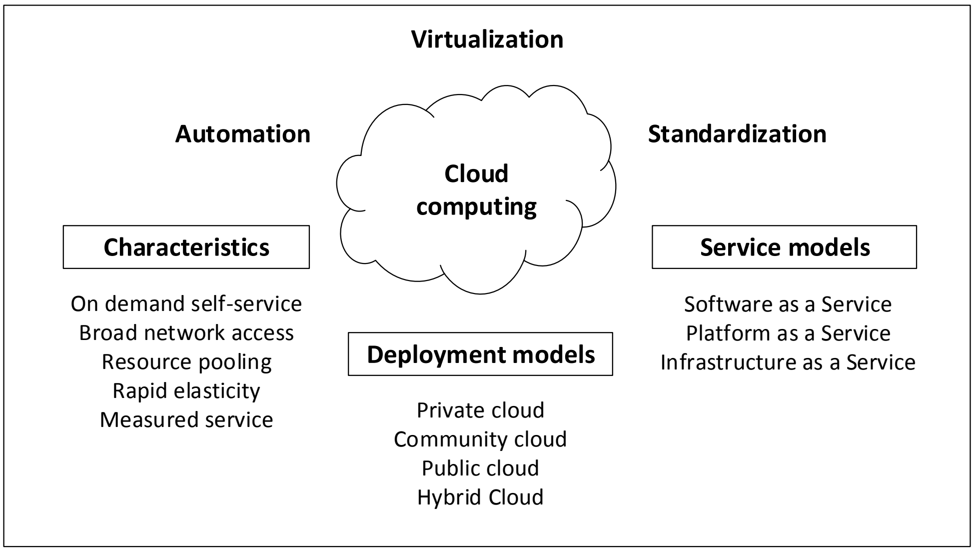

Figure 2.6. *The components of a cloud computing (adapted from Schouten 2014)*

The essential characteristics of cloud computing can be described as the following:

- **On-demand self-service** lets the consumer provision cloud resources whenever they are required automatically without human-interaction to the service provider.
- **Broad network access** allows access to cloud resources from a wide range of devices.

- **Resource pooling** is used to describe a situation where computing resources are pooled to serve multiple consumers using different physical and virtual resources without any apparent changes to the end user.
- **Rapid elasticity** is the ability to provide high scalable services
- **Measured service** is the measurement and monitoring of resource usage to control and optimize resource distribution.

(Mell & Grance 2011, p. 2)

Organizations utilize the cloud technology “as a service” and can thereby focus on their core business without worrying about setting up and maintaining the cloud components. Mell and Grance (2011, p. 2) have found out three typical cloud service models:

- **Software as a Service** or **SaaS** provides the consumer with applications that run on cloud infrastructure. The applications can be accessed through thin clients such as web browsers or a program interface. In SaaS, the consumer has no control over deployed infrastructure or the applications in the cloud.
- **Platform as a Service** or **PaaS** provides the consumer a platform to deploy and use consumer-created applications created using programming languages and other supported tools. The consumer has control over deployed applications and some hosting configuration settings but not over the underlying cloud infrastructure.
- **Infrastructure as a Service** or **IaaS** provides virtualized hardware and components so that the consumer can build his own IT platform including operating systems and applications. The consumer has control of all the virtualized hardware but not the underlying physical infrastructure.

(Mell & Grance 2011, p. 2)

Cloud services can be “deployed in different ways depending on the organizational structure and the provisioning location” (Kandawal 2014). Mell and Grance (2011, p. 2) categorize the deployment models into the four following:

- **Private cloud** is cloud infrastructure deployed for exclusive use by a single organization that consists of multiple consumers or business users. The private cloud can be owned and managed by the organization, a third party or a combination of the two. The private cloud can be located either on or off the organization premises.
- **Community cloud** is cloud infrastructure intended to be used by a community of consumers from an organization that have shared concerns. The community cloud can be owned and managed by one of the organization, a third party or a combination of them. The community cloud can be located either on or off the organization premises.

- **Public cloud** is cloud infrastructure intended for open use by the general public. The public cloud can be owned by a business, academic, or government organization, or a combination of them. The public cloud exists on the premises of the provider.
- **Hybrid cloud** is a composition of the infrastructures described in the deployment models above. The infrastructures are connected together by standardized technology that enables data and application portability. However, the hybrid cloud can still be viewed as a unique entity with high-end resource management.

(Mell & Grance 2011, p. 2)

Surveys of The Data Warehouse Institute have consistently shown that BI/DW professionals prefer private clouds over public ones. This is mostly due to paranoia over data security and governance. It is also common to first experiment with analytic tools and databases on a public cloud and to then transfer them to a private cloud. (Russom 2011, p. 29.)

Cloud computing and Big Data are strongly connected. Cloud computing (eg. the Hadoop ecosystem) provides the underlying infrastructure that can serve as an effective platform to address Big Data related issues (volume, velocity, variety) and perform Big Data analytics in a timely manner. Big Data utilizes distributed storage technology based on cloud computing rather than local storage. (Hashem et al. 2015, pp. 102-103.) A good example of Big Data processing in a cloud environment is MapReduce. MapReduce accelerates “the processing of large amounts of data in a cloud and thus is the preferred computational model of cloud providers” (Dean & Ghemawat 2008 in Hashem et al. 2015, p. 103). Big Data cloud providers include famous names like Google, Microsoft, Amazon and Cloudera. According to Hashem et al. (2015, p. 109), research on Big Data in the cloud still remains in early stages and the main challenges of Big Data in cloud computing are related to scalability, availability, data integrity, transformation, data quality, heterogeneity, privacy, legal issues and governance.

2.3 Capturing value from Big Data

Data has always had strategic value, but when working in the Big Data realm it has become a new form of asset class offering complete new opportunities (Bilbao-Osorio et al. 2014; Davenport 2014, p. 45). These opportunities can benefit not only the corporate world but also the public sector (Beardsley et al. 2014, p. 73; Rastas & Asp 2014, p. 8), and scientific disciplines including atmospheric science, astronomy, medicine, biology, genomics and biogeochemistry (Khan et al. 2014, p. 5). However, organizations that have already been dealing with large data sources will be early benefiters (Villars et al. 2011, p. 5).

According to the Big Data survey of Russom (2011, p. 12) the vast majority of business organizations and its business users consider Big Data more of an opportunity than a problem. Beyer et al. (2011 in Fox & Do 2013, p. 742) claim, that those organizations that adopt Big Data initiatives into their information management strategies by 2015 will "begin to outperform their competitors within their industry sectors by 20 percent in every available financial metric". This is backed up by studies of McAfee and Brynjolfsson (2012, p. 64) who state that "the more companies characterized themselves as data-driven, the better they performed on objective measures of financial and operational results". The study also found out that "data-driven organizations were, on average, 5% more productive and 6% more profitable than their competitors." In a 2011 report the McKinsey Global Institute (Manyika et al. 2011, p. 2) suggests that Big Data may lead to an increase in profit margins by as much as 60 percent in retail. Furthermore, the 2010 IBM Global CFO Study (Gartenberg 2011) showed that "companies that excel at finance efficiency and have more mature business analytics and optimization outperform their peers, with 49% higher revenue growth, 20 times more profit growth, and 30% higher return on invested capital."

In the light of this evidence it can be said without a doubt, that adopting Big Data into ones business has positive implications. Forward-thinking leaders that implement a full spectrum of Big Data capabilities will gain competitive advantage, while others will be left behind. However, the different ways of capturing value from Big Data must be first discovered and understood.

There are many ways that Big Data can be used to create value (Manyika et al. 2011, p. 2). Villars et al. (2011, p. 6) argue, that the ultimate value of Big Data implementations will be judged based on one or more of three criteria, namely usefulness, fidelity and timeliness, complementing the three Vs of Big Data (see chapter 2.1). Herodotou et al. (2011, p. 261) continue by adding cost-effectiveness to these criteria. Furthermore, Ciobo et al. (2013) identify three profitable and sustainable growth areas, namely customer intimacy, product innovation, and operations. However, this chapter utilizes the proposal of Beardsley et al. (2014), where Big Data is generally acknowledged to create value in four main ways. It creates **data transparency** through proper data management, making high-quality data available in a timely manner. It helps organizations with **customer segmentation** and creating new customer offerings by tailoring products and services. It helps to improve the decision-making process for a variety of business users through **data-driven analytics.** And it enables companies to innovate completely **new business models**, areas, products and services. (Beardsley et al. 2014, p. 73.) These value-creation ways will be discussed in more detail in the following sections.

2.3.1 Data transparency through proper data management

Rastas and Asp (2014, p. 9) present a value chain for utilizing data to its full potential. The value of the data increases when moving through the stages of data generation, data storing, data analysis, and data usage. The data value chain is similar to the data life cycle, proposed by Khan et al. (2014, p. 8), where the stages consist of collecting, filtering and classification, data analysis, storing, sharing and publishing, and data retrieval and discovery. Both of the models present the main idea that through various stages, raw data eventually transforms into valuable insight. The general value chain for data is proposed by Gustafson and Fink (2013) and illustrated in figure 2.7. Big Data heavily influences the data value chain and the data life cycle and makes significant improvements to all the stages.

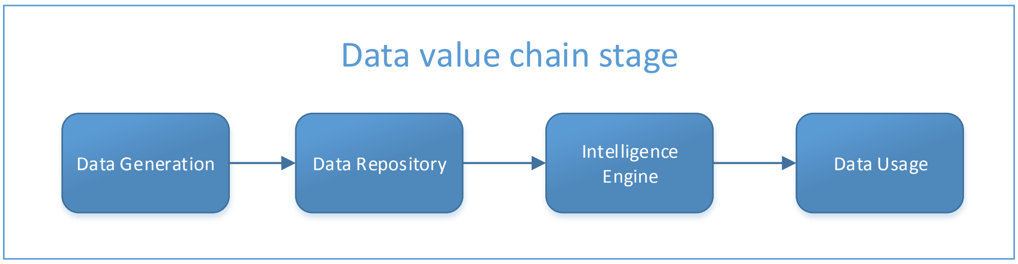

Figure 2.7. *The data value chain (adapted from Gustafson & Fink 2013)*

Data becomes valuable only after proper data management (Alanko & Salo 2013, p. 4). Data management is "the development, execution and supervision of plans, policies, programs and practices that control, protect, deliver and enhance the value of data and information assets" (Mosley 2007, p. 4). The responsibility of data management within an organization usually belongs to data management professionals and data stewards (Mosley 2007, p. 4). Bain and Company (Wegner & Sinha 2013, p. 1) suggest that successful data management is the right mix of four elements, namely data, people, tools, and intent. Firstly, data should be of high quality, consistent, reliable, available and easily accessible (Khan et al. 2014, p. 5). The concept is also known as data transparency. Manyika et al. (2011, p. 5) define data transparency as "making data easily accessible to relevant users in a timely manner." Open transparent data in organizations enables concurrent engineering, reduces time to market, and improves the quality of the product or service (ibid). Secondly, data should be handled by data-driven people with expertise in various areas. The data management team consists of data scientists, business analysts and technical specialists, which all play an important role in the data management environment. Data scientists provide data insights with statistical methods and business analysts turn these insights into relevant business information. The technical specialists deploy and maintain the hardware and software solutions needed for processing all this data. Thirdly, state-of-the-art data management tools, such as database administration tools, should be used to help in this endeavor. And finally, organizations should be built around data. The organizational intent should be data-driven with clearly defined data management strategies. (Wegner & Sinha 2013, p. 1.)

The emergence of Big Data has lead organizations to extend their data management skills by bringing together both old and new data management technologies and practices, resulting in Big Data Management (BDM) (Russom 2013, p. 4). There are many technological options for managing Big Data, including top trends Hadoop and NoSQL (see chapter 2.2). BDM can meet the requirements of growing data volume, variety and velocity, and enable advanced analytics and data discovery for generating valuable insights (Russom 2013, p. 7). BDM must not only be conducted on a technology level, but also on a business level so that it supports organizational business goals (Russom 2013, p. 13). The overall goal for BDM is to maintain a large data store in its original form, with little or no alteration (Russom 2013, p. 22). Russom (2013, p. 11) predicts that BDM will grow into a majority practice within the next few years.

BDM includes a number of data disciplines. The DAMA institute (Mosley 2013) argues that those areas include data architecture, data modeling, data storage, data security, data integration, content management, reference and master data management, business intelligence and data warehousing, meta-data management, and data quality. According to Russom (2013, p. 137), data governance, Business Intelligence and Data Warehousing management, and data quality management have the strongest involvement with BDM.

The functional area binding all other data management areas together is data governance. Data governance embodies “the exercise of control and authority over data-related rules of law, transparency, and accountabilities of individuals and information systems to achieve business objectives” (Malik 2013 in Hashem et al. 2015, p. 112). In other words, data governance ensures that the data is formally managed, and that data can be trusted, through different policies relating to optimization, privacy, and monetization of data (Soares 2012, p. 6). Managing Big Data requires a rigorous data governance structure (Gupta 2014, p. 88). Big Data governance covers IT as well as business functions at an enterprise level and it is critical for obtaining maximum business benefit from the collected data (Venkatasubramanian 2013, p. 2). Venkatasubramanian (2013, p. 4) identifies key areas that should be addressed in governing the Big Data environment:

1. **Enterprise data assets:** A complete documented directory of all data assets in the enterprise.
2. **Unambiguous owner:** Ownership of a particular data asset.
3. **Data characteristics:** Assigning and defining data characteristics including accuracy, accessibility, consistency, completeness and update.
4. **Housekeeping:** Storing, archiving and backing up data.
5. **Preventing data leakage:** Control mechanism to prevent data leakage.
6. **Data handling procedures:** Procedures for handling data by authorized users.
7. **Audit procedure for data:** Procedures to monitor and manage the ongoing data governance process

(Venkatasubramanian 2013, p. 4)

Business Intelligence includes “the applications, infrastructure and tools, and best practices that enable access to and analysis of information to improve and optimize decisions and performance” (Gartner 2014b), while data warehousing is "the process of taking data from legacy and transaction database systems and transforming it into organized information in a user-friendly format” and to encourage the BI related activities (Kimball & Caserta 2004, p. 22). Therefore, Business Intelligence and Data Warehousing (BI/DW) management can be defined as an activity to enable access to decision support data for reporting and analysis. This includes all the planning, implementation and control activities to store, protect and access data found within electronic files and physical records. (Mosley 2013.) In today’s BI/DW environment, architectural changes are mostly made to provide a better platform for Big Data, advanced analytics and real-time operations (Russom 2014, p. 8).

A quality perspective in data management is critical (Wang et al. 1995 p. 349). There are many ways how the quality of data is defined. One is the definition of Eppler (2014), who describes data quality as “the fitness for use of information.” In other words, the higher the data quality, the better it meets the requirements of the user (ibid.). Wang et al. (1995, p. 350) identify four main attributes for data quality, namely accessibility, interpretability, usefulness, and credibility. Data quality management can thus be defined as business processes that ensure these attributes during the stages of the data value chain (data generation, storage, analysis and usage). Data quality management is the basis of a working Big Data information system network and ensures the quality of information for Big Data applications and analytics (Oracle 2009).

In data management, reacting quickly to occurring events is crucial, since data tends to lose its value over time. Hackathorn (2004, p. 3) has proposed a value-time curve to illustrate the decreasing value of data over time as it passes through stages of use (figure 2.8). The longer it takes for organizations to respond to a new business event, the less value they can extract from it. In the era of Big Data, growing volume, velocity and variety of data affects the value-time curve immensely as organizations have difficulties to capture and analyze real-time data in a more complex environment.

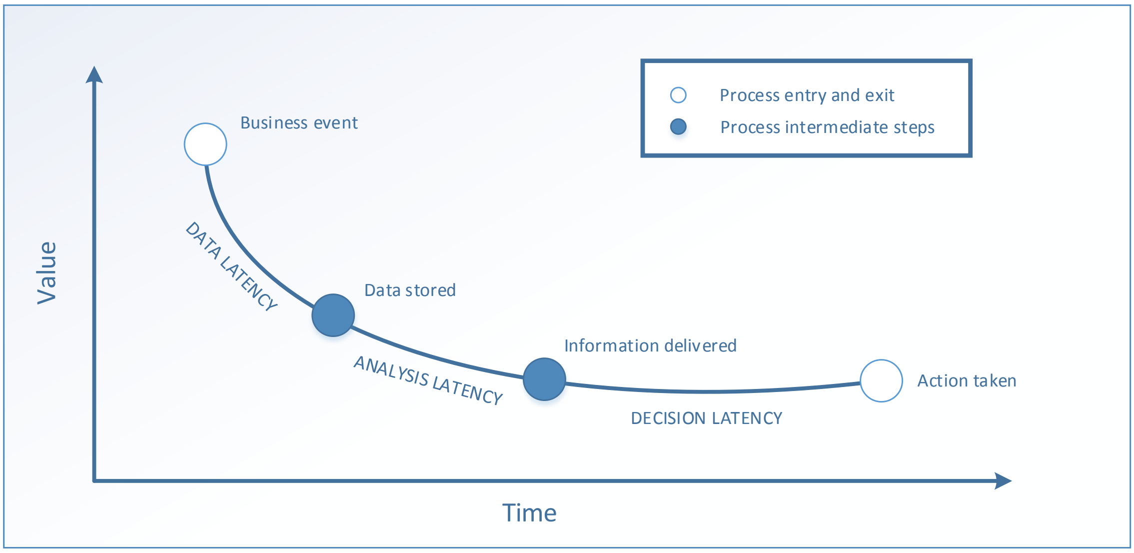

Figure 2.8. *The value-time curve for data (adapted from Hackathorn 2004, p. 3)*

The value-time challenge can be overcome by implementing automation to organizational data management whenever possible. Due to the hectic Big Data environment, humans can no longer compete against machines with real-time processing capabilities. Automating data management tasks results in managing data more quickly and more effectively, at the same time opening up human resources. Automation is especially well suited to “the complexity of predicting and anticipating events.” (Quinn & Taylor 2014, p. 62-63.)

2.3.2 Customer segmentation and new offerings

Customer segmentation is the premise of every marketing organization. It gives companies “an understanding of the most attractive segments, including their size, profitability, and growth potential”, ultimately resulting in competitive advantage. However, traditional methods are not efficient anymore to describe the modern customer and his behavior in existing markets. (Million 2014.) Fortunately, the explosion of Big Data and its technological advances aid in today’s segmentation endeavor and open up complete new approaches. According to Biehn (2013), the contribution of executives, sales managers, marketers and pricings experts is needed to determine what insights are valuable and of benefit to the company. Million (2014) talks about *Segmentation 2.0*, a new way to gain insight from Big Data by dividing customers into small micro-segments. Big Data assisted micro-segmentation utilizes statistical data analysis and methods to group customers into similar buckets (Biehn 2013), and allows for organizations to identify certain customer characteristics, such as attitude and behavior (Million 2014). This enables better targeting of content, offerings, products and services, all through finer promotion and advertising (Manyika et al. 2011, p. 6; Delgado 2014; Million 2014). Targeted campaigns effectively serve the needs of individuals and eliminate the need to come up with a general advertising slogan. Analyzing the purchase behavior, organizations can determine which customer segments are likely to buy a product, either at launch or at a specific seasonal time. (Delgado 2014.)

Today's customer is more and more connected via online and social-media. Million (2014) identifies three new types of Big Data sources, including activity-based data, social networking profile data, and social influence data. Activity-based data is information such as web site tracking information, purchase histories and mobile data. Social networking profile data include the customer's work history and group membership, while social influence data includes all the social media likes, follows, comments, and reviews. When the sources for micro-segmentation are identified, the real value can be extracted through leveraging these sources. (Million 2014.) Information gathered through social media can be used to identify potential new customers or help maintain the loyalty of existing customers. For example, transactional data can be correlated with social media data, resulting in possibilities of special promotions towards individual consumers (Datameer 2014). Million (2014) describes real-world cases of successful Big Data assisted segmentation across many industries, including telecom, retail, manufacturing, healthcare and finance. Customer segmentation is closely guided by Big Data analytics, which is discussed next.

2.3.3 Improved decision making with data-driven analytics

The primary purpose of traditional small data analytics is to support internal business decisions. Analytics have since evolved into executive support, online analytical processing, Business Intelligence and now into **Big Data analytics**. (Davenport 2014, pp. 45-46.) Big Data analytics are the act of translating data into intelligence and business advantage, and differ from traditional analytics by focusing on the analysis of high data volume, data velocity and data variety (McAfee & Brynjolfsson 2012, p. 62). Big Data analytics can thus reveal new insights previously hidden due to the restrictions of traditional data systems (Goss & Veeramuthu 2013, p. 222). Russom (2011) favors the term "discovery analytics", since the business user ultimately tries to discover new business facts previously unknown to the organization, and calls it "the primary path" to gain business value (Russom 2011, p. 5; Russom 2013, p. 7). Furthermore, Big Data analytics can be seen as a driver of process and performance improvement (IBM 2013, p. 3).

Big Data analytics improve and support the decision making process of an organization (Manyika et al. 2011, p. 6; McAfee & Brynjolfsson 2012, p. 66; Alanko & Salo 2013; Khan et al. 2014, p. 5) and enables managers to decide on the basis of evidence rather than intuition (McAfee & Brynjolfsson 2012, p. 63). Data-driven decision making can be thus seen as the usage of scenarios and simulations that provide "immediate guidance on the best actions to take when disruptions occur" (LaValle et al. 2011, p. 22). Supported decision making is rather augmented than fully automated, still requiring impact from the business user (Manyika et al. 2011, p. 5).

According to Fan and Liu (2013 in Khan et al. 2014, p. 10), analyzing data with Big Data analytics has two main objectives: to understand the relationships among features, and to develop methods of data mining that can predict future observations. Data mining has been widely accepted as means of extracting potentially valuable information from large, incomplete, fuzzy and noisy datasets (ibid). Data mining uses methods of association rule learning, cluster analysis, classification and regression (Manyika et al. 2011, p. 28). The general rule is that “the larger the data sample, the more accurate are the statistics and other products of the analysis” (Russom 2011, p. 9). Techniques for analyzing large datasets, in addition to data mining, include data visualization, statistical analysis, and machine learning (Manyika et al 2011, p. 28). Data visualization attempts to present the information in such a way that target users can consume it effectively and understandably. Visualizing data will become increasingly valuable through transforming data into information that can be used immediately, versus having to rely on further time consuming interpretation (LaValle et al. 2011, p. 23).

There are generally three models of Big Data analytics, namely descriptive, predictive and prescriptive (figure 2.9). The purpose of **descriptive analytics** is to “look at past performance and understand that performance by mining historical data to look for the reasons behind past success or failure” (Oracle 2012). It is the simplest and most popular class of analytics, and it simply summarizes “what” has happened (Bertolucci 2013). Descriptive analytics are limited in their predictive abilities, resulting in the development of more predictive models (Oracle 2012). **Predictive analytics** “utilize a variety of statistical, modeling, data mining, and machine learning techniques to study recent and historical data, thereby allowing analyst to make predictions about the future” (Bertolucci 2013). It is important to understand, that predictive analytics only forecast what might happen, since future events are always uncertain. The most advanced model of analytics is **prescriptive analytics** that combines the previous two models, taking advantage of the data of descriptive models and the hypotheses of predictive models (Oracle 2012). According to Cutts (2014), prescriptive analytics involve “not only predicting the probability of future outcomes, but also automatically taking action based upon predicted outcomes.” This information helps decision makers see the possible consequences of those decisions available, and taking the right course of action (Bertolucci 2013).

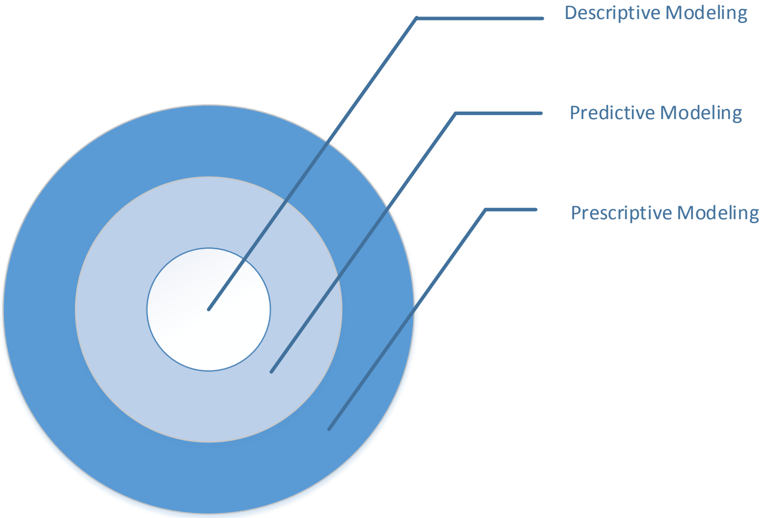

Figure 2.9. *Three models of Big Data analytics (adapted from Oracle 2012)*

According to the study of Russom (2011), three key benefits in using Big Data analytics could be identified. Firstly, business users felt that Big Data analytics could massively improve anything involving customer interaction. This includes better-targeted social-influencer marketing, customer-base segmentation, recognition of sales and market opportunities, and analysis of customer behavior. Secondly, Big Data supports the organizations' Business Intelligence functions. Big Data and Business Intelligence together create business insights, drive appropriate business changes, improve planning, reporting and forecasting processes, and identify the root cause of cost. Finally, Big Data improves other analytical areas such as fraud detection, risk management and market trends. (Russom 2011, pp. 10-11.)

2.3.4 New innovative business models, products and services

According to Hartmann et al. (2014, p. 5), Big Data provides value creation opportunities in two key ways: by providing information for innovating new business models, products and services, and by improving and optimizing current business practices. Both value creation ways are linked closely to the term data-drivenness, meaning that the practice relies on data as a key resource (Hartmann et al. 2014, p. 6). Andrade et al. (2014, p. 85) talk about data-driven innovation, which improves business efficiency and creates new revenue opportunities by linking together product innovation and exploiting new data sources. One form of data-driven innovation is data-driven business development (Devlin et al. 2012, p. 5). The Danish Business Association (IRIS Group 2014, p. 5) defines data-driven business model development as a platform, compelled by data, for "how to market the enterprise, how to carry out product development or how to best service customers." Hartmann et al. (2014, p. 6) argue that data-driven business development is not only limited to companies conducting analytics, but also includes companies that focus on the collection and processing of data.

One vital driver for data-driven business development is development of new business models, also seen as the highest level of organizational maturity. The development of business models includes both the optimization of existing models and creation of completely new models (Manyika et al. 2011, p. 5; Andrade et al. 2014, p. 81; IRIS Group 2014, p. 8). There are many ways Big Data can be used to create data-centric business models, one of them being the sale of data to other organizations (Ciobo et al. 2013; Hartman et al. 2014, p. 5). The data can be either internal data from existing or self-generated data sources, or external data that is publicly available or customer provided. A new service model *Data-as-a-service* has been proposed to “aggregate and provide access to a wide range of public and private data by partnering with data providers, aggregators, and clients” (Hartmann et al. 2014 p. 5). However, a company may sell not just the data, but also new products and services that rely on that data. A second emerging business model *Analytics-as-a-service* utilizes Big Data and provides “business intelligence reporting, text analytics, and advanced analytics such as predictive modeling, all made in composable forms to allow for direct consumption, integration and customization” (ibid). New data-centric business models improve competitiveness by increasing sales and profitability, operational efficiency, and risk management procedures (Radcliffe 2014, p. 5). A data-driven business model may even establish a completely new enterprise, providing job opportunities for data scientists and technical specialists.

Big Data is also used for incremental improvement and optimization of organizational business practices and services. Business improvement can happen through process optimization, customer relationship management, process innovation, and collaboration of employees. (Hartmann et al. 2014, p. 6.) Improving business practices and generating new business models is facilitated by the trends of Big Data. Big Data has greatly affected the Internet’s evolution and has created the “Internet of Things”, a network of physical objects that can communicate internally or with the external environment (Gartner 2014c), and also influenced by the increasing migration of many social activities on the web (Andrade et al. 2014, p. 81). Social media information can be thus used rapidly for developing better products and services by eg. analyzing the customer feedback data (IRIS Group 2014, p. 10). Data obtained from the use of actual products is helpful for developing the next generation of products simultaneously creating innovative service offerings (Manyika et al. 2011, p. 6). Identifying dissatisfied customers and improving the quality of product and service ultimately affects the overall customer satisfaction (Davenport 2014, p. 47).

2.4 Challenges of implementing Big Data initiatives

In contrast to Big Data opportunities, a great number of challenges can be identified when implementing Big Data initiatives within an organization. Barriers to Big Data adoption are generally managerial and cultural rather than technological (LaValle et al. 2011, p. 21; Villars et al. 2011, p. 7; McAfee & Brynjolfsson 2012, p. 68). Based on relevant literature, key areas where Big Data adoption faces major challenges have been identified. These include the lack of both business and technical professionals, and data privacy and security concerns.

Big Data applications create pressure for organizations to understand the new technologies. A significant constraint on creating value from Big Data will thus be the shortage of talent and the lack of Big Data professionals (Russom 2011, p. 12; Alanko & Salo 2013, p. 9; Andrade et al. 2014, p. 85; Gupta 2014, p. 88). New Big Data technologies do require a skillset that IT departments do not necessarily possess, which makes integrating all the relevant internal and external sources of data a challenge. (McAfee & Brynjolfsson 2012, p. 66.) Manyika et al. (2011, p. 10) argue that organizations need people with deep expertise in statistics and machine learning, and managers and analysts who can utilize Big Data with a highly analytical approach. However, this type of talent is hard to produce, taking years of training. According to the study of Russom (2013, p. 10), a total of 40 percent of the respondents find that their organization is having insufficient staffing and data management skills. Another critical aspect of Big Data is how decisions are made and who gets to make them. An issue arises with the lack of executive level talent, meaning that organizational leaders do not understand or know how to make the right decisions and how to unlock the value in Big Data (Manyika et al. 2011, p. 12). Gupta (2014, p. 89) argues, that it is virtually impossible to deliver value from Big Data if business leaders do not have a data-driven mindset. There are a number of genuinely data-driven senior executives, but McAfee and Brynjolfsson (2012, pp. 65-66) believe that these people generally rely too much on experience and intuition and not enough on data. Russom (2013, p. 10) identifies a major problem with Big Data Management through the lack of proper governance, stewardship and business sponsorship.

A big barrier for freely implementing Big Data initiatives are the juristic issues and restrictions related to collecting data (Alanko & Salo 2013, p. 10). Wu et al. (2014 in Williams et al. 2014, p. 314) argue extensive data collection being intrusive and revealing information without the consent of the creator. Pospiech and Felden (2012 in Williams et al. 2014, p. 314) continue, that Big Data technologies allow for new ways of collecting and aggregating data from a number of different sources, which creates additional insights possibly revealing confidential information. This all raises ethical concerns around confidentiality and ultimately around personal privacy (Manyika et al. 2011, p. 11). Debates and regulations in the form of data collection laws have since emerged (Alanko & Salo 2013, p. 10; Williams et al. 2014, p. 314). Different countries have different laws and regulations to achieve data privacy and protection, and in most countries monitoring of user communication is not allowed (Hashem et al. 2015, p. 111). Contrary to the rest of the world, there is a strong disagreement between the European Union legislators on data collection laws in the EU. This is a key reason for the dominance of US and Indian vendors on the Big Data market. (Alanko & Salo 2013, p. 10.) The intrusion of privacy through applications of Big Data has been recently witnessed worldwide in the case of the infamous NSA surveillance controversy. Another related concern is data security. Data breaches can expose not only personal and corporate information but also national security secrets. Big Data software does not have its own safeguards that would protect the data from inappropriate access. Organizations thus have to ensure that data security practices and policies apply also in the context of Big Data. (Villars et al. 2011, p. 13.)

3. MATURITY MODELING

As organizations feel pressure to gain competitive advantage, retaining their market position, identifying ways of cutting costs, improving quality, reducing time to market, and inventing or reinventing new products and services becomes increasingly important (De Bruin et al. 2005, p. 1; Mettler 2009, p. 1). Maturity models have been developed to assist organizations in this endeavor. In short, maturity models allow an organization to have its methods and processes assessed according to management best practice, often against a clear set of external benchmarks (APGM 2014). The overall adoption of maturity models is expected to increase, a prediction supported by a number of maturity models proposed by academics, software companies and consultancies (Pöppelbuß & Röglinger 2011, p. 2). Recent literature also suggests an increasing academic interest in maturity models (Mettler 2009; Becker et al. 2010).

In chapter 3.1, the typology, concepts and characteristics behind maturity models are defined. This chapter also describes the different domains maturity models can be utilized in. Chapter 3.2 goes through the history of maturity models and introduces the forerunner models that are well-known as of today. Chapter 3.3 describes how Big Data is connected to the concept of maturity and examines the state of Big Data maturity models. Lastly, the strengths of maturity models as well as the criticism behind them are discussed in chapter 3.4. Maturity model development and the decisions to be made within the development framework are discussed more specifically in chapter 4.

3.1 The concept of maturity and maturity models

In general, “maturity” can be defined as “the state of being complete, perfect or ready” (Simpson & Weiner 1989) or literally as “ripeness” (Fraser et al. 2002, p. 245). Maturity thus implies “an evolutionary progress in the demonstration of a specific ability or in the accomplishment of a target from an initial to a desired or normally occurring end stage” (Mettler et al. 2010, p. 334). An evolutionary progress implies that the subject may pass through a number of states on the way to maturity. The bottom state stands for an initial state i.e. an organization having little capabilities in a specific domain, while the highest stage represents a conception of total maturity. (Becker et al. 2009, p. 213.) Maturity is normally measured as capabilities or “abilities to fulfill specified tasks and goals” (Wendler 2012, p. 1318).

Independent from specific domains, maturity models refer to “manifold classes of entities” (Pöppelbuß & Röglinger 2011, p. 3). Mettler (2009, p. 4) argues, that maturation is reflected in a one-dimensional manner and that maturing subjects can be divided into three key groups: **1) process maturity** i.e. to which extend a specific process is explicitly defined, managed, measured, controlled, and effective (Fraser & Vaishnavi 1997 in Mettler 2009, p. 4); **2) object maturity** i.e. to which extend a particular object reaches a predefined level of sophistication (Gericke et al. 2006 in Mettler 2009, p. 4); and **3) people capability** i.e. to which extend the workforce is able to enable knowledge creation and enhance proficiency (Nonaka 1994 in Mettler 2009, p. 4). Kohlegger et al. (2009, p. 56) use a similar categorization system for maturing entities, and make a distinction between person, object, and social system maturity. Mettler (2009, pp. 5-6) in his research raises questions about the artefact type maturity is associated with, or whether maturity is associated with models, methods or theories. His conclusion is, that maturity artefacts position themselves in-between models and methods, addressing both the identification of problems as well as guidelines on how to solve these problems (ibid).

A **maturity model** conceptually represents “phases of increasing quantitative or qualitative capability changes of a maturing element in order to assess its advances with respect to defined focus areas” (Kohlegger et al. 2009, p. 59). In other words, maturity models are an instrument to rate organizational capabilities of maturing elements, and to select appropriate actions to take the elements to a higher level of maturity (De Bruin et al. 2005; Becker et al. 2009; Kohlegger et al. 2009; Mettler 2009). “The fundamental underlying assumption of maturity models is that a higher level of maturity will result in higher performance” (Boughzala & de Vreede 2012, p. 307), as well as improved predictability, control and effectiveness (Vezzetti et al. 2014, p. 900).

The purpose of maturity models is highly versatile, but typically the purpose of use can be divided into three groups: descriptive, prescriptive and comparative. According to Kohlegger et al. (2009, p. 59), descriptive models explain changes observed in reality, and prescriptive (or normative) models guide committed individuals into making those changes. Finally, maturity models can serve a comparative purpose as means of benchmarking (Röglinger et al. 2012, p. 330). Benchmarking can compare an actual situation with industry-specific best practices in order to support management decisions for continual improvement (Hamel et al. 2013, p. 1411). Hain and Back (2011, p. 1) argue that maturity models essentially are used as a representation of the as-is situation, recommendation for action, and an instrument for controlling. They also raise awareness of the analysis aspect and serve as a reference frame for improvements, ensuring a certain quality and avoiding errors (Wendler 2012, p. 1318). Furthermore, Pfeffer and Sutton (1999 in Mettler 2009, p. 1) identify maturity models to be helpful to close a so-called “knowing-doing gap” within an organization. Maturity assessment in organizations can be either done through external audit or individual self-assessment (Mettler et al. 2010, p. 333). Fraser et al. (2002, p. 247) argue that the latter should be approached as a team exercise involving people from different functional groups, to ultimately eliminate single-respondent bias.

It is observed, that all maturity models share the common property of defining specific elements. These basic elements of maturity models are a number of levels, a descriptor for each level, a generic description or summary of the characteristics of each level as a whole, a number of dimensions, a number of elements or activities for each dimension, and a description of each element or activity as it might be performed at each level of maturity. (Fraser et al. 2002, p. 246.) However, certain distinctions can be made between maturity models based on different factors. One factor is that maturity models can be constructed in either a top-down or bottom-up approach. With a top-down approach definitions are written first and then the assessment items are developed to fit the definitions. With a bottom-up approach the assessment items are developed first and then definitions are written to reflect the developed items. (De Bruin et al. 2005, p. 5). Furthermore, Fraser et al. (2002, p. 246) distinguish maturity models by categorizing them according to their composition and structure type:

1. **Maturity grids** typically contain "text descriptions for each activity at each maturity level and are of moderate complexity, requiring at most a few pages of text."
2. **Likert-like questionnaires** can be considered to be a simple form of maturity models. The questions are simply statements of well-known practices, which organizations use to score their relative performance on a scale from 1 to n. (Hybrid models combine the questionnaire approach with more detailed definitions of maturity.)
3. **CMM like models** have a more formal and complex approach, where a number of key practices and goals are specified to reach an acceptable level of sophistication.

(Fraser et al. 2002, p. 246)

Maturity models have proliferated across multiple domains (De Bruin et al 2005, p. 2). The most heavily dominated maturity model application fields are information systems and software development (Wendler 2012, p. 1317; Vezzetti et al. 2014, p. 900). Fraser et al. (2002, p. 244) have identified maturity models being proposed to other areas such as quality management, supplier relationships, R&D effectiveness, product development, innovation, product design, collaboration and product reliability. Pöppelbuß and Röglinger (2011, p. 2) go further by identifying practical business areas such as digital government, IT management and governance, knowledge management, and business process management. However, until today, the development and application of maturity models has spread out to nearly any conceivable domain (Vezzetti et al. 2014, p. 900).

3.2 Forerunners of maturity models

Since the 1970s, a multitude of different maturity models have been developed in science and practice. More than hundreds of maturity models have been published in the field of information systems alone (Becker et al. 2009, p. 213). In this domain, the evolutionary model of Nolan is often quoted as the origin of the maturity perspective (Vezzetti et al. 2014, p. 900). Nolan, in his original model, suggested that organizational growth of IT evolved through four stages, namely initiation, contagion, control and integration (Nolan 1973). Simultaneously, Crosby developed and proposed a model of organizational behavior by describing it at five stages of maturity for each of six aspects of quality management (Crosby 1979). Crosby's Quality Management Maturity Grid (QMMG) also had a strong evolutionary theme, suggesting that organizational quality management excellence evolves through five phases, namely uncertainty, awakening, enlightenment, wisdom and certainty. Nolan's and Crosby's hypotheses stimulated research in the maturity model domain and led to the development of numerous maturity models based on a sequence of stages or levels (Fraser et al. 2002, p. 244; Röglinger et al. 2012, p. 330).

The popularity of maturity models was especially strengthened by the introduction of the Capability Maturity Model (CMM) for software development (Mettler 2009, p. 3). Developed by the Carnegie Mellon Software Engineering Institute (SEI), it is the most well-known maturity model being accepted as the de facto standard by the software industry (De Bruin et al. 2005, p. 1; Ahmed & Caprez 2010, p. 544). According to Paulk et al. (1993, p. 53), the CMM provides "a conceptual structure for improving the management and development of software products in a disciplined and consistent way." The CMM offers guidelines for organizations to determine their current process maturity and develop a strategy for improving software quality and processes (Ahmed & Caprez 2010, p. 544). The CMM proposes a five stage evolutionary path and defines five different levels of process maturity, illustrated in figure 3.1.

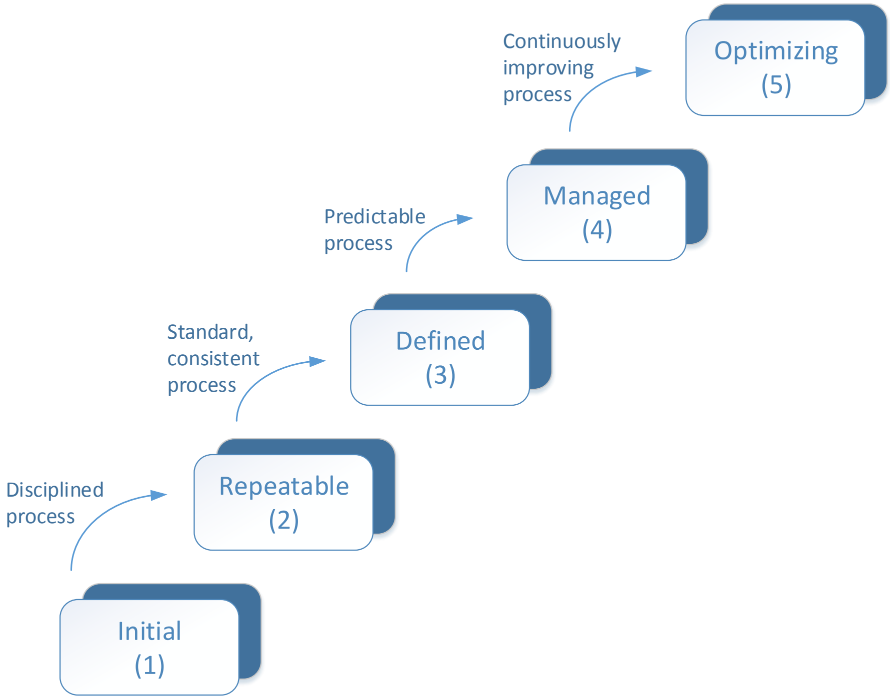

Figure 3.1. *The five levels of the Capability Maturity Model (adapted from Paulk et al. 1993, p. 8)*

The whole CMM framework ultimately consists of the four different aspects described in detail in Paulk et al. (1993) and summarized below:

- **Maturity Levels** are well-defined evolutionary entities toward achieving a mature software process. Each maturity level indicates a level of process capability. The CMM consists of five maturity levels, namely Initial, Repeatable, Defined, Managed and Optimizing
- **Key Process Areas (KPAs)** indicate the areas an organization should focus on to improve its software process and to achieve process capability goals. There are a number of KPAs located at each maturity level, and 18 in total.
- **Common Features** are attributes and practices that indicate whether the implementation and institutionalization of a KPA is effective, repeatable, and lasting. The five common features are commitment to perform, ability to perform, activities performed, measurement and analysis, and verifying implementation.
- **Key Practices** describe the infrastructure and activities that contribute most to the effective implementation and institutionalization of the key process area.

(Paulk et al. 1993, pp. 30-41)

A number of studies regarding CMM have shown links between maturity and quality in the software domain (Fraser et al. 2002, pp. 247-248). According to Kaur (2014, p. 47), implementing CMM into the software development process helps forging a shared vision and providing consistency for the software product. However, CMM has also been criticized on its overemphasis on the process perspective and its disregard on people's capabilities (Bach 1994 in Mettler 2009, p. 2). Concerns were also raised due the strong formalization of improvement activities accompanied by extensive bureaucracy that hinder people from being innovative (Herbsleb & Goldenson 1996 in Mettler 2009, p. 2). Furthermore, Smith and Fingar (2004 in Rosemann & De Bruin 2005, p. 3) argue that CMM-based maturity models cannot capture the need for business process innovation.

3.3 Big Data maturity models

Big Data maturity can be defined as “the evolution of an organization to integrate, manage, and leverage all relevant internal and external data sources” (Halper & Krishnan 2013, p. 5). Bilbao-Osorio et al. (2014) describe Big Data maturity as an approach for organizational progress assessment and to identification of relevant initiatives. It involves building an ecosystem that includes technologies, data management, analytics, governance, and organizational components (Halper & Krishnan 2013, p. 5).

Maturity models can be used as an artefact to measure Big Data maturity. According to Halper and Krishnan (2013, pp. 5-6), a maturity model for Big Data helps creating structure around a Big Data program and determine where to start. It is a great tool for organizations to define goals around the program and communicate their Big Data vision across the entire organization. Big Data maturity models also provide a methodology to measure and monitor the state of the program, the effort needed to complete the current maturity stage, and the steps to advance to the next stage. Furthermore, Big Data maturity models measure and manage the speed of both the progress and adoption of Big Data programs within organizations. (ibid.)

The goal of a Big Data maturity model is to provide a capability assessment tool that focuses on specific Big Data key areas in organizations, to help guide development milestones, and to avoid pitfalls. Krishnan (2014) suggests, that the previously mentioned key areas are the subcomponents of the “people, processes, technology” – triangle, namely alignment, architecture, data, data governance, delivery, development, measurement, program governance, scope, skills, sponsorship, statistical model, technology, value, and visualization. According to El-Darwiche et al. (2014, p. 45) the Big Data maturity stages depict the various ways in which data can be used within an organization. Radcliffe (2014, p. 6) argues that Big Data maturity models are the key tools for setting the direction and monitoring the health of the organizations Big Data program. An underlying assumption is that a high Big Data maturity level correlates to the increase of top-line revenues and reduction of operational expenses. However, reaching the highest level of Big Data maturity often involves major investments over many years. (El-Darwiche et al. 2014, p. 45.)

3.4 Strengths and criticism of using maturity models in organizations

Current literature identifies several key strengths connected to maturity models. Development of new maturity models will not stop in the future, due to them helping managers to “balance divergent objectives with regard to obtaining and retaining competitive advantage, assembling new products and services, reducing costs and time to market, and enhancing quality” (Mettler et al. 2010, p. 334). The team of De Bruin et al. (2005, p. 1) argue that maturity models assist organizations in gaining and retaining competitive advantage by identifying ways of cost reduction, quality improvement, and time-to-market reduction. Becker et al. (2009, p. 221) continue, that maturity models are a major importance especially for IT management, who regulate the organizational IT performance and economic efficiency. In addition to IT management, maturity models are also valuable in the domain of digital government and knowledge management (Pöppelbuß & Röglinger 2011, p. 2). Boughzala and de Vreede (2012, p. 307) identify key areas in which maturity models exceed, mostly regarding the application of the model. Maturity models are simple to use, they can be applied from many perspectives, they help in team building activities, and they can be used either as self-assessment or through a third party auditor (ibid).

However, maturity models have also been the target of criticism. Mettler (2009, p. 3) points out the most important point of critique, namely the poor theoretical foundations and the lack of documentation. As argued by De Bruin et al. (2005, p. 3), there is little documentation on how to develop maturity models that are theoretically sound, rigorously tested and widely accepted. Many authors of maturity models simply build on their predecessors without much thinking about the appropriateness of their design decisions (Kohlegger et al. 2009, p. 51). Whilst built on good practices, the maturity models do not necessarily guarantee that an organization will achieve success (Mettler 2009, p. 3). Furthermore, maturity models often lack in documentation regarding their development process (Becker et al. 2009, p. 216), resulting in low reliability. A rising number of maturity models implicate problems with respect to the irretrievability. “As no classification for precisely allocating different kinds of maturity models exist, the search for and the selection of specific models is time consuming and exhausting” (Mettler et al. 2010, p. 334). Furthermore, Mettler (2009, p. 3) suggests that many maturity models do not describe how to carry out improvement actions, and act only as descriptive ways to assess the current situation.

4. SYSTEMATIC LITERATURE REVIEW OF MATURITY MODEL DEVELOPMENT AND CLASSIFICATION

A systematic literature review or a systematic review is “an exhaustive summary of the high-quality literature on a particular topic” (King’s College 2014, p. 3). Combing results of several studies gives more reliability and precision than one study alone (CRD 2009). Crowther et al. (2014, p. 3140) point out that systematic reviews are highly objective and transparent, and aim “to reduce bias with the use of explicit methods to perform a comprehensive literature search and critical appraisal of the individual studies.” The search process should be as transparent as possible and documented in a way that enables it to be evaluated and reproduced (CRD 2009, p. 16). Furthermore, systematic reviews attempt to identify if certain subtypes of evidence are absent from the literature (Salminen 2011, p. 9; Crowther et al. 2014, p. 3140).

Chapter 4.1 introduces Fink’s (2005) model for conducting a systematic literature review. Fink proposes a seven phase model, which starts off by data collection and ends in the synthesis of results. The data collection process is introduced in chapter 4.2 and includes phases of selecting the appropriate databases, choosing the right search strategy, and establishing practical and methodological inclusion and exclusion criteria. The selected academic papers are then introduced in chapter 4.3. The final phase of Fink’s model is to synthesize the results, which is done after careful analysis in chapter 4.4. The synthesis yields results in the form of a generic maturity model development framework and a maturity model classification system framework.

4.1 Fink’s systematic literature review model

Literature review models provide guidelines and help the researcher selecting the right keywords for searching the information. The guidelines also help with limiting the information pool and analyzing the data with high quality. This research utilizes the systematic literature review model proposed by Fink (2005, p. 4), where the research process is divided into seven tasks (figure 4.1).

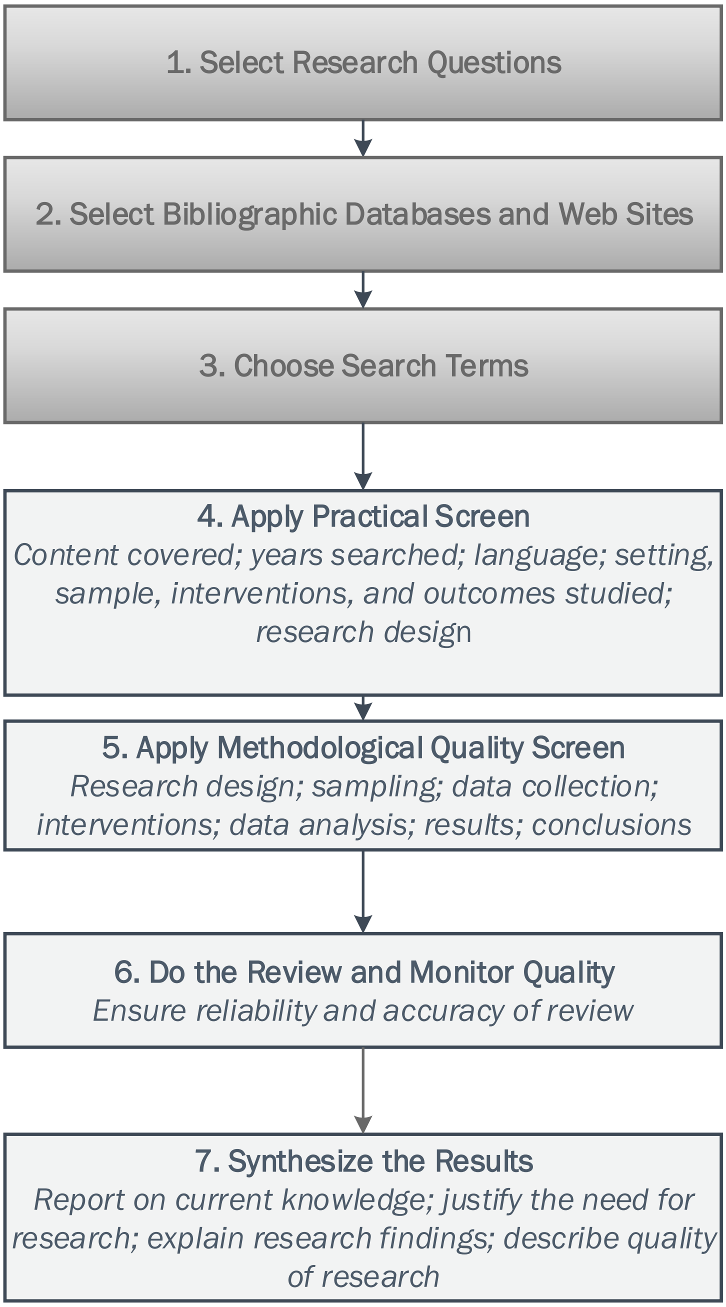

Figure 4.1. *Fink's model for conducting a systematic literature review (adapted from Fink 2005, p. 4)*

First, a set of research questions must be selected. In phase two the appropriate bibliographic databases and websites are selected. In phase three the search terms or phrases that are used to query the databases are selected. The next phases four and five concern filtering the results and applying both practical and methodological screening criteria. This helps in including only the relevant data and excluding all other unnecessary data. Finally in phases six and seven the actual review is conducted and the results are synthesized. (Fink 2005, pp. 3-4.)

4.2 Collection of data

The premise of a systematic literature review is to form research questions based on a research problem. The research questions guide the researcher in selecting the appropriate sources for data collection and constructing the right search terms that query these data sources. The objective of this systematic literature review is to find best practices and decisions of scoping, designing, developing, evaluating and classifying maturity models. Therefore, the research questions formed in chapter 1.2 can be utilized:

- What are the best practices for generic development and classification of maturity models?

In this study, the development process is defined as “the process of creating something over a period of time” and the classification process as “the systematic arrangement in groups or categories according to established criteria” (Merriam-Webster.com 2015). Furthermore, systematic reviews in general are performed at a single specific point in time to avoid becoming outdated. The date at which the systematic review was performed has to be documented precisely allowing future researchers to update the review by repeating the search from that time point. (Bown & Sutton 2010, p. 671.) The following data was collected between the time period of December 10th 2014 and December 11th 2014.

4.2.1 Bibliographic databases and search strategy

Conducting a thorough search is a key factor in minimizing bias in the review process. Thorough searching is best achieved by using a variety of search methods (electronic and manual) and by searching multiple, possibly overlapping resources. (CRD 2009, pp. 16-22.) An electronic or bibliographic database is a collection of articles, books and reports that can provide data to answer research questions. They are usually accessed via an online connection and provide full copies of the original research, from a range of different countries and years. (Fink 2005 p. 5.) The papers found in bibliographic databases have been through some sort of screening and quality control, which increases the reliability and validity of the information sources (Warwick 2014). According to Crowther et al. (2014, p. 3142) it is recommended additionally to manually search the reference lists of found studies as a final check that no relevant studies have been missed. Manual searching or “hand searching” is an important way to identify publications that have not yet been included and indexed by bibliographic databases (CRD 2009. p. 18).

According to the Centre of Reviews and Dissemination (CRD 2009, p. 17) there can be no agreed standard for what constitutes an acceptable search in terms of the number of databases. However, it is important to take into consideration that one search portal may only search a subset of a particular database and for the most comprehensive searches multiple portals in addition to multiple databases should be used (Bown & Sutton 2010, p. 671). The types of bibliographic databases are usually selected according to the topic of the review. In the context of this research, maturity modeling is seen to fit the subject areas of engineering, computer science and business management, thus resulting in the selection of interdisciplinary databases where these domains are present.

In this research, peer-reviewed articles found in bibliographic databases are selected as the main source of information. At first, seven databases were selected based on a popularity-of-use list made by the Tampere University of Technology (TUT 2014). These subscription based databases were Scopus, Web of Science, IEEE Xplore, SpringerLink, ScienceDirect, EBSCO and ACM Digital Library. It was discovered, that Scopus and ScienceDirect are both owned by the company Elsevier (Elsevier 2014). To reduce biased redundant data, ScienceDirect was dropped from the list. Another decision was made to also discard "Web of Science" due to the very low availability of its content. In addition, Google Scholar was added to the list due to the demand for a manual ad-hoc search, being described later on in this chapter. The final list of the six selected bibliographic databases can be found in table 4.1.

Table 4.1. *The list of the selected bibliographic databases*

Name	***Description***
Scopus	With 55 million records, Scopus is the largest abstract and citation database of peer-reviewed literature: scientific journals, books and conference proceedings. Delivering a comprehensive overview of the world's research output in the fields of science, technology, medicine, social sciences, and arts and humanities, Scopus features smart tools to track, analyze and visualize research. (Elsevier 2014.)
IEEE Xplore	The IEEE Xplore digital library is a powerful resource for discovery and access to scientific and technical content published by the IEEE (Institute of Electrical and Electronics Engineers) and its publishing partners. IEEE Xplore provides Web access to more than 3-million full-text documents from some of the world's most highly cited publications in electrical engineering, computer science and electronics. (IEEE 2014.)
SpringerLink	SpringerLink provides researchers with access to millions of scientific documents from journals, books, series, protocols and reference works (Springer 2014).
EBSCO	EBSCO Information Services provides a complete and optimized research solution comprised of research databases, e-books and e-journals—all combined with the most powerful discovery service and management resources to support the information and collection development needs of libraries and other institutions and to maximize the search experience for researchers and other end users. (EBSCO 2014.)

ACM Digital Library	ACM hosts the computing industry's leading Digital Library, and serves its global members and the computing profession with journals and magazines, conferences, workshops, electronic forums, and Learning Center. (ACM 2014).
Google Scholar	Google Scholar provides a simple way to broadly search for scholarly literature. From one place, you can search across many disciplines and sources: articles, theses, books, abstracts and court opinions, from academic publishers, professional societies, online repositories, universities and other web sites. (Google 2014.)

After establishing the bibliographic databases, the search strategy must be defined. Search strategies are "explicitly designed to be highly sensitive so that as many potentially relevant studies as possible are retrieved" (CRD 2009, p. 19). Search terms are the keywords and phrases that you use to get relevant journal articles, books and reports. They are based on the words and concepts that frame the research question. (Fink 2005, p. 5.)

In this research, the search words seek to answer the research question previously mentioned in chapter 4.2 by taking into account all the synonyms connected with the concept of maturity modeling. The advanced search functionalities of the databases (e.g. Boolean operators 'AND', 'OR' and 'NOT') were utilized to construct a query that would cover a large sample of maturity modeling literature. After careful examination, the following search string was created and used to query the bibliographic databases:

```
("maturity modeling"
OR "maturity modelling"
OR "maturity model design"
OR "maturity model development"
OR "maturity model evaluation"
OR "maturity model framework")
```

Depending on the database, this query had to be modified so that it matched the syntax of the search platform. If possible, the selected terms were searched against full-text documents and the metadata. The advanced search capabilities of the SpringerLink engine did not fully support multiple Boolean operators and this resulted in over 30000 results returned. However, adjustments to the screening criteria reduced this data dramatically.

It was observed, that some authors appeared frequently in the reference list of the articles acquired through the systematic literature review. The mostly cited authors, when discussing the design and development of maturity models, were Becker, De Bruin, Kohlegger and Mettler. An ad-hoc search was carried out in Google Scholar combining the term "maturity model" and the name of the authors resulting in the following query:

```
("maturity model" AND ("becker" OR "de bruin" OR "kohlegger" OR "mettler"))
```

This resulted in the addition of 2200 unique papers, later to be investigated in the screening process.

4.2.2 Practical and methodological inclusion and exclusion criteria

Literature searching may result in a large number of records, but only a few of them are relevant. There is a need for a screening process to identify the articles that are meaningful to one's research. Screening is done by defining inclusion and exclusion criteria whilst collecting the data. (Fink 2005, pp. 54-55.) A strict screening process is one characteristic of systematic reviews that distinguishes it from other literature review models (Salminen 2011, p. 11). It is important to find the right balance between including and excluding the research material. Too narrowly defined criteria grow the risk of missing potentially relevant studies and reducing the generalizability of the research. Conversely, if criteria are too strictly defined there will not be enough data to allow meaningful combination of results. (CRD 2009, p. 10; Bown & Sutton 2010, p. 671.)

Fink proposes a two phase screening process to sort out the relevant and strong studies from the others, namely practical screening and methodological screening. Using both screens ensures the systematic review's efficiency, relevance, and accuracy. The practical screen is used to identify a broad range of articles that cover the topic of interest, are in a language you read, are in a publication you respect, and can be obtained in a timely manner. The methodological screen is for quality, and helps you narrow your search by identifying the best available studies. Methodological quality of a study refers to how well it has been designed and implemented, and how rigorously it uses justified research standards. (Fink 2005, pp. 55-59.)

In this research, the advanced filtering and sorting options of the bibliographic databases helped the practical screening process. Practical screening was done by reducing the results based on language, publication date, citations and availability. Filtering based on the title and abstract was made by skimming through the articles. This narrowed the selection down significantly. The inclusion and exclusion criteria for all databases are listed below:

- **Inclusion criteria**
  - Language: *English*
  - Publication date: *Last 10 years (2004-2014)*
  - Title: *Combinations of the words "maturity" and "model"*
  - Abstract: *A mention of designing, developing or evaluating maturity models.*
- **Exclusion criteria**
  - Cited: *0 times*
  - Availability: *Full-text not available*

Most bibliographic databases were able to apply the inclusion and exclusion criteria so that the results were limited effectively. However, it was observed that SpringerLink still returned too many results (n=20200). To analyze the results in a timely manner, a criterion was added to only include articles from the subject areas of business management, computer science and engineering. This resulting in a much better selection (n=217).

Methodological screening produced the following inclusion and exclusion criteria:

- **Inclusion criteria:**
  - The paper clearly answers the research question and presents a unique approach for generic maturity model development or classification
- **Exclusion criteria:**
  - The content from the same author(s) is overlapping
  - The paper does not follow scientific research standards

During the methodological screening process, the papers were classified in three different types:

- **Relevant papers** fully satisfy the methodological screening criteria
- **Secondary papers** are related to maturity model development, but clearly use another methodology as its primary source
- **Excluded papers** are not relevant to the concept of maturity model development or classification

It was agreed upon, that only the relevant papers were to pass the methodological screening process. The secondary papers contained various guidelines, models and methods that mostly referenced and repeated the existing development procedures. Excluded papers were not included due to them being out of the research area.

Table 4.2. *Results of the systematical literature review searching and screening process*

Database	*Keyword search*	*Practical screening*	*Methodological screening*
Scopus	145	7	1
IEEE Xplore	85	4	0
SpringerLink	32553	5	1
EBSCO	36	2	0
ACM DL	238	2	0
Google Scholar	2200	7	5
Other	N/A	N/A	1
Total	***35257***	***27***	***8***

After keyword searching the databases and applying the practical screening criteria, 27 unique papers remained. After applying methodological screening criteria and removing the papers that are overlapping or out of the area, 7 papers remained. Afterwards, the references of the most relevant papers were manually checked, and as a result, another 1 paper was added, bringing the total to 8. The evolution of the screening process can be seen in table 4.2.

4.3 Description of data

The systematic literature review resulted in the final selection of eight research papers. These papers were selected based on the strict screening criteria defined in the previous chapter. Basic information about the authors, title, year, publication and summary of the content of the papers are listed in appendix A.

In the following sections of this chapter, a brief introduction to all the development and classification proposals are presented, ordered by the publication date of the paper. The two papers of Mettler (Mettler 2009; Mettler et al. 2010) are presented as together. After establishing a basic overview of all the methodologies, they are analyzed and synthesized in the chapter 4.4.

4.3.1 De Bruin et al. proposal

The group of De Bruin et al. (2005) proposes a generic maturity model development methodology consisting of six phases which have to be followed in order, as illustrated in figure 4.2. These phases are iterative in nature, helping to make adjustments throughout the whole development process. Each phase presents a major decision to be addressed in that phase, usually in the form of different criteria or characteristics. (De Bruin et al. 2005, p. 3.)

Figure 4.2. *The phases of maturity model development (adapted from De Bruin et al. 2005)*

Before moving to phase one, De Bruin et al. (2005) talk about the defining purpose of the model. Purpose refers to whether the model is descriptive, prescriptive or comparative in nature. Highly descriptive models tell you what the state of maturity is, but do not provide information to improve it. Prescriptive models on the other hand indicate how to approach improvement, and how to achieve better business performance and value. Comparative models extend these two by further providing benchmarking possibilities across a number of industries or regions. It is argued, that these three models represent evolutionary phases of a model's lifecycle, suggesting that a comparative maturity model is the most advanced and complete. Thus it can be concluded, that comparative models are best for capturing domain and industry specific issues. (De Bruin et al. 2005, p. 3.)

In the first phase **the scope** of the desired model is defined. This is done by determining the focus of the model and which stakeholders will assist in the development process. Focus of the model refers to whether the model is intended for a specific domain, or for general use. Focusing the model within a domain, rather than on general usage, will determine specificity and extensibility of the model. Scoping greatly influences all the remaining phases. (De Bruin et al. 2005, p. 4.) Phase two consists of defining **the design** of the model. This is done by defining the needs of the intended audience and how these needs will be met. The target audience can be either internal or external, consisting of either executives and managers, or external auditors and partners. The needs of these groups vary, since the model can be applied from one to multiple entities/regions. A maturity model should have the right balance of simplicity and complexity, only then providing sufficient information to the audience. One should also consider how the stages of the model should be designed. This is done either by a top-down or bottom-up approach and selecting if the model should be built based on a maturity gird, Like-scale questionnaire or CMM-like model. Furthermore, the naming and labeling of the stages should be clear and consistent. (De Bruin et al. 2005, pp. 5-6.)

After establishing the scoping and design principles, the model is **populated**. This is done by identifying a number of domain components and their sub-components that are mutually exclusive and collectively exhaustive. Domain components can be found by examining domain specific critical success factors and barriers through exploratory data collection methods such as the Delphi method, Nominal Group technique, case studies and focus groups. Using standard methods that ultimately complement each other is the key in identifying the relevant content of the constructed model. (De Bruin et al. 2005, pp. 6-8.) Once the model is filled with content, the model components must be **tested** for validity, reliability, and generalizability. The group of De Bruin et al. proposes a testing protocol that tests both the construct of the model and the model instruments. Several testing methods can be used here, including case studies, surveys or interviews. (De Bruin et al. 2005, p. 9.)

The final phases of the models are **deployment** and **maintenance.** Deployment ensures that the model is made available for verification. A critical criterion for a verified model is the generalizability of the model, and only then it can be accepted for wider use. Finally, the model's growth and use has to be maintained. Evolution of the model occurs as the domain knowledge and understanding deepens, resulting in the need for constantly evaluating and enhancing the model components. (De Bruin et al. 2005, pp. 9-10)

In conclusion, the paper argues for the importance of developing maturity models using a standardized generic methodology, since it achieves great value through high generalizability (De Bruin et al. 2005, p. 10). The De Bruin et al. proposal is the oldest one among the reviewed papers, meaning that there is little or no bias in the results. However, the development framework is limited in that it is only practically tested with models within two domains, namely business process management and knowledge management.

4.3.2 Becker et al. proposal

Becker et al. (2009) propose generic procedures for developing and evaluating maturity models based on design science research. The paper builds the foundation of its methodology on the guidelines of the design science approach of Hevner et al. (2004), which are transformed into eight design requirements. These requirements are then compared to the design processes of six existing maturity models. The results of this research ultimately provided the elements for constructing the eight procedures of the procedure model for developing maturity models, simplified in figure 4.3.

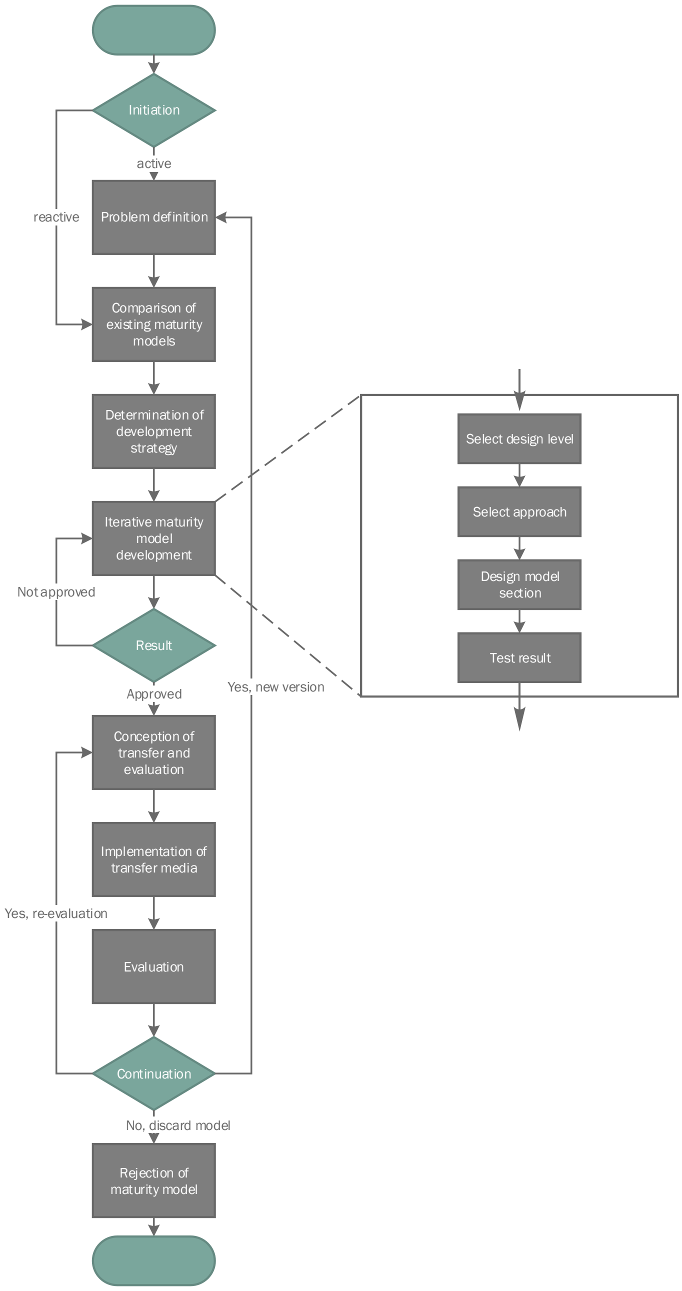

Figure 4.3. *Procedure model for developing maturity models (adapted from Becker et al. 2009, p. 218)*

The eight phases of the procedure model are as follows: **1) Problem definition**: determine the target domain and target group; **2) Comparison of existing maturity models**: compare existing models as a basis for incentive and inspiration; **3) Determination of development strategy**: choose between a completely new model design, enhancement of an existing model or combination of the design of several models; **4) Iterative maturity model development:** select design level, select approach, design model section and test results; **5) Conception of transfer and evaluation:** determine the different forms of result transfer for both academic and user communities; **6) Implementation of transfer media:** make the maturity model accessible through transfer media such as self-assessment questionnaires; **7) Evaluation:** evaluate the maturity model by comparing defined goals to real-life observations; **8) Rejection of the model (optional):** rejection of the designed model if results are truly negative. Becker et al. argue the phases four and seven, namely iterative maturity model development and evaluation, are centric phases of the model, putting emphasis on the iterative nature of a development process. The outcome of these phases may result in reiteration of the whole design process, and modification of certain entities. Also, due to nature of business domains constantly changing and evolving, old maturity models become obsolete and there is a need for validation through regular evaluations. (Becker et al. 2009, pp. 217-219.)

Becker et al. (2009) identified a major problem with the lack of documentation provided by maturity model designers, yielding very little information about the model's development process. Thus, the main purpose of this paper was to build a sound framework for designers to develop well-founded maturity models. However, the procedure model was strictly developed based on the approach of Hevner et al. (2004), and it is possible that excluding other approaches may leave important success criteria unnoticed. (Becker et al. 2009, p. 221.)

4.3.3 Kohlegger et al. proposal

Kohlegger et al. (2009) propose a model for the creation or re-creation of a maturity model based on a structured content analysis of 16 existing models. The model consists of a set of maturity assessment questions that help the developer to develop new or revise existing maturity models in the domains of business information systems and computer science, and especially in knowledge management. Furthermore, it gives an overview of the different conceptions of maturing and fundamental principles of maturity models. Kohlegger et al. test the model's applicability by providing a case example with the knowledge maturity model. (Kohlegger et al. 2009, p. 51.)

First, a total of 76 maturity models for the structured content analysis were identified based on an exhaustive internet search. This number was then reduced by dividing them into three categories, namely persons, objects and social systems, and including only the five most cited models for each category. Additionally, one model was added subsequently, bringing the final number to 16. The models were then analyzed and distinct model characteristics were extracted to form the maturity assessment questions. (Kohlegger et al. 2009, pp. 53-55.)

The results of the study are presented in the form of questions that are divided into three main categories: **defining questions**, **design questions** and **usage questions**. These questions try to identify certain attributes attached to the target model. The final questionnaire and possible answers are summarized in table 4.3. Two of the assessment questions were not formally addressed in the study, leaving out details about the classification of the question-specific attributes, and thus are marked not applicable.

Table 4.3. *The maturity assessment questionnaire (adapted from Kohlegger et al. 2009, pp. 56-57)*

Category	**Question**	**Possible answers**
Defining questions	How do elements change in time?	Change in number Change in nature
	What does maturing mean?	Change in quality Change in capability Change in risk Other change
	What is the direction of change?	Increasing change Decreasing change
	What is the maturing subject?	Person: competence Object: document, infrastructure, product, service Social system: group, team, community, process, routine, structure
Design questions	Has the model a conceptual mother model?	No mother model CMM SPICE Other model
	What is the model used for?	N/A
	Who uses the model?	Internal assessment team External assessment team Model is not used practically
	Does the model complement other models?	No model is complemented CMM
	How is model designed?	Iterative Cyclical
	How do the stages build on each other?	Upper level comprises lower level Upper level is new concept
	How does the subject process from one level to the next?	Defined goals have to be fulfilled Matures implicit
	What is the number of stages?	Metric value (0-n)
	Is there a “not existing” -stage?	There is a “not existing” -stage There isn’t a “not existing” -stage
	What do the level descriptions include?	Trigger descriptions Activity descriptions (tasks, processes) Conceptual level description
	What is the degree of detail of the trigger description?	One trigger per stage Many triggers per stage No triggers per stage
	Is level-skipping allowed?	Explicitly allowed Not recommended
	Are there parallel maturing processes possible for one unit?	Parallel maturing possible Parallel maturing not possible
	What is the number of goal levels?	Metric value (0-n)

	What is the method of goal benchmarking?	Metric based Non-metric based
	Where do assessment data come from?	Interviews Documents Questionnaire Data
Usage questions	What is the model used as?	Conceptual model Applied model
	Is tool support available?	Supported by assessment model Supported by software tool Not supported by tool
	What is the model description based on?	N/A
	Is certification available?	Certification is available Certification is not available

The questionnaire proposed by Kohlegger et al. is very useful for both developing maturity models and classifying the models on several different attributes and characteristics. The questionnaire also acts as a complete benchmarking tool for selecting and comparing maturity models based on the similarities or differences between them. However, this model favors maturity models that assess maturity in the domains of knowledge, knowledge-intensive processes and knowledge infrastructure, reducing in the applicability in more practical domains. Also, the paper analyzes and investigates existing maturity models on their textual descriptions, not relying on empirical evidence such as testing the model in a practical environment, resulting in the lack of reliability. (Kohlegger et al. 2010, pp. 59-60.)

4.3.4 Mettler et al. proposal

This chapter describes the content of Mettler's research in his two research papers (Mettler 2009; Mettler et al. 2010), the first focusing on the development of maturity models and the latter on constructing a classification system around these models. Mettler, in his first paper (Mettler 2009), proposes a phase model for both development and application of maturity models. The model differentiates between two perspectives, namely the developer's and user's perspective, which closely interact with each other. Both of these perspectives consist of four phases tied with specific decision parameters and characteristics. The decision parameters can be investigated in more detail in Mettler (2009, pp. 8-10). The phases of maturity model development and application are illustrated in figure 4.4 below.

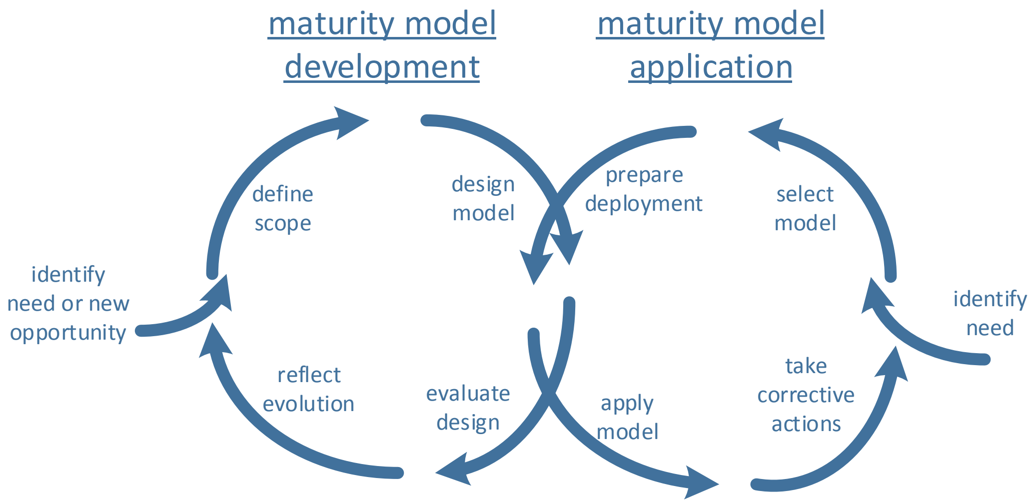

Figure 4.4. *Phases of maturity model development and application (adapted from Mettler 2009, p. 8)*

From the **developer's perspective**, developing maturity models consist of: **1) Define scope:** determine the focus/breadth, level of analysis/depth, novelty, audience and dissemination; **2) Design model:** determine maturity definition, goal function, design process, design product, application method and respondents; **3) Evaluate design**: determine subject of evaluation, time-frame and evaluation method; **4) Reflect evolution:** determine the subject of change, frequency and structure of change. (Mettler 2009, p. 8.) From the **user's perspective**, applying maturity models consist of: **1) Select model:** selection of model based on origin, reliability, practicality, accessibility, design mutability and application method; **2) Prepare deployment:** decide on driver/responsibility, realization, application area, respondents and training; **3) Apply model:** decide over execution and frequency of application; **4) Take corrective actions:** decide on target setting, implementation and implementer. (Mettler 2009, p. 10.) Mettler emphasizes that the order of the phases is of great importance. Mettler also argues that understanding the definition of maturity model is crucial for developing a working maturity model.

With his model, Mettler (2009) tries to improve the development process of maturity models to better address information systems related issues by differentiating his model into a development and implementation perspective, whilst underlining the importance of iterativeness throughout the whole process. Mettler's findings also indicate, that developers lack knowledge on how to design theoretically sound and acceptable models, and that the maturity model development methodology should be standardized. However, the model has its limitations. Mettler bases his research on guidelines on design research of Hevner et al. (2004) and the methodology of De Bruin et al. (2005), which already address the issues of standardizing the development methodology, following in slightly biased results (Mettler 2009, p. 11.)

Mettler in his second paper (Mettler et al. 2010) addresses issues with respect to retrievability and reusability of maturity models. It can take a lot of time to find, select and implement the most appropriate maturity model for your purpose, if the function and purpose of the model is not presented in a systematical manner. Mettler et al. thus propose a classification system for maturity models in the domain of information systems. The classification system uses a characteristic-based approach and is divided into three dimensional perspectives, namely general model attributes, maturity model design attributes, and maturity model use attributes (see table 4.4)

Table 4.4. *Classification system of maturity models (adapted from Mettler et al. 2010, p. 336)*

Dimension:	*Attribute:*	*Values:*
General model attributes	Name	Name of model
	Acronym	Acronym of name
	Primary source	Primary source
	Secondary source	Secondary source
	Addressed topic	Name of domain
	Origin	Academic Practice
	Audience	Management-oriented Technology-focused No clear distinctions
	Year of publication	Year of publication
	Access	Freely available Pay a fee
Maturity model design attributes	Concept of maturity	Process maturity Object maturity People capability
	Composition	Maturity grids Likert-like questionnaires CMM-like models
	Reliability	Verified model Validated model
	Mutability	Form of model Functioning of model
Maturity model use attributes	Method of application	Self-assessment Third-party assisted assessment Certified practitioners
	Support of application	No supporting materials Textual description or handbook Software assessment tool
	Practicality of evidence	Implicit improvement activities Explicit recommendations

The **general model attributes** are used to describe the origin and basic characteristics of a maturity model. This provides an overview of the model, helping developers and business users to identify such attributes as the target domain, target audience and primary publication source. These attributes are easy to define and usually present in all published maturity model. The more difficult attributes to define are attributes related to the development and use of the model, which are closely connected to Mettler's (2009) maturity model development framework. **Maturity model design attributes** describe the focus and structure of the model by defining the concept of maturity, composition, reliability and mutability. The concept of maturity tells the user if the model focuses on either process maturity, object maturity or people capability. This influences the composition of the model, whether the model is structured as a maturity grid, Likert-like questionnaire or CMM-like model. Through defining the reliability, it can be determined whether the model is verified or validated. The difference between these two are, that verified models only represent the conceptions of the developer while validated models represent a more accurate real world usage perspective. Lastly, mutability communicates the level of modification requirements to form and functioning, due to the constantly changing environment and emergence of new technologies and practices. Finally, **maturity model use attributes** describe the method of application, support of application, and practicality of evidence. The method of application tells the user how the model is intended to be used, whether it is self-assessment, third-party assisted assessment or certified practitioners. The support of applications describes how the model is documented and how well it gives assistance to conduct the assessment. Practicality of evidence is the last attribute, distinguishing between implicit improvement activities and explicit recommendations. (Mettler et al 2010, pp. 337-339.)

All these attributes were based on a detailed analysis of 117 existing maturity models. Mettler argues, that the main problem in developing a classification system lies in limiting the scope for attribute selection. There should be as few attributes as possible while at the same time diversely explaining all the important factors needed for addressing domain specific maturity issues. However, this representation may not be the most accurate presentation since maturity model classification is never unambiguous. Mettler concludes his paper by stating that the most value is gained by integrating the classification system into the maturity model development framework. (Mettler et al. 2010, p. 339.)

4.3.5 van Steenbergen et al. proposal

The group of van Steenbergen et al. (2010) proposes a generic methodology for developing maturity models, using a design science research approach. This model makes a distinction between fixed-level and focus area maturity models, and focus on the latter one. A fixed-level maturity model has a fixed number of maturity levels each associated with a number of processes that have to be implemented. It is argued, that fixed-level models are not well suited for incremental improvement within an organization, since they cannot identify the interdependencies between the maturity processes. This has resulted in the demand for focus area models. A focus area maturity model achieves maturity in a functional domain by addressing issues in specific focus areas eg. development of a process or training of a competence. Each focus area can be divided into a number of capabilities and attributes that are dependent on the selected functional domain. (van Steenbergen et al. 2010.)

The paper identifies four common phases for developing maturity models: **1) Scope**: identify and scope the functional domain by deciding what to include and exclude; **2) Design model**: determine focus areas, capabilities and dependencies with the help of critical success factors **3): Develop instrument**: develop assessment instrument such as questionnaires and define improvement actions; **4) Implement and exploit**: implement maturity model, evaluate iteratively and communicate results. (van Steenbergen et al. 2010, pp. 10-14.)

The approach of van Steenbergen et al. (2010) is derived from existing approaches of De Bruin et al. (2005), Mettler (2009) and Becker et al. (2009), using a lot of the existing methodology for classification and evaluation of maturity models. However, this model extends the current methodology by identifying best practices to develop focus area specific maturity models. Focus area models create value by supporting organizations in incrementally improving their practices and capabilities. (van Steenbergen et al. 2010, p. 15.)

4.3.6 Lahrmann et al. proposal

Lahrmann et al. (2011) propose a methodology for developing maturity models by identifying five main development phases: **1) Identify need or new opportunity**: identify a business need using creativity techniques, focus groups, case studies, literature reviews or surveys; **2) Define scope**: Scope the domain by establishing inclusion and exclusion criteria using informed arguments or scenarios; **3) Design model:** construct the model using either a top-down approach using Delphi methods, case studies or literature reviews, or bottom-up approach using algorithmic analysis, informed arguments or ontologies; **4) Evaluate design:** evaluate the model on utility, validity, reliability and generalizability, using functional testing, structural testing, surveys, focus groups or interviews**; 5) Reflect evolution:** maintain and further develop the model based on the emergence of new practices and technologies, using field studies or interviews. (Lahrmann et al. 2011, p. 179.)

The generic phases, proposed by Larhmann et al. (2011), are influenced by the existing methodologies, but a major advancement is presented for the design phase, namely applying quantitative methods such as the Rasch algorithm and cluster analysis to help constructing the model. The main idea of the Rasch algorithm is to analyze the trade-off between the ability of a respondent and the difficulty of a defined item. In the case of maturity models, the ability of a responded corresponds to the ability of the organization based on an assessment questionnaire, and the difficulty of an item to a specific maturity characteristics. Applying the Rasch algorithm in the design phase works well, since the ability of the organization and the difficulty of a maturity item fit the basis consideration of maturity models. The Lahrmann et al. approach is effective for building a maturity model that address both the current state as well as the corresponding target state. However, it is limited to mature domains only since there is always a need for a relatively large sample for identifying items and maturity levels. (Lahrmann et al. 2011, pp. 182-188.)

4.3.7 Pöppelbuß and Röglinger proposal

Pöppelbuß and Röglinger (2011) propose a framework for general design principles for maturity models. Here, design principles are defined as entities that give insight into the principles of form and function that maturity models should meet. The design principles were identified based on an extensive literature review of maturity models. (Pöppelbuß & Röglinger 2011, p. 1.) The framework can be seen in table 4.5 below.

Table 4.5. *A framework of general design principles for maturity models (adapted from Pöppelbuß & Röglinger 2011, p. 6)*

GROUP		DESIGN PRINCIPLES
(1) BASIC	**1.1**	**Basic information**
		a) Application domain and prerequisites for applicability
		b) Purpose of use
		c) Target group
		e) Differentiation from related maturity models
		f) Design process and extent of empirical validation
	1.2	**Definition of central constructs related to maturity and maturation**
		a) Maturity and dimensions of maturity
		b) Maturity levels and maturation paths
		c) Available levels of granularity of maturation
		d) Underpinning theoretical foundations with respect to evolution and change
	1.3	**Definition of central constructs related to the application domain**
	1.4	**Target group-oriented documentation**
(2) DESCRIPTIVE	**2.1**	**Intersubjectively verifiable criteria for each maturity level and level of granularity**
	2.2	**Target group-oriented assessment methodology**
		a) Procedure model
		b) Advice on the assessment of criteria
		c) Advice on the adaption and configuration of criteria
		d) Expert knowledge from previous application
(3) PRESCRIPTIVE	**3.1**	**Improvement measures for each maturity level and level of granularity**
	3.2	**Decision calculus for selecting improvement measures**
		a) Explication of relevant objectives
		b) Explication of relevant factors of influence
		c) Distinction between an external reporting and an internal improvement perspective

3.3	**Target group-oriented decision methodology**	
	a) Procedure model	
	b) Advice of the assessment of variables	
	c) Advice on the concretization and adaption of the improvement measures	
	d) Advice on the adaption and configuration of the decision calculus	
	e) Expert knowledge from previous application	

The design principles are categorized intro three main groups. From the latter two, groups are chosen accordingly to the maturity model's purpose of use. **Basic design principles** provide information about the basics of the model, the central constructs of the model both related to maturity/maturation and application domain, and how the model is documented for its target group. **Design principles for descriptive purpose of use** define the assessment criteria for each maturity level and level of granularity, as well the assessment methodology of the model. **Design principles for prescriptive purpose of use** define generic improvement measures for each maturity level and level of granularity, and basic selection guidelines of improvement measures and target group oriented decision methodology. (Pöppelbuß & Röglinger 2011, pp. 5-8.)

The paper found out that the purpose of use in investigated maturity models was poorly documented and that the design principles for prescriptive maturity models were hardly addressed at all. The descriptive design principles, however, were covered well in general. The paper also has its limitations. The presented design principles are based on literature from other authors, making the content biased with respect to maturity model development. Furthermore, the framework could be tested with only a few maturity models in a restricted domain. (Pöppelbuß & Röglinger 2011, p. 10.)

4.4 Analysis and synthesis of data

According to the reviewed literature, the development of maturity models, and especially the generic development phases and steps, falls in most cases within the guidelines of design science research (DSR) and accordingly to the approach of Hevner et al. (2004). Hevner et al. provide seven guidelines for the development of an artefact, either a construct, a model, a method, or an instantiation, that helps solving defined organizational problems. The guidelines are very helpful in guiding the researcher through the whole development process from start (problem identification) to finish (communication of results). Becker et al. (2009) use the DSR approach of Hevner et al. as the basis for their argument and translate the guidelines into a consideration of requirements, later on used in developing the steps of the procedure model. Hevner et al. is heavily referenced in papers of Mettler (2009), van Steenbergen et al. (2010), Lahrmann et al. (2011), and Pöppelbuß and Röglinger (2011). Additionally to Hevner et al., the DSR approach of Peffers et al. (2008) is referenced by van Steenbergen et al. (2010) and Lahrmann et al. (2011).

Saturation of content was detected when moving chronologically through the papers. To eliminate the bias, or the tendency of treating a specific approach more superior to others (Thomas & Segal 2006, p. 399), it must first be investigated what the papers are cross-referencing. During the investigation a link was detected between several German speaking researchers. Pöppelbuß can be found as the co-author in the proposal of Becker et al., and Mettler in the proposal of Lahrmann et al. Furthermore, Becker has been in the same research team as De Bruin et al. co-author Rosemann. The first proposal in chronological order is from De Bruin et al. (2005), who propose a development framework based on their empirical research with the help of two universities. This empirical research, including consolidation of different methodologies, makes the proposal original and unbiased. Becker et al. (2009) address the paper of De Bruin et al. by analyzing their BPMM model, a by-product of the maturity model development framework. Kohlegger et al. (2009) approach the construction of a development methodology by examining 16 different maturity models with as structured content analysis, referencing neither De Bruin et al. nor Becker et al. Mettler (2009) in his paper tries to further enhance the ideas of De Bruin et al. by introducing decision parameters for development from the perspectives of the developer and user. The research approach of van Steenbergen et al. (2010) stems from the formulated ideas by De Bruin et al., Becker et al. and Mettler. Lahrmann et al. (2011) build their methodological foundations on the ideas of De Bruin et al., Becker et al., Mettler and van Steenbergen et al. Lastly, Pöppelbuß and Röglinger (2011) extend the proposals of De Bruin et al., Becker et al., Mettler and Kohlegger et al. by formulating their ideas into model design principles.

4.4.1 Lack of standardized maturity model development methodology and dissatisfactory documentation of development procedures

The systematic literature review yielded two key problematic findings: the lack of standardized maturity model development methodology, and the dissatisfactory documentation of the development process of existing maturity models. Whilst there are numerous available maturity models, there is little documentation on how to develop a maturity model that is theoretically sound, rigorously tested and widely accepted (De Bruin et al. 2005, p. 2; Kohlegger et al. 2009, p. 51; Mettler 2009, p. 1). It is important to develop maturity models using a consistent generic methodology, since value can be then achieved through the high generalizability and standardization of the model (De Bruin et al. 2005, p. 10). Standardization transforms the model into a form of high quality (Ahlemann 2007 in Pöppelbuß & Röglinger 2011, p. 4).

The second key finding in the literature review was that existing maturity models lacked proper documentation of the development process (Becker et al. 2009, p. 216). Documentation of the research process is of vital importance for the scientific procedure, and all the design processes of the maturity model should be “documented in detail, considering each step of the process, the parties involved, the applied methods, and the results" (Becker et al. 2009, pp. 214-216; Pöppelbuß & Röglinger 2011, p. 3). Only maturity models with detailed documentation available can be effectively compared (Becker et al. 2009, p. 216). Pöppelbuß and Röglinger (2011 p. 7) in their proposal state, that the maturity model should always provide documented guidance and advice for the maturity assessment process. This can be done by "elaborating on the assessment steps, their interplay, and how to elicit the criteria's values" (Maier et al. 2009 in Pöppelbuß & Röglinger 2011 p. 7). These problems are answered in the next section by introducing a generic maturity model development framework consisting of four main phases and several sub-phases, and a classification system framework of decisions to be made within the development process.

4.4.2 Generic maturity model development framework and classification system framework

The reviewed literature suggests that maturity model development can be divided into several phases. Most of the authors, including De Bruin et al., Mettler, van Steenbergen et al. and Lahrmann et al., present their models on a more generic level, while Becker et al. drill down into a more detailed level and include sub-phases. The synthesis favors the Becker et al. approach and illustrates maturity model development as generic main phases containing several sub-phases. Furthermore, variation in the ordering of the sub-phases was detected. The team of De Bruin et al. (2005, p. 3) and Mettler (2009, p. 8) put emphasis on the importance of the main phase order, since previous decisions affect greatly the following phases. However, there is an understanding that most sub-phase activities within a main phase can be conducted concurrently and independently (Mettler 2009, p. 8), rendering this issue insignificant. All sub-phases contain decisions, which depict the choices that have to be made regarding the development activity. Different authors use different terminology related to the choices to be made. The team of De Bruin et al. describes a decision as a criterion, which is divided into characteristics (De Bruin et al. 2005, p. 4). Kohlegger et al. translate the decisions into questions and provide the reader with possible answer options (Kohlegger et al. 2009, p. 56). Mettler uses the term decision parameter and its subcategory characteristics during development, and the term attribute and attribute examples during classification (Mettler 2009, p. 8; Mettler et al. 2010, p. 336). In this research the choice was made to further on use the terms "decision attributes" and "decision attribute characteristics" to describe the possible decisions to be made within a phase. These decision attributes can later on be extracted as attributes for the benchmarking framework. The generic maturity model development framework with its phases is illustrated in figure 4.5.

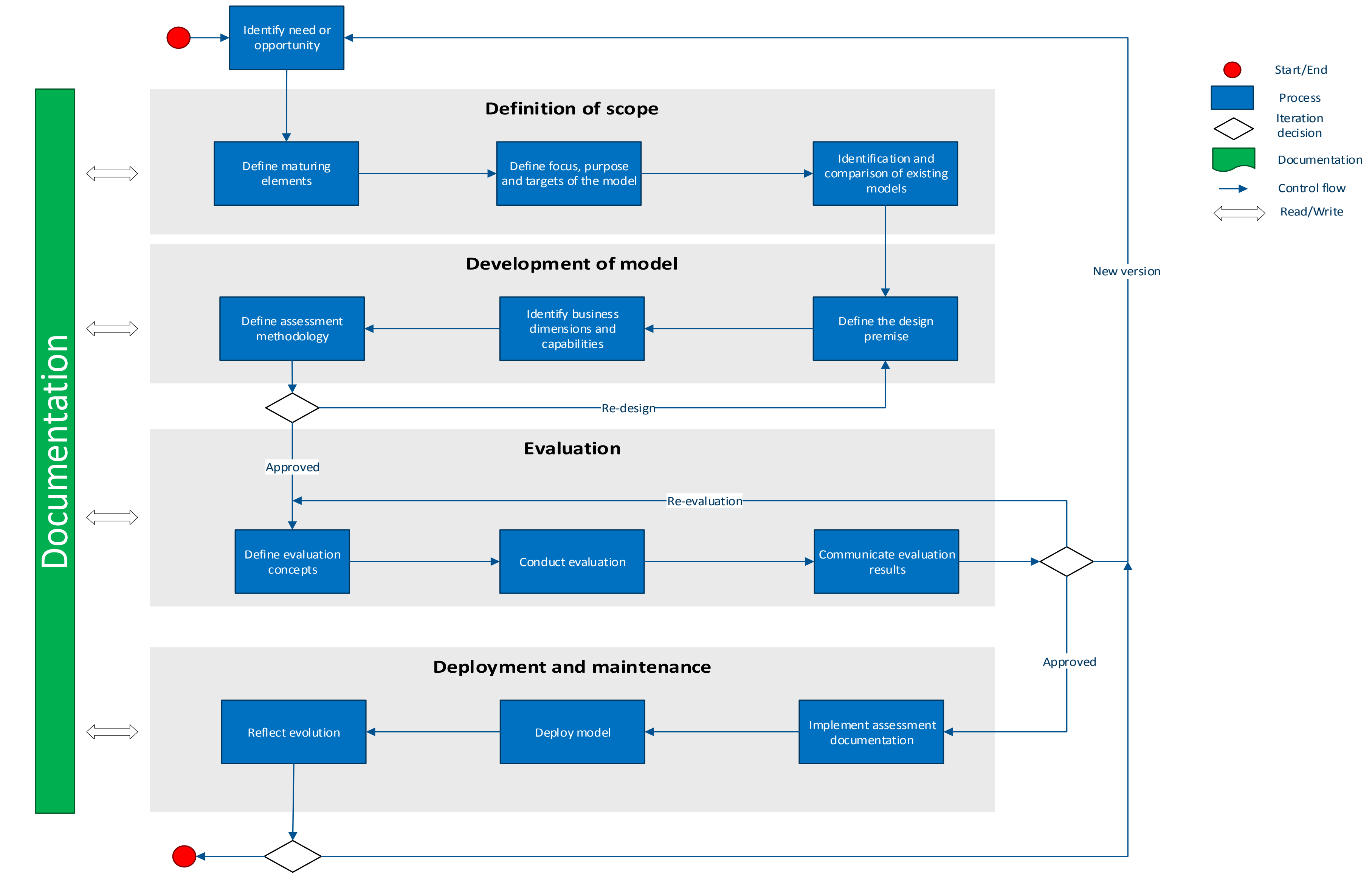

Figure 4.5. *The generic maturity model development framework – phases within the development process*

In the very beginning, before entering the development cycle, one must *identify the need or opportunity* for a new maturity model. This activity is present in the proposals of Mettler (2009, p. 8) and Lahrmann et al. (2011, p. 179), and originates from DSR where either a business need or an economically valuable opportunity initiates the development of an artefact. Immediately after this, one enters the first main phase called **the definition of the scope,** consisting of three sub-phases. Scoping is present in all of the proposals and it is mostly associated with setting the outer boundaries for model application and use (De Bruin et al. 2005, p. 4). In other words, this is the phase where inclusion and exclusion criteria are applied.

As suggested by Kohlegger et al. (2009, p. 57), Mettler (2009, p. 8), and Pöppelbuß and Röglinger (2011, p. 6), the first sub-phase includes *defining the maturing elements*. It has to be determined whether the measured maturity is process-, object-, or people-focused. Kohlegger et al. (2009, p. 57) additionally define the form of change affecting the maturing element, whether it is quality change, capability (readiness) change, risk change, or some other change. In the second sub-phase one must *define focus, purpose and targets of the model*. Decision to be made here are related to defining the focus of the model, whether it is for general or domain-specific use (De Bruin et al. 2005, p. 4; Mettler 2009, p. 8), and purpose of the model, whether the model is descriptive, prescriptive or comparative (De Bruin et al. 2005, p. 4; Mettler 2009, p. 8; Pöppelbuß & Röglinger 2011, p. 6). Furthermore, one must define the target domain and industry (van Steenbergen et al. 2010, pp. 10-11; Pöppelbuß & Röglinger 2011, p. 6) and target audience (De Bruin et al. 2005, p. 4; Mettler 2009, p. 8; Kohlegger et al. 2009, p. 58; Pöppelbuß & Röglinger 2011, p. 6). Once these are specified, *existing maturity models* operating in the same domain can be *identified and compared*. As highlighted by Becker et al. (2009), Kohlegger et al. (2009, pp. 57-58), van Steenbergen et al. (2010, pp. 10-11), and Pöppelbuß and Röglinger (2011, p. 6), this step is intended to find possible solutions that will act as a complement model and starting point for development.

After defining the scope, the phase called the **development of the model** is entered. This is where the artefact, in this case the maturity model, is designed and constructed. A lot of variation is found between the proposals regarding the activity of designing, constructing and populating the model. The team of De Bruin et al. (2005, p. 3) separates the development process into two phases, the design and population phase. Kohlegger et al. (2009, pp. 56-57) look into more detail of the construct of the model by defining level relationships, transitions and stage triggers. Both van Steenbergen et al. (2010, p. 12) and Lahrmann et al. (2011), greatly focus during this phase on the definition of domain capabilities and dependencies. However, a common feature found in all the proposals is that upon completion of the development phase, the research team is provided with a maturity model frame, populated with relevant domain-specific information, and ready to be evaluated.

First, the model *design premise* must be defined (Becker et al. 2009, p. 218; Mettler 2009, p. 8; Mettler et al. 2010, p. 336). This sub-phase includes many decisions, including the design approach, dimensionality of the model, the composition of model elements, and the design process. In a top-down approach one first defines the business dimensions and then fills them with relevant information (Lahrmann et al. 2011, p. 179), and in a bottom-up approach this sequence is reversed. The team of De Bruin et al. (2005), Becker et al. (2009) and van Steenbergen et al. (2010) all prefer a top-down approach over a bottom-up approach when designing maturity models. Mettler (2009, p. 8) suggests a distinction between one-dimensional and multi-dimensional models, and classifies models (Mettler et al. 2010, pp. 337-338) based on whether the model is built like a grid, a Likert-like questionnaire or a CMM-like model. One must also discuss the possibility of choosing between iterative and cyclical model design (Kohlegger et al. 2009, p. 56). The next step in developing maturity models is to *identify a number of business dimensions and capabilities.* This answers the basic questions of "what needs to be measured" and "how it can be measured." The order of whether to identify business dimensions and capabilities before or after model structure depends on the selected design approach. The proposal of De Bruin et al. (2005, p. 6) is to include business dimensions and capabilities that are mutually exclusive and collectively exhaustive, through the identification of domain-specific critical success factors. The team of van Steenbergen et al. (2010, pp. 11-12) also use critical success factors to identify focus area capabilities, which do not rely on a frame with a fixed number of levels. Lahrmann et al. (2011, p. 179) propose a quantitative approach to identify the domain capabilities by applying the Rasch algorithm, while Becker et al. (2009, p. 218), Mettler (2009, p. 9), and van Steenbergen et al. (2010, p. 11) prefer qualitative exploratory research methods. To increase understandability for the end user, the business dimensions and capabilities should be well-defined with textual descriptions in relation to the maturing entities (Pöppelbuß & Röglinger 2011, p. 7). After the identification of business dimensions and capabilities, the developer is provided with the architectural frame of the model, resulting in metric values associated with maturity levels and business dimensions. The relationship and transition between the maturity levels is addressed by Kohlegger et al. (2009, pp. 56-57), and Pöppelbuß and Röglinger (2011, p. 7l) in their proposals, which can help to determine if the maturing element moves from a level to another implicitly or explicitly. In the third sub-phase *the assessment methodology* is defined. This includes both defining the methods of application and the artefact used in the assessment. Becker et al. (2009, p. 218) call this sub-phase "conception of transfer and transfer media." Both De Bruin et al. (2005, p. 8) and van Steenbergen et al. (2010, p. 13), when talking about the assessment artefact, use the term "assessment instrument." Usually the assessment is done by interpreting the provided textual document. The assessment instrument can also be constructed either as a traditional or software assisted questionnaire by formulating control questions for each identified domain capability (Becker et al. 2009, p. 218; van Steenbergen et al. 2010, p. 13). It is recommended to use electronic quantitative data collection methods, because they increase availability and generalizability of the model (De Bruin et al. 2005, p. 8). The number of questions in the assessment instrument must be of a right balance to ensure all topics are covered and that the responses stay reliable (De Bruin et al. 2005, p. 8). Furthermore, one must define how the instrument is used. Three distinct approaches can be distinguished, namely self-assessment, third-party assisted or certified professionals assisted (De Bruin et al. 2005, p. 4; Becker et al. 2009, p. 219; Kohlegger et al. 2009, p. 57). Self-assessment models are often not made generally accessible due to commercial reasons (Becker et al. 2009, p. 219). According to Becker et al. (2009, p. 218), the first iteration decision has to be made after a cycle of the development main phase, in order to comply with the DSR guidelines. The model design must be internally tested for comprehensiveness, consistency and problem adequacy, to ensure that the model is of high quality and sufficiency (ibid.). If these criteria are not fulfilled, the development phase will start again.

Once the designed model is approved internally, the **evaluation** phase is entered. According to Becker et al. (2009, p. 219), evaluation establishes "whether the maturity model provides the projected benefits and an improved solution for the defined problem." The evaluation phase is also concerned with evaluating forms of reliability, namely verification i.e. determining that the model meets the developer's specifications (Mettler 2009, p. 9), and validation i.e. the model measures what it was intended to measure (De Bruin et al. 2005, p. 9). Further evolution criteria are the utility and generalizability of the model (Lahrmann et al. 2011, p. 179).

The whole evaluation process consists of *defining the evaluation concepts, conducting the evaluation* and *communicating the results*. The subject of the evaluation can be either the development process of the model, or the final design product. However, it is recommended that both subjects are present in the evaluation process to fully address the rigor of the model. (Mettler 2009, p. 9.) Lahrmann et al. (2011) mention evaluating methods such as functional testing, structural testing, surveys, focus groups, and interviews. If a method with user testing is selected, the appropriate test users have to be chosen. The team of De Bruin et al. (2005, p. 9) differentiate between evaluating the construct of the model and the assessment instrument, while authors like Becker et al. (2009, p. 219) and Mettler (2009, p. 9) perceive the evaluation process as more holistic. Becker et al. (2009, p. 219) address the possibility of conducting the evaluation publicly via web-based self-assessment, which potentially generates a good amount of test data. Results of the evaluation are communicated to the appropriate group via publications or evaluation reports. The outcome of the evaluation may cause a reiteration of the evaluation process, and in some cases of the whole development process. (Becker et al. 2009; Mettler 2009, p. 8.)

The final phase of the whole maturity model development process is the **deployment and maintenance**. The deployment process begins with *implementing assessment documentation*, which emphasizes on preparing documented guidance to assist the end user in the application of the model. Mettler et al. (2010, p. 339) identify three stages of assistance, namely “no supporting materials”, “handbook or manual”, and “software assisted”, the latter being the most advanced level of assistance. Another aspect that needs to be addressed in the assessment documentation is the practicality of evidence or how suggestions for improvement are presented to the user. The practicality of evidence can be either implicit and general improvement activities, or explicit and specific recommendations. Explicit recommendations are desirable when the model addresses a delimited domain (Mettler et al. 2010, p. 339.) The team of De Bruin et al. (2005, p. 9) argue, that after evaluation the *model must be deployed* and made available for use to verify the generalizability of the model. The De Bruin et al. approach is different from Becker et al. (2009, p. 218), who consider the deployment already happening within the evaluation phase. This argument is backed up by van Steenbergen et al. (2010, p. 13), who argue that the very first application of the model can be used to evaluate the model. However, deploying the model to a great number of end users will generate insight into the general acceptance of the model. For classification purposes, the model is categorized based on the degree of reliability after observing the outcome of the deployment. The model can be verified, validated or certified, the latter being the highest form of reliability (Kohlegger et al. 2009, p. 56). After the deployment, the continued relevance of the model will be ensured by maintaining the model over time (De Bruin et al. 2005, p. 10). Mettler (2009, p. 10) and Lahrmann et al. (2011, p. 179) use the term *reflecting evolution* to describe the need for continuous model maintenance due to the changing nature of the domain. Model elements will get obsolete and new best practices will emerge, and therefore it is important to figure out how to handle alterations in the deployment process (De Bruin et al. 2005, p. 10; Becker et al. 2009, p. 219; Lahrmann et al. 2011, p. 179). Mettler (2009, p. 10) distinguishes between reflecting the model through form (the underlying meta-model or model schema), or functioning (the way how maturity is assessed). It has also to be determined, whether evolution is non-recurring or continuous (ibid). The maintenance will further support the model’s standardization and global acceptance (De Bruin et al. 2005, p. 10). If maintenance requirements are identified, an iteration cycle will be launched. As seen in the generic development framework (figure 4.5), all main-phases should throughout the development process be documented in detail.

Table 4.6. *Maturity model classification system framework – the decisions of generic maturity model development*

Sub-phase	***Decision attributes***	***Decision attribute characteristics***
Basic information	Name	Name of the model
	Primary source	Author(s)
	Origin	Academic Business
	Year of publication	Year
Define maturing elements	Maturing subject	Process maturity Object maturity People capability
Define focus, purpose and targets of the model	Domain focus of the model	General Domain-specific
	Industry considerations	No focus on industries General focus on industries Detailed focus on industries
	Purpose of use	Descriptive Prescriptive Comparative
	Target domain	Name of domain/industry
	Target audience	Management-oriented Technology-focused Both
Identification and comparison of existing models	Innovation	New model Enhancement Combination
Define the design premise	Design approach	Top-down Bottom-up
	Composition	Grid Likert CMM-like
	Design process	Iterative Cyclic
	Maturity levels	0-n
	Business dimensions	0-n
Identify business dimensions and capabilities	Domain capabilities and focus areas	Domain areas identified by the model
Define assessment methodology	Assessment instrument	Textual document Traditional questionnaire Software assessment tool
	Total number of questions for business dimensions	0-n
	Assessment method	Self-assessment Third-party Certified practitioners
Define evaluation concepts	Subject of evaluation	Form Functioning Both
Communicate evaluation results	Total number of respondents that have tested the model	0-n
	Reliablity	Verified Validated Certified
Reflect evolution	Evolution	Non-recurring Continuous
Implement assessment documentation	Application support	No supporting materials Handbook or manual Software assisted
	Practicality of evidence	Implicit improvement activities Explicit recommendations
	Visualization	No visualization Traditional visualization Interactive visualization

All the identified decision attributes and their characteristics are summarized in the maturity model classification system framework, shown in table 4.6. Decisions such as name, primary source, origin, and year of publication were added to the top of the list to describe the basic information of each model. This research defines a “domain” as a field of action, thus perceiving Big Data as a domain of its own. However, some maturity models focus their attention additionally to industries. Industries are defined here as mature and well-known economic regions of actions (eg. finance, retailing, manufacturing, telecom, healthcare). The industry focus is especially present in comparative models that benchmark the results across the industry of the assessor. Thus the attribute “Industry considerations” was added to the framework, to depict the level of focus that models have on industries (no focus, general focus, detailed focus). Furthermore, the decision attribute “visualization” was added to the framework for the development subphase “implement assessment documentation”. Assessment materials can either be presented with no visual aid, as a traditional visualization, or as an interactive visualization. The addition is in line with the findings of LaValle et al. (2011, p. 22) and Manyika et al. (2011, p. 33), who both state that visualizing the data will become greatly valuable since visualization increases understandability.

5. EVALUATION OF BIG DATA MATURITY MODELS

The terms “assessment” and “evaluation” differ in the context of maturity models. Assessment is understood as the act of utilizing the maturity model to measure organizational capabilities, while evaluation is the act of measuring the effectiveness of the maturity model itself. It is important that maturity models are effective in the sense that they identify the right improvement proposals. To show that a maturity model is effective, one can conduct a comparative evaluation. (Helgesson et al. 2012, p. 456.) In this research, comparison is understood as normative comparison, meaning that the aim is to explain invariances of the models and point out the best model among all alternatives being studied (Routio 2007). A form of comparative evaluation is benchmarking, and it can be associated with both qualitative and quantitative means (Johnson 2012).

In this chapter, the decision attributes identified in the systematic literature review are utilized to comparatively evaluate existing Big Data maturity models. In chapter 5.1, the target models are identified in a similar manner to chapter 4 using the approach of Fink (2005). After having selected the final maturity models for evaluation, they are all validated on each decision attribute. As a result, a table is created with information that depicts decision attribute characteristics for every maturity model. Chapter 5.2 defines the structure of the evaluation as well as the criteria evaluation is based upon. Here, the approach of Vezzetti et al. (2014) is adapted, resulting in a benchmarking evaluation. The results of the benchmarking evaluation process are depicted in chapter 5.3. The results are divided into five smaller sections. The first four sections examine the detailed benchmarking results on specific criteria and the fifth section examines the overall benchmarking scores.

5.1 Big Data maturity model selection process

There are a number of maturity models available on the web but how many of those models measure maturity in the domain of Big Data? For selecting the appropriate models used in the benchmarking process in the following chapters, the approach of Fink (see chapter 4.1) is again adapted. The maturity model selection process was conducted on the 17th of March 2015. It was noticed that searching bibliographic databases described in table 4.1 for Big Data maturity models provided only empty results. This suggests, that Big Data maturity models have been developed commercially and publicly, not academically. Thus, the search was conducted with the search engine “Google Search” using the following search combinations:

```
big data maturity model
“big data maturity model”
“big data” AND “maturity model”
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By applying practical and methodological screening criteria such as “ten last years”, “English documents only”, “most relevant”, and “availability”, the total search results were reduced drastically. Exclusion based on accessibility resulted in the exclusion of models such as T-systems’ commercial service “Big Data Readiness Assessment”, Shan’s “Big Data Maturity Model.” and SAP’s “Big Data Maturity Model.” After removing duplicates, the final selection was reduced to eight different maturity models, developed independently from each other. The final eight models are introduced in order of discovery below in table 5.1 with the help of the maturity model classification system framework.

Table 5.1. *The Big Data maturity models and their decision attribute characteristics*

Decision attribute	***Halper***	***Betteridge***	***IDC***	***Infotech***	***Radcliffe***	***El-Darwiche***	***van Veenstra***	***Knowledgent***
Name	Big Data Maturity Model & Assess-ment Tool	Big Data & Ana-lytics Maturity Model	CSC Big Data Maturity Tool	Big Data Maturity Assessment Tool	Big Data Maturity Model	Big Data Maturity Framework	Maturity Model for Big Data Developments	Big Data Maturity Assessment
Primary source	Halper & Krishnan (2013)	Betteridge & Nott (2014)	IDC (2013)	Infotech (2013)	Radcliffe (2014)	El-Darwiche et al. (2014)	van Veenstra et al. (2013)	Knowledgent (2014)
Origin	Educational (TDWI)	Business (IBM)	Business (IDC)	Business (Info-Tech)	Business (Radcliff Advisory Services)	Business (Strategy&)	Business (TNO)	Business (Knowledgent group inc)
Year of publication	2013	2014	2013	2013	2014	2014	2013	2014
Maturing subject	Process, Object, People	Process, Object, People	Process, Object, People	Process, Object, People	Process, Object, People	Process, Object, People	Process, Object	Process, Object
Domain focus of the model	Domain-specific	Domain-specific	Domain-specific	Domain-specific	Domain-specific	Domain-specific	Domain-specific	Domain-specific
Industry con-siderations	General focus on industries	No focus on industries	General focus on industries	No focus on industries	No focus on industries	No focus on industries	No focus on industries	No focus on industries
Purpose of use	Comparative	Descriptive	Comparative	Prescriptive	Prescriptive	Prescriptive	Prescriptive	Descriptive
Target domain	Big Data	Big Data & Analytics	Big Data & Analytics	Big Data	Big Data	Big Data	Big Data	Big Data
Target audience	Management & IT	Management	Management & IT	Management	Management	Management	Management	Management & IT
Innovation	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Design approach	N/A	N/A	N/A	N/A	N/A	Top-down	N/A	N/A
Composition	Likert-like	Grid	Likert-like	Likert-like	Grid	Grid	Grid	Likert-like
Design process	Iterative	N/A	N/A	N/A	N/A	Iterative	N/A	N/A
Maturity levels	6	5	5	4	6	4	4	5

Decision attribute	*Halper*	*Betteridge*	*IDC*	*Infotech*	*Radcliffe*	*El-Darwiche*	*van Veenstra*	*Knowledgent*
Business dimensions	10	6	5	4	8	5	0	5
Domain capabilities and focus areas	Organization, Infrastructure, Data management, Analytics, Governance	Business strategy, Information, Culture & execution, Architecture, Governance	Intent, Data, Technology, People, Process	Staffing, Business focus, Big data management & governance, Technology, Data type & quality	Vision, Strategy, Value & metrics, Governance, trust & privacy, People & organization, Data sources, Data management, Analytics & visualization	Technical & Organizational capabilities, Data availability, Sponsorship, Data-driven decision-making, Customer segmentation	Efficiency, Effectiveness, New solutions, Transformation	Business environment, Technology platform, Operating model, Analytics, Core information disciplines
Assessment instrument	Software assessment tool	Textual document	Software assessment tool	Traditional questionnaire	Textual document	Textual document	Textual document	Software assessment tool
Total number of questions for business dimensions	84	0	79	34	0	0	0	40
Assessment method	Self-assessment	Self-assessment	Self-assessment	Self-assessment	Self-assessment	Self-assessment	Self-assessment	Self-assessment
Subject of evaluation	Form & Functioning	N/A	Functioning	N/A	N/A	N/A	N/A	N/A
Total number of respondents	600	N/A	2000	N/A	N/A	N/A	N/A	N/A
Reliability	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Evolution	Continuous	N/A	Continuous	N/A	N/A	Continuous	N/A	Continuous
Application support	Software assisted	No supporting materials	Software assisted	No supporting materials	Handbook	Handbook	Handbook	Software assisted
Practicality of evidence	Explicit	N/A	Explicit	Implicit	Implicit	Explicit	Implicit	N/A
Visualization	Traditional	No visualization	Interactive	No visualization	Traditional	Traditional	Traditional	Traditional

The information for each decision attribute per model was validated and filled based on the provided materials from each maturity model. Further on, each model is referred to in figures by the name of its author. If the model is developed by several people, the name that appears first in the authors section is chosen. Unavailable information was marked with the abbreviation “N/A.” Unavailable information was especially the case when examining attributes regarding to the documentation of the maturity model development process.

5.2 Benchmarking framework and evaluation criteria

Benchmarking is “the process of identifying, sharing, and using knowledge and best practices” (Lemke et al. 2001, p. 1). It is used for comparative reasons to measure performance using a specific indicator resulting in a metric or performance that is then compared to others (Johnson 2012, p. 40). Whilst mostly applied by organizations to measure business processes and business performance, benchmarking can be also performed for a variety of artefacts including maturity models (Vezzetti et al. 2014). There is a large number of benchmarking models and choosing the right methodology is an essential key in making benchmarking a success (Jetmarova 2011, p. 76).

For evaluating the eight Big Data maturity models, the choice was made to adaptively use the benchmarking framework proposed by Vezzetti et al. (2014, pp. 908-915). Originally applied in the Product Lifecycle Management -domain, the benchmarking framework highlights the strengths and weaknesses of existing maturity models by taking into account “the basic features of the model, such as name, origin, year of the publication, the construction and organization of the model and the application method or tool support” (Vezzetti et al. 2014, p. 916). Vezzetti et al. (2014, p. 908) have divided the benchmarking process into three distinct steps. First, appropriate maturity models have to be selected for comparison. This was already done in chapter 5.1 by selecting eight Big Data –focused maturity models. The selection process consisted of constructing a search string, applying that string to query the chosen search engine, applying inclusion and exclusion criteria to delimit results, and populating the classification system framework with information from the final maturity models.

In the second step, the variables for comparing maturity models are selected. According to Mettler (2010, p. 6), typical measures for evaluating maturity models are the actuality, completeness, consistency, relevancy, trustworthiness, comprehensibility, ease of use, performance, and stability of the model. It was decided, that the Big Data maturity models are evaluated on specific criteria complementing these measures. These criteria were transformed into the following categories:

- Completeness of the model structure (completeness, consistency)
- The quality of model development and evaluation (trustworthiness, stability)
- Ease of application (ease of use, comprehensibility)
- Big Data value creation (actuality, relevancy, performance)

Each of these categories represents an aggregated criteria group consisting of several decision attributes (table 5.2), identified in the systematic literature review. The first criteria group, completeness of the model structure, emphasizes on how extensively the model was built. Decision attributes included in this group are especially the attributes that can be characterized as metric values (e.g. number of maturity levels, business dimensions). Secondly, the quality of model development and evaluation addresses the key problematic findings of the systematic literature review. This criterion focuses on how well the maturity model development process was documented, if best practices and standardized methods were used for development, and how well the model was tested. The third criteria group, ease of application, addresses the supporting tools presented to the end user when applying the model in practice. Evaluation focuses on the quality of guidelines for maturity assessment as well as the improvement recommendations. The fourth and the last criteria group, Big Data value creation, evaluates the maturity model based on how well it applies to the Big Data domain emphasizing on business value creation.

Table 5.2. *Aggregated criteria groups and their decision attributes*

Completeness of the model structure	***Quality of model development and evaluation***	***Ease of application***	***Big Data value creation***
Purpose of use	Design approach	Assessment instrument	Maturing subject
Industry considerations	Design process	Assessment method	Domain focus of the model
Composition	Subject of evaluation	Application support	Target domain
Maturity levels	Total number of respondents that have tested the model	Practicality of evidence	Target audience
Business dimensions	Reliablity	Visualization	Domain capabilities and focus areas
Innovation	Evolution		
Total number of questions for business dimensions			

The final step of the benchmarking process is to define and calculate a relative score for each attribute per maturity model. The score for each attribute per model depends on how well the attribute meets the criteria it is grouped with, and is based on arguments found in the previously examined literature. In other words, a decision attribute with a characteristic seen as a good practice for that specific criteria, is awarded a better score. For example, three distinct characteristics can be identified for the decision attribute "purpose of use", namely descriptive, prescriptive and comparative. Upon investigating academic literature it can be concluded, that these three characteristics represent chronological and evolutionary phases of a model's lifecycle and domain-specific issues are addressed in more detail when moving from descriptive models to comparative models (De Bruin et al. 2005, p. 3; Pöppelbuß & Röglinger 2011, p. 4). Thus, descriptive models are assigned a score of one, prescriptive a score of two, and comparative a score of three. If information about a specific attribute is not available for a model, the attribute is automatically scored as zero. After assigning scores for the attributes of each criteria group per model, two final benchmarks can be extracted. The first final benchmark is a detailed benchmark that compares the models according to the criteria groups, and the second total benchmark compares the models as a whole. For better representation, the final results are visualized with a radar chart.

5.3 Benchmarking results

The next sections describe the results of the benchmarking process. The first four sections address the benchmarks according to each criteria group, while the fifth section examines the overall benchmarking scores. The overall benchmarking scores are presented in two different ways. First, as a more detailed benchmark comparing models in each criteria group. And secondly, as a total benchmarking score comparing models as a whole.

5.3.1 Completeness of the model structure

The aggregated criteria group "completeness of the model structure" comprises of decision attributes such as "purpose of use", "industry focus of the model", "composition", "innovation", "maturity levels", "business dimensions", and "total number of questions for business dimensions". For the attribute "purpose of use", a score was assigned on the basis of the type of purpose specified by the maturity model (1=descriptive; 2=prescriptive; 3=comparative). The attribute "industry considerations" was scored in terms of how broadly models focused on industries during prescriptive actions (0=no focus on industries; 1=general focus on industries; 2=detailed focus on industries). For the attribute "composition", a score was assigned based on how the maturity model was structured (1=grid; 2=Likert-like; 3=CMM-like). For the attribute "innovation", a score was assigned in regard to how well the model has utilized existing maturity models in the scoping phase (1=new model; 2=enhancement; 3=combination). For attributes "maturity levels", "business dimensions" and "total number of questions for business dimensions", a value was assigned according to the number of maturity levels, business dimensions, and questions asked in the assessment.

Table 5.3. *Completeness of the model structure – attributes and scores*

Max score	*Completeness of the model structure*	*Halper*	*IDC*	*Inf*	*Bett*	*El-D*	*Radcl*	*van V*	*Knowl*
3	Purpose of use	3	3	2	1	2	2	2	1
2	Industry considerations	1	1	0	0	0	0	0	0
3	Composition	2	2	2	1	1	1	1	2
3	Innovation	0	0	0	0	0	0	0	0
6	Maturity levels	6	5	4	5	4	6	4	5
10	Business dimensions	10	5	4	6	5	0	0	5
84	Total number of questions for business dimensions	84	79	34	0	0	0	0	40

The results for the decision attributes in the criteria group "completeness of the model structure" are visible in table 5.3. A radar chart (figure 5.1) was used to visualize the final score. For efficiency, the values have been normalized using the maximum score of each attribute row.

Figure 5.1. *Results of "completeness of the model structure" for each maturity model*

There is great variance between the Big Data maturity models when examining the completeness or extensiveness of the model, as seen in the figure 5.1 above. The models of Halper and Krishnan (2013), and IDC (2013) provide the end users with all descriptive, prescriptive, and comparative functionality, while the models of Infotech (2013), El-Darwiche et al. (2014), Radcliffe (2014) and van Veenstra et al. (2013) serve a descriptive-prescriptive purpose of use. The models of Betteridge and Nott (2014), and Knowledgent (2014) were the only ones acting as a descriptive model, not providing any recommendations or improvement activities. Upon investigation it was also noted, that none of the models were structured as a CMM-like model, but merely as a maturity grid or Likert-like questionnaire. Since CMM-like models provide the right amount of complexity, also defining specific goals for key process areas and considering common implementation and infrastructural activities, can all evaluated Big Data maturity models be seen to lack in composition.

Another criteria measured is the numeric value regarding the models structural objects. Whilst others have built their model traditionally with 4 to 5 maturity levels, include Halper and Krishnan (2013), and Radcliffe (2014) a sixth level. This additional level in both models can be called a “non-existing” level, and it addresses the issues and several hurdles with closing a specific “knowledge-gap.” The non-existing levels can be identified as crucial time-consuming phases and assist in smoothly transitioning over problematic barriers. Halper and Krishnan, and Radcliffe also exceed having defined a total of 8-10 business dimensions, and covering a wide area of capabilities. Notable is, that van Veenstra et al. (2013) do not specify any business dimensions at all, relying only on maturity levels and embedded prescriptive and general recommendations. The “total number of questions for business dimensions” –attribute correlates with models that provide some sort of assessment tools to the end user. Whilst Halper and Krishnan, and IDC (2013) ask a total of ca. 80 questions in their assessment, do Infotech (2013) and Knowledgent (2014) ask only the half of that amount, namely ca. 40 questions. However, a great number of questions can consume a great amount of time, hence the importance of the overall score for each maturity model. None of the Big Data maturity models provided information about the attribute “innovation”, or whether the maturity model uses a conceptual mother model.

5.3.2 Quality of model development and evaluation

The aggregated criteria group “quality of model development and evaluation” comprises of decision attributes such as “design approach”, “design process”, “subject of evaluation”, “total number of respondents that have tested the model”, “reliability”, and “evolution”. For the attribute “design approach”, a score is awarded based on the type of approach used in developing and constructing the conceptual model (1=bottom-up; 2= top-down). The attribute “design process” addresses whether the model is designed cyclically or iteratively (cyclical=1; iterative=2). For the attribute “subject of evaluation”, a score is assigned on the basis of what is considered to be the target of testing and evaluation as a part of the model's development process (form=1; functioning=1; form and functioning=2). The attribute "the total number of respondents that have tested the model" is awarded a score in relation to how many users have tested and used the model. For this, the latest information provided is used. For the attribute "reliability", a score is assigned on the basis of the general and public acceptance of the model (1=verified; 2=validated; 3=certified). Lastly, the attribute "evolution" measures whether the model is maintained continuously or not (0=non-recurring; 1=continuous).

Table 5.4. *Quality of model development and evaluation – attributes and scores*

Max score	*Quality of model development and evaluation*	*El-D*	*Halper*	*IDC*	*Bett*	*Inf*	*Radcl*	*van V*	*Knowl*
2	Design approach	2	0	0	0	0	0	0	0
2	Design process	2	2	0	0	0	0	0	0
2	Subject of evaluation	0	2	1	0	0	0	0	0
2000	Total number of respondents that have tested the model	0	600	2000	0	0	0	0	0
3	Reliablity	0	0	0	0	0	0	0	0
1	Evolution	1	1	1	0	0	0	0	1

The results for the decision attributes in the criteria group "quality of model development and evaluation" are visible in table 5.4. A radar chart (figure 5.2) was used to visualize the final score. For efficiency, the values have been normalized using the maximum score of each attribute row. Since there are a lot of zero score entries, the radar charts axis is formatted to scale more optimally.

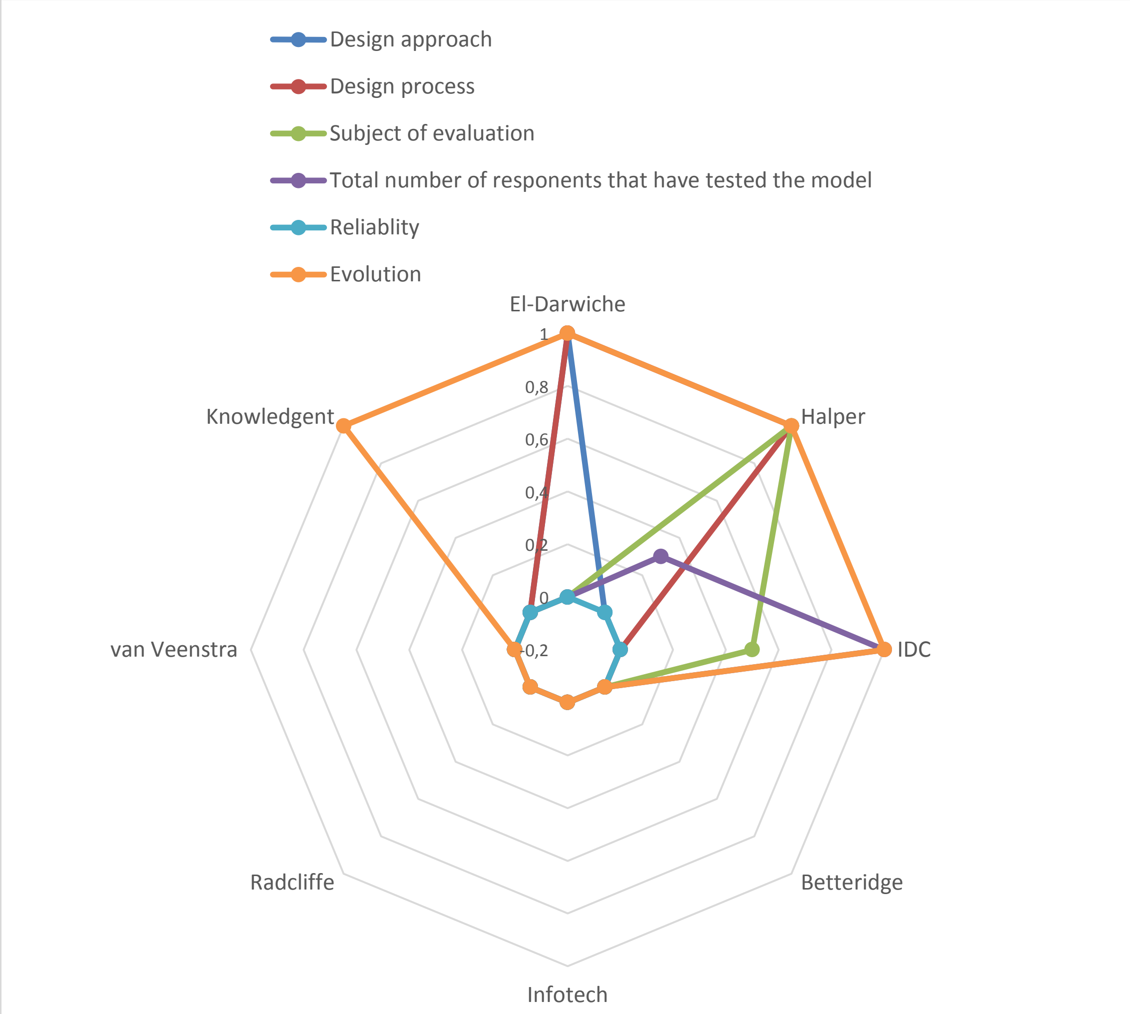

Figure 5.2. *Results of "quality of model development and evaluation" for each maturity model*

It was a challenge to evaluate the Big Data maturity models on the criterion quality of model development and evaluation, since development processes were documented poorly or the information was not accessible. A questionnaire regarding the development processes (see appendix B) was sent out to the immediate authors of all the models. This however yielded only answers from the team of El-Darwiche et al. (2014). The unavailable information for this criteria group is in line with the findings of the systematic literature review, namely that maturity models lack in documentation when looking into the model's development processes.

Information for the design approach was available for El-Darwiche et al. (2014) who state that the maturity model design is based on their collective experience in the industry. El-Darwiche et al. see their model as a hybrid model, consisting of both top-down and bottom-up design approaches. Furthermore, El-Darwiche et al. argue that the model is subject to iterative refinement due to more and more organizations continuously adopting Big Data practices. The iterative design process is also mentioned by Halper and Krishnan (2013), who state that best practices will be added to the model as information is gathered from observations and success stories.

The quality of evaluation or testing during the development process was measured with the subject of evaluation, total number of respondents that have tested the model, and reliability. The subject of evaluation for the model Halper and Krishnan (2013) was identified as both form and functioning. The Big Data maturity model of Halper and Krishnan is presented as an evolutionary model and its practices are under constant evaluation, affecting both the content and structure of the model. The subject of evaluation for IDC (2013) is only the model functioning (or the way the maturity model is being used). Evidence for this is that IDC's Big Data maturity model stems from an IDC research paper published in 2013, and it was during the years transferred to a software tool hosted by CSC. However, during this transfer the content of the model was unaffected. The total number of respondents that have tested the model could be also found only for the models of Halper and Krishnan, and IDC. Halper mentions in a "TDWI Big Data maturity model" related blog post that ca. 600 respondents have participated in the assessment as of 2014 (Halper 2014). This number is however topped by the Big Data and Analytics Assessment maturity model from IDC, who credit over 2000 respondents from major industries around the world to have tested the model. For all maturity models, no information was found regarding the reliability or the degree of public acceptance. One reason for the low acceptance rate can be the fairly young age of all the maturity models examined.

The quality of model maintenance was evaluated with the criterion "evolution." For the models of Halper and Krishnan (2013), IDC (2013), El-Darwiche et al. (2013), and Knowledgent (2014), a clear continuous pattern of reflecting evolution is identified. Especially Knowledgent's model was detected to be under continuous change, even having modifications happening during the benchmarking process. The rest of the models were identified to serve more of a one-time purpose.

5.3.3 Ease of application

The aggregated criteria group "ease of application" comprises of decision attributes such as "assessment instrument", "assessment method", "application support", "practicality of evidence" and "visualization". Values were assigned based on the type of instrument (1=textual document; 2=traditional questionnaire; 3=software assessment tool), method of assessment (1=self-assessment; 2=third-party assisted; 3=certified practitioners), and type of application support (0=no supporting materials; 1=handbook; 2=software assisted). For the attribute "practicality of evidence", a score was assigned according to the type of recommendations given after the assessment (1=implicit improvement activities; 2=explicit recommendations). Lastly, the attribute "visualization" evaluated the type of visualized assistance provided (0=no visualization; 1=traditional visualization; 2=interactive visualization).

Table 5.5. *Ease of application – attributes and scores*

Max score	*Ease of application*	*Halper*	*IDC*	*El-D*	*Radcl*	*van V*	*Inf*	*Bett*	*Knowl*
3	Assessment instrument	3	3	1	1	1	2	1	3
3	Assessmentt method	1	1	1	1	1	1	1	1
2	Application support	2	2	1	1	1	0	0	2
2	Practicality of evidence	2	2	2	1	1	1	0	0
2	Visualization	1	2	1	1	1	0	0	1

The results for the decision attributes in the criteria group "ease of application" are visible in table 5.5. A radar chart (figure 5.3) was used to visualize the final score. For efficiency, the values have been normalized using the maximum score of each attribute row.

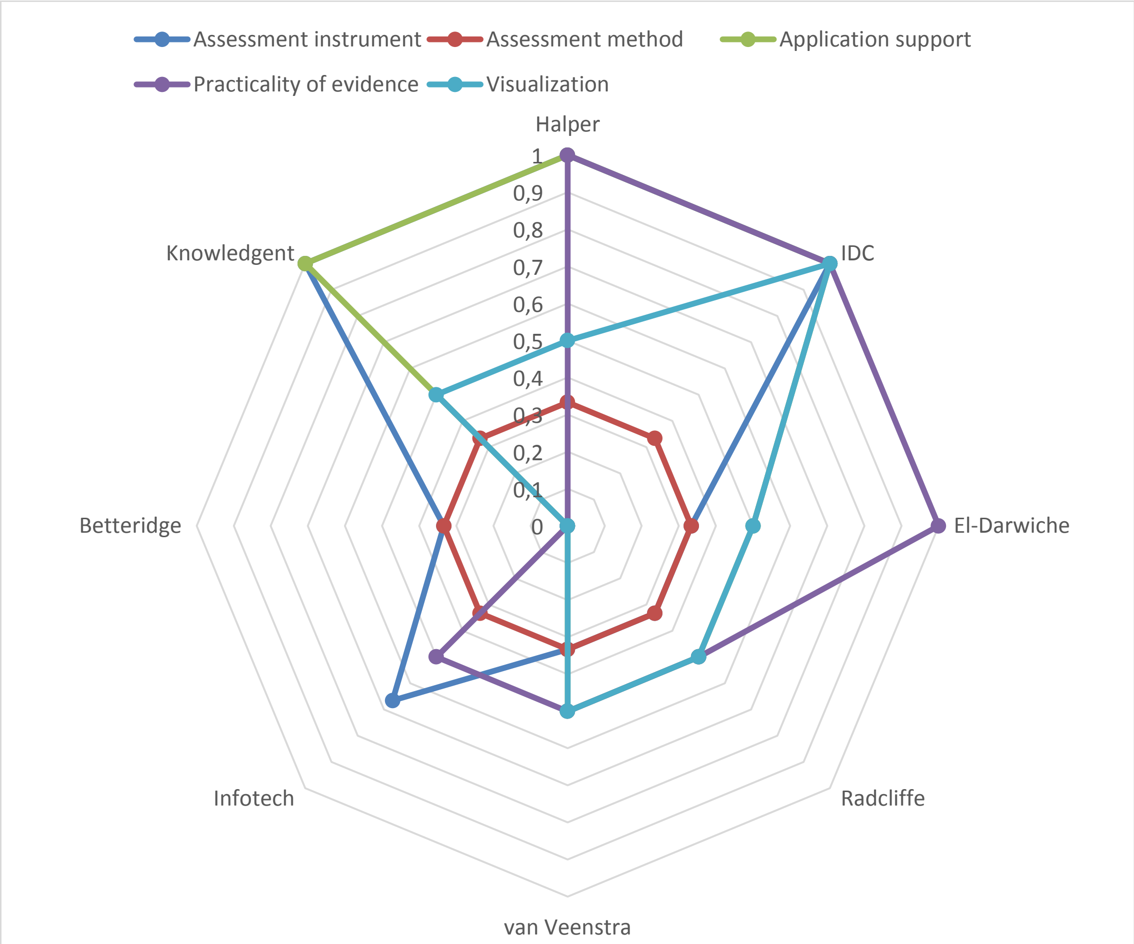

Figure 5.3. *Results of "ease of application" for each maturity model*

In terms of ease of application, the Big Data maturity models differ in the way they are practically used, and in the way materials are provided for assistance. However, the assessment method for every model was identified as the same, namely self-assessment.

This was mostly due the fact that assessments conducted by third-parties or certified practitioners have usually commercial intent (eg. the Big Data readiness assessment of T-Systems), not falling into the boundaries of the examined commercial-free models.

Within the models, all three types of assessment instruments could be identified. Halper and Krishnan (2013), IDC (2013) and Knowledgent (2014) offer their Big Data maturity assessment instrument as a software tool, accessible via a web browser. In all three cases, the software assessment tool automatically calculates a maturity score based on the answers given to a certain number of questions. In addition, Halper and Krishnan, and IDC calculate a benchmarking score, comparing the assessor's results to industry averages. Infotech (2013) offer their assessment instrument as a traditional questionnaire and the calculation is done with the help of spreadsheet functionality. This type of traditional questionnaire is not as intuitive as the web-based software assessment. The rest of the authors present their maturity model in the form of a textual document, not providing an assessment directly to the end user. This means that the end user has to, on his own, figure out the best way to utilize the descriptive and prescriptive content of these models to measure their Big Data maturity and capabilities.

The form of the assessment instrument is closely tied to the application support. All models that include a software assessment tool provide software assisted application support. Instructions are embedded within the software tool and guide the user in using the maturity model in the most effective way. The application support of Halper and Krishnan (2013) is especially of high quality due to them additionally providing a guide book for interpreting the assessment score, and an introduction webinar video. Radcliffe (2014), El-Darwiche et al. (2014) and van Veenstra et al. (2013) have published their maturity model to the public via a white paper or a research paper. These papers act as handbooks that guide the user in identifying certain maturity topics associated with their organization. Furthermore, Radcliffe's argues that the Big Data maturity model works the best when combining it with his Big Data framework that details the components of the Big Data big picture. Both Betteridge and Nott (2014), and Infotech (2013) do not provide any supporting materials, presenting all information within the frame of their maturity model.

The practicality of evidence measures whether recommendations are given on a more general implicit level or on a more specific explicit level. Halper and Krishnan (2013), IDC (2013), and El-Darwiche et al. (2014) all provide detailed information about steps that need to be taken to overcome boundaries and to transition from a lower maturity level to a higher one. While Halper and Krishnan, and IDC offer explicit recommendations per every business dimension, focus El-Darwiche et al. more on giving advice on the procedures built on top of these dimensions, namely environment readiness and internal capabilities. As for Radcliffe (2014), van Veenstra et al. (2013) and Infotech (2013), improvement activities are in the form of good practices organizations in general should implement within each maturity level. Knowledgent (2014) as a descriptive model did not provide any improvement activities or recommendations. Betteridge and Nott (2014) advertise their model as a prescriptive model arguing that it "provides guidance on the steps required to realize the desired target state." However, this statement is faulty due to the fact that neither implicit nor explicit recommendations are directly given.

When examining the visualization, IDC (2013) is the only one building their visualization in an interactive way. A visual chart is built for every business dimension as well as an overall score and alignment score. These charts can then be modified by interacting with specific parameters. Halper and Krishnan (2013), Radcliffe (2014), El-Darwiche et al. (2014), van Veenstra et al. (2013), and Knowledgent (2014) all illustrate their maturity model as a traditional figure, helping the end user to quickly understand and adapt the model's basic concepts. No visualization was identified for the models of Betteridge and Nott (2014), and Infotech (2013), both presenting their model as only textual.

5.3.4 Big Data value creation

The final criteria group "Big Data value creation" contains decision attributes such as "maturing subject", "focus of the model", "target domain", "target audience", and "domain capabilities and focus areas." The "maturing subject" of a maturity model is process maturity, object maturity, people capability, or combinations of these. Thus, a point is awarded for every maturing subject mentioned within the model. For the attributes "focus of the model" and "target domain", a value is assigned based on what domain the maturity model operates in. Domain-specific models are assigned a value of 2, while more general models assigned a value of 1. Furthermore, maturity models that target Big Data specific topics are awarded a score of 1, while every other domain is awarded 0. For the attribute "target audience", a score is assigned based on what audience the model is directed to (1=management; 1=IT; 2=both management and IT). Finally for the attribute "domain capabilities and focus areas", maturity models are awarded one point for every Big Data domain capability and sub-capability (figure 2.1) mentioned. The maximum score of 24 is awarded if all capabilities are addressed in the maturity model.

Table 5.6. *Big Data value creation – attributes and scores*

Max scores	*Big Data value creation*	*Halper*	*IDC*	*Inf*	*Bett*	*El-D*	*Radcl*	*van V*	*Knowl*
1	Focus of the model	1	1	1	1	1	1	1	1
1	Target domain	1	1	1	1	1	1	1	1
3	Maturing subject	3	3	3	3	3	3	2	2
2	Target audience	2	2	1	1	1	1	1	2
24	Domain capabilities and focus areas	23	20	13	10	19	15	17	12

The results for the decision attributes in the criteria group “Big Data value creation” are visible in table 5.6. A radar chart (figure 5.4) was used to visualize the final score. For efficiency, the values have been normalized using the maximum score of each attribute row.

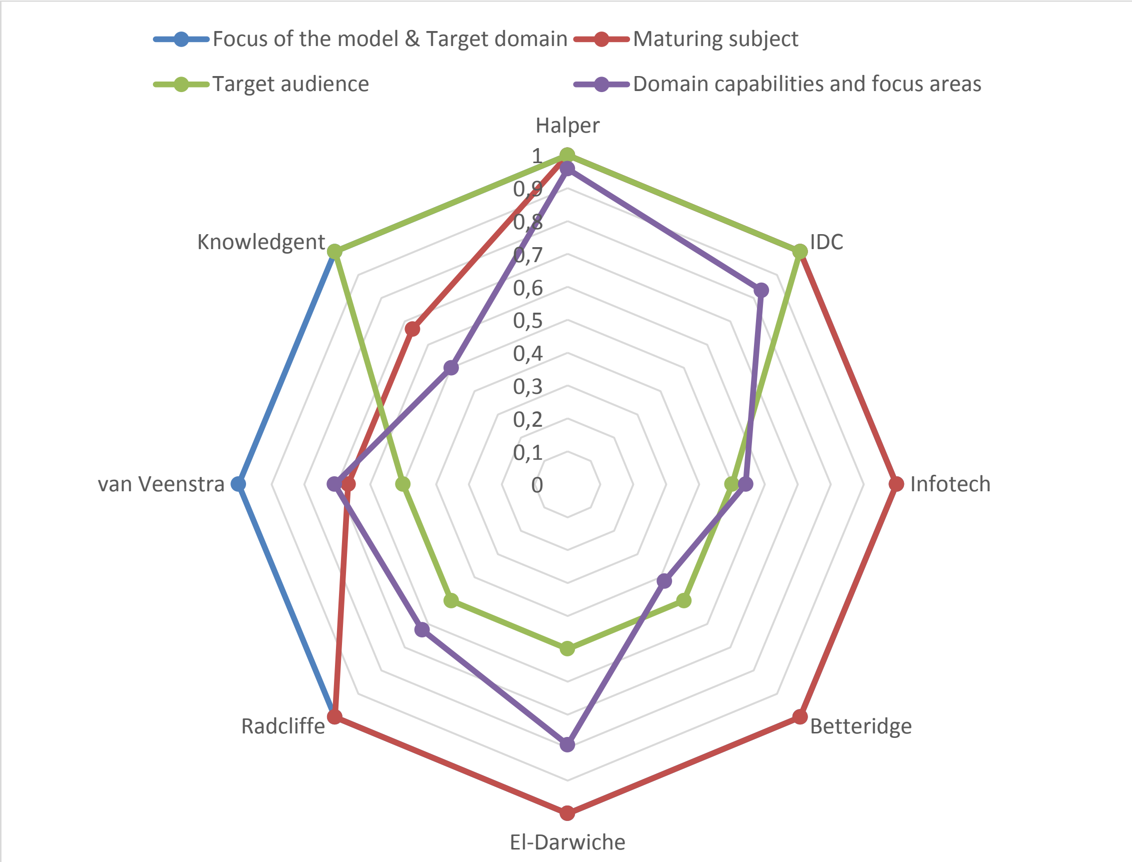

Figure 5.4. *The results of “Big Data value creation” for each maturity model*

As seen in the figure 5.4 above, all evaluated maturity models have the right focus and target in terms of the Big Data domain and its capabilities. However, when examining the maturing subject of the maturity models, both van Veenstra et al. (2013) and Knowledgent (2014) do not fully address the people capabilities in forms of talent and competence management. Most variance in this category is seen in the attributes of target audience and domain capabilities. Halper and Krishnan (2013), IDC (2013) and Knowledgent all clearly state that their model’s intention is to serve the needs of both managerial and technical people, while the rest of the models have a strong business and management focus. When examining the domain capabilities and focus areas that maturity models mention, Halper and Krishnan are clear winners addressing almost all capabilities identified previously in this research. IDC, El-Darwiche et al. (2014) and van Veenstra et al. are close seconds addressing all main topics, but they leave out more specific information valuable to Big Data business value creation. Radcliffe (2014), Infotech (2013), Knowledgent, and Betteridge and Nott (2014) score the least points in this category, poorly addressing analytical and technological capabilities as well as topics of customer segmentation.

5.3.5 Overall benchmarking scores

The previous benchmarking results form a basis for calculating the overall benchmarking score (table 5.7). First, the total score of each criteria group is calculated for every maturity model by summing together the normalized attribute values. These sub-totals are later used in visualizing the detailed benchmarking score. Finally, the total benchmarking score for every maturity model is calculated by summing together the total criteria group scores.

Table 5.7. *Overall benchmarking scores for the Big Data maturity models*

Criteria group	***Halper***	***IDC***	***El-D***	***Knowl***	***Inf***	***Radcl***	***van V***	***Bett***
Completeness of the model structure	5,17	4,44	2,17	2,81	2,80	2,80	1,67	2,1
The quality of model development and evaluation	3,30	2,50	3,00	1,00	0,00	0,00	0,00	0,00
Ease of application	3,83	4,33	2,67	2,83	1,50	2,17	2,17	0,67
Big Data value creation	4,96	4,83	4,29	4,17	4,04	4,13	3,88	3,92
Total score	***17,26***	***16,11***	***12,13***	***10,81***	***8,35***	***8,29***	***7,71***	***6,68***

The detailed benchmarking scores for every Big Data maturity model are visualized in figure 5.5 as a radar chart. Results in the radar chart are presented as normalized values for efficiency. The models are ordered on the total score from highest to lowest.

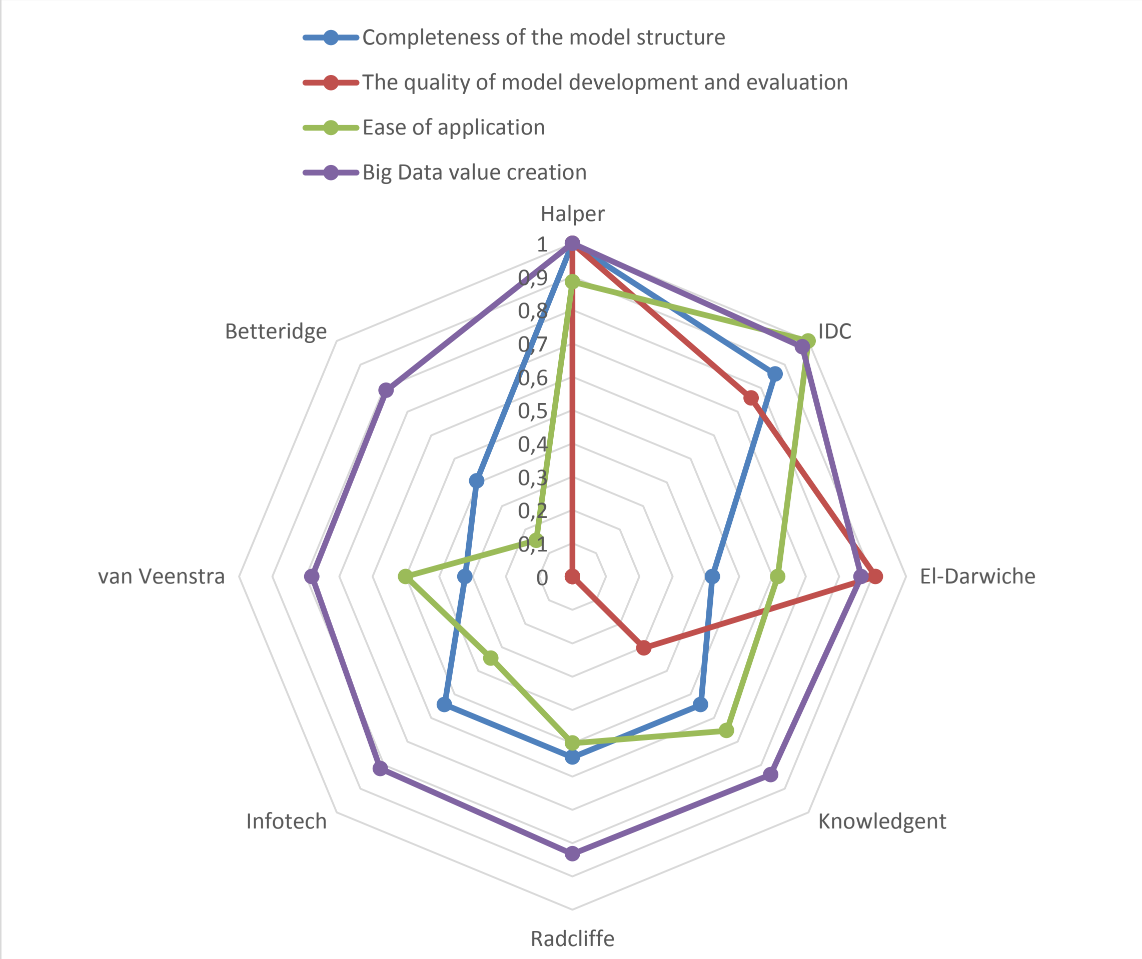

Figure 5.5. *Detailed benchmarking scores of Big Data maturity models*

The detailed benchmark reflects the variation between Big Data maturity models in specific criteria groups. Whilst Big Data value creation is balanced, all other criteria differ greatly between the maturity models. Halper and Krishnan's (2013) Big Data maturity model and assessment tool is ranked first in model completeness, model quality and Big Data value creation, while IDC (2013) ranks first in the ease of application.

Model completeness and extensiveness is well represented in models of Halper and Krishnan (2013), and IDC (2013). These models are structured as prescriptive-comparative models and provide benchmarking functionality to the end user. The maturity assessment is done on a Likert-scale, by asking a number of questions for a good variety of business dimensions. Results are then compared to a variety of mature industries, but only on a general level. Knowledgent (2014) and Infotech (2013) offer a similar Likert-like assessment tool for measuring organizational maturity, but haven't yet implemented benchmarking capabilities. The rest of the models, namely Radcliffe (2014), van Veenstra et al. (2013) and Betteridge and Nott (2014), are grid-like composites, not relying on direct maturity assessment tools. However, Radcliffe distinguishes himself from others by combining his maturity model with an extensive Big Data business dimension framework, addressing six maturity levels in relation to eight business dimensions. The team of van Veenstra et al. build their gird-like model somewhat abnormally, not directly addressing any business dimensions.

By examining the quality of model development and evaluation we can conclude that the models of Halper and Krishnan (2013), IDC (2013) and El-Darwiche et al. (2014) perform very strong in this category, in contrast to the rest of the models. The strong performers have provided information about the underlying methodological assumptions of their maturity model. These methodological choices are also in line with good development practices, making them credible for practical use. The radically low scores for the rest of the models can be explained by the lack of documentation in relation to the models' development processes. This finding confirms the argument found earlier in the systematic literature review that maturity model authors document their development processes in a dissatisfactory manner.

The category "ease of application" is dominated by models associated with a software type tool, namely Halper and Krishnan (2013), and IDC (2013). Software assisted maturity assessment with visualized results ensures that the model is easy to use and as comprehensible as possible to the end user. The rest of the models, with the exception of Betteridge and Nott (2014), have a balanced approach affecting the ease of application, lacking only a bit in the way assistance is provided to the end user. Betteridge and Nott score very low in this category, not providing any application support for their model. Furthermore, Betteridge and Nott have intended their Big Data maturity model as solely descriptive, meaning that using the model in a practical scenario is difficult.

Big Data value creation scores are distributed surprisingly even. However, the benchmark tends to lean towards Halper and Krishnan (2013) and IDC (2013), them addressing all general maturing subjects and a great number of Big Data capabilities. The models are also customized to not only address the decision makers and management within a business, but also the technical specialists that operate the Big Data systems.

The total benchmarking score for the Big Data maturity models is shown in table 5.7 and illustrated in figure 5.6. The radar chart visualizes the total score of each maturity model as a shared percentage of the sum of all total scores. Three distinct categories can be identified based on the obtained results, namely top performers, mid performers, and low performers.

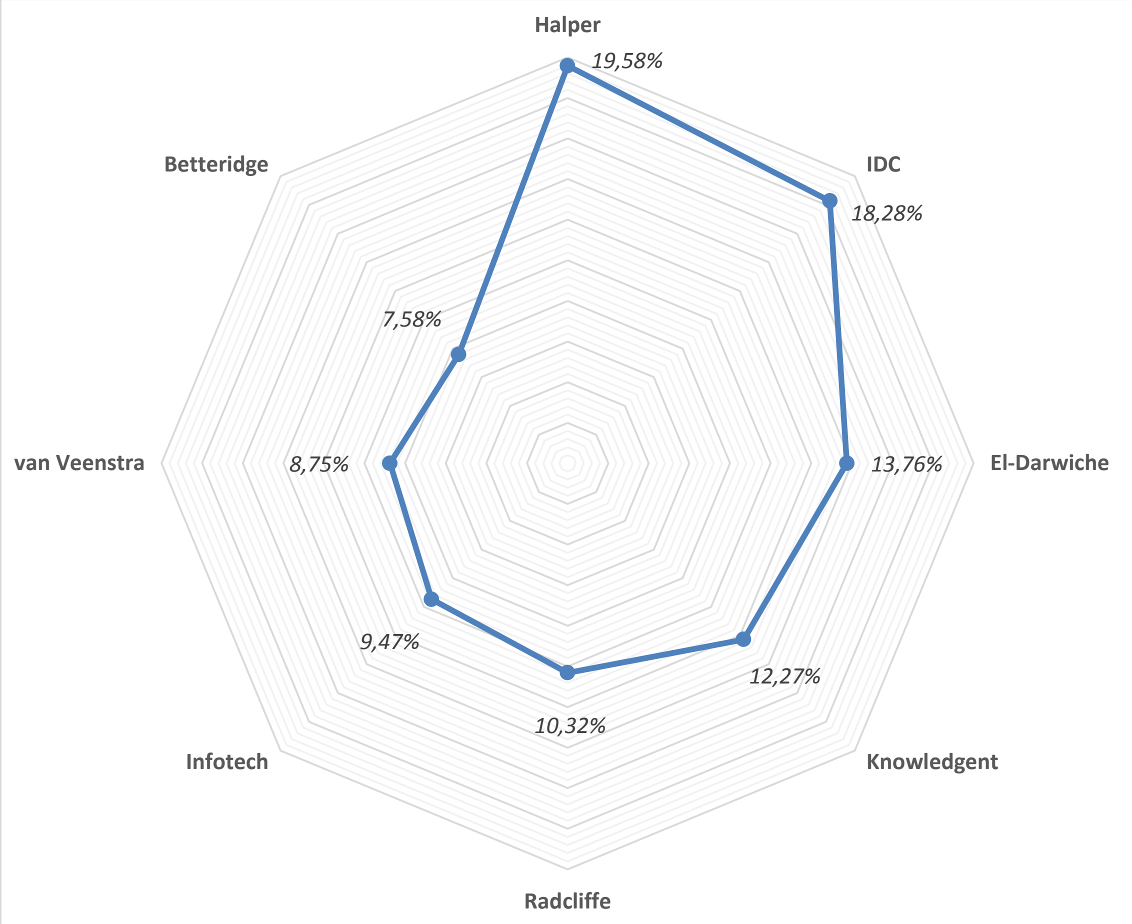

Figure 5.6. *Total benchmarking scores of Big Data maturity models*

As seen in the radar chart above (figure 5.6), the models of Halper and Krishnan (2013), and IDC (2013) have the strongest overall performance, their score being closely tied together (ca. 18-20% of the total). The good overall score for these top performers are a result of steady scores in each criteria group. The overall results communicate that the top performer models are extensive, balanced, well-documented, easy to use, and they address a good number of Big Data capabilities utilized in business value creation. The models of El-Darwiche et al. (2014) and Knowledgent (2014) are close seconds, having both a share of ca. 12-14 % of the total. These mid performers address Big Data value creation in a commendable manner, but fall a bit off when examining the completeness of the model and ease of application. Furthermore, Knowledgent suffers heavily from poor quality of development, having barely documented any of its development processes. The rest of the models, namely the models of Infotech (2013), Radcliffe (2014), van Veenstra et al. (2013) and Betteridge and Nott (2014), fall in the category low performers, having each a share of ca. 8-10% of the total. Whilst their content is well aligned with business value creation through Big Data capabilities, they all lack quality of development, ease of application and extensiveness. Lowest scores were awarded to Betteridge and Nott, and van Veenstra et al., since both are providing low level guidance for the maturity model's practical use, and they completely lack in documentation, ultimately resulting in poor quality of development and evaluation.

6. CONCLUSIONS

This chapter presents the conclusions and key findings of the research. The key findings are outlined by reflecting on the research questions formed in chapter 1.2. Furthermore, the research and its methods are evaluated from a critical point of view in terms of reliability and validity. A critical review is necessary to address the possible weaknesses, problems and limitations that have occurred during the research process. Lastly, a brief discussion is held about the future research opportunities.

6.1 Research summary and conclusions

The objective of this research was to design a benchmarking process to evaluate available Big Data maturity models in terms of business value creation and good practices of maturity modeling. As a result, maturity models could be effectively compared to determine the best available model for business organizations to practically assess and improve their Big Data maturity. The research objective was translated into a main research question, comprising of several elements and concepts. To define these elements and concepts, and to support the research process, this main research question was further on divided into six sub-questions. Sub-questions one to three were designed to define key concepts such as Big Data and maturity modeling as well as how to utilize Big Data in business value creation. The fourth sub-question supported in analyzing and summarizing best practices of maturity model development and classification. Lastly, sub-questions five and six guided in selecting the appropriate maturity models for comparison and designing an efficient benchmarking process around them. Hence, in the next section all sub-questions are gone through chronologically and provided with an answer. As they unfold one-by-one, enough information is obtained to ultimately answer the main research question.

What is Big Data and what are the characteristics behind it?

Big Data in its simplicity is a term for complex and large information assets, addressing both technological and business implications. It is a result of the explosive growth of data led by the digitization of our society, and has since its emergence been a topic of interest among both business and academic societies. To distinguish Big Data from traditional data processing and analytics, it is often associated with the attributes of high-volume, high-variety and high-velocity. Volume, also perceived as the primary attribute of Big Data, refers to the large amount of data available, usually measured in terabytes and petabytes. The fast growth of the Internet and the evolution of handheld devices have contributed to the generation of high-volume Big Data. All data is argued to grow on an annual rate of ca. 40 %. However, Big Data also contains excess data that may not be in any forms valuable to the end user. Velocity refers to the rate at which data is captured. Data is now captured in real time or near real time, requiring organizations to react more quickly to occurring changes. Big Data technologies try to overcome this challenge by connecting the important data streams and capturing the most valuable information for intelligent analysis. Lastly, variety refers to the different forms data is occurring in our everyday life. Big Data is a mix of structured and unstructured data, which together present a challenge for data management. The sources of Big Data are usually categorized into human-sourced information, process-mediated data and machine-generated data. While process-mediated and machine-generated data is highly structured, human-sourced information is highly subjective and unstructured in forms of media files and social network data.

Technology is a necessary component for Big Data. Technological solutions have been developed to address the issues with traditional data processing systems, ultimately capturing value from the vast amount of complex data. There are a growing number of technologies used to aggregate, manipulate, manage and analyze Big Data, the most prominent being NoSQL systems, Hadoop, and cloud computing. NoSQL systems are high-scalable and high-performance database systems that handle agile processing of large information sets. These NoSQL systems are unstructured in nature, trading off consistency requirements for speed and agility. They can be classified into key-value, document, wide-column, and graph storage systems, all having unique functional and structural characteristics. NoSQL systems are mostly open-source and they build their processing on cheap hardware, making them very cost-efficient. However, they are far from advanced database technologies and will not replace traditional relational systems in the near future. Hadoop is an open-source software project, providing distributed processing of large datasets across clusters of computers using simple programming models. It can be viewed as a software ecosystem, consisting of primary components Hadoop Distributed File System (HDFS) and MapReduce, and a plethora of third-party open-source software components. HDFS acts as a file system that stores data across the Hadoop cluster. MapReduce distributes the processing load across the Hadoop cluster by performing complex computational procedures. MapReduce is credited as a major game changer in Big Data processing and provides key advantages such as increased functionality, simplicity, scalability, speed, built-in recovery, minimal data motion and freedom to focus on business logic. Lastly, cloud computing can be defined as a model for network access to a shared pool of computing resources. Cloud services, depending on their service model, provide the end user access to reliable software, hardware and infrastructure, all delivered over the Internet and remote data centers. Cloud computing serves as a platform to address Big Data related issues and perform complex analytics in a timely manner. Big Data technologies have a respectable presence in the business world, but also have their limitations. Hadoop lacks query processing strategies and infrastructure in respect to data processing and management, while NoSQL lack robustness, functionality, familiarity, support and maturity. Thus companies build their data environments on top of hybrid solutions, making use of both traditional and Big Data technologies.

How can organizations utilize and create value from Big Data in their business?

Data has always been valuable to organizations, and with Big Data even more value creation opportunities have emerged. Several studies in the 2010s have shown that adopting Big Data initiatives in organizations increase competitiveness and productivity, as well as improve financial and operational results. There are many ways Big Data can generate value, but these ways usually complement the 3V's. A common driver for all value creation ways is the organizational talent management, ensuring that the Big Data ecosystem is operated by the right level of professionalism. Big Data is generally acknowledged to create value in four main ways, namely data transparency through proper data management, customer segmentation, data-driven analytics and business model innovation.

Data transparency can be translated as "making data easily accessible to relevant users in a timely manner" (Manyika et al. 2011, p. 5). Achieving open transparency improves data quality, consistency, reliability, availability and accessibility. This makes open transparent data valuable in the forms of improved product and service offerings, reduced time-to-market, and efficient concurrent engineering. Data transparency is achieved through proper Big Data management (BDM), a concept of collectively managing data, people, tools and intent together as a whole. Data disciplines such as data governance, BI/DW and data quality management have the strongest involvement in BDM. BDM requires expertise in the new Big Data technologies, as well as in the new business practices. The value of data increases as it is more processed and refined, but value is also lost over a period of time. To overcome the value-time challenge, automation should be implemented to BDM. Automated BDM processes support managing the data more quickly and more effectively, at the same time opening up human resources.

Customer segmentation is viewed as the premise of a marketing organization. It provides market insights such as segment size, profitability, and growth potential, as well as analysis of customer behavior and attitude. Big Data enables new segmentation procedures and utilizes statistical methods to group customers into certain micro-segments. These micro-segments assist in targeting product and service offerings and designing promotions and advertisement campaigns to the right group of people. Sources for gathering customer data exist online, as more and more customers are connected to the Internet of Things. Customer data can be categorized into activity-based data, social networking profile data and social influence data that together form a pool of information for identifying potential new customers and maintaining the loyalty of existing customers.

The main goal of Big Data analytics is to translate data into business advantage and support internal business decisions. Big Data analytics meet the requirements of handling data that is of high volume, high velocity and high variety. Thus, business insights can be acquired that traditional solutions might miss. Analyzing data with Big Data analytics generally has to objectives: to understand relationships among features, and to develop methods of data extraction that can predict future observations. These objectives are reached through extensive methods such as data mining, data visualization, statistical analysis, and machine learning. Furthermore, analytics can be performed on certain levels, namely descriptive, predictive or prescriptive. While descriptive analytics analyze events in the past, focus predictive analytics more on forecasting and predicting future events. Prescriptive analytics combine both descriptive and prescriptive approaches, and automatically take actions based upon predicted outcomes. Big Data analytics as a whole is highly valuable for organizations in many ways. Firstly, it massively improves anything involving customer interaction. Secondly, it supports the BI functions by creating business insights, driving appropriate business changes, improving planning, reporting and forecasting processes, as well as identifying root causes of cost. Thirdly, it improves other analytical areas such as fraud detection, risk management and market trends.

Big Data provides value creation opportunities in the forms of business model, product and service innovation as well as optimization of current business practices. These value creation ways are closely linked to the term data-drivenness, highlighting data as a key resource. Data-driven business development facilitates the development of new data-centric business models that mostly revolve around the sale of data. New service models such as data-as-a-service and analytics-as-a-service provide access to a wide range of data as well as analytical capabilities, and improve competitiveness by increasing sales and profitability, operational efficiency and risk management procedures. Big Data has greatly affected the creation of IoT. Information residing in the IoT can be used for developing next generation products and innovate service offerings, ultimately boosting overall customer satisfaction. Organizational business practice improvement happens through process optimization, customer relationship management, process innovation and collaboration of employees, all facilitated by the recent trends of Big Data.

What are maturity models and the concepts behind them?

Maturity models area conceptual artefacts that allow organizations to have their methods and processes assessed according to best practices. Since the term “maturity” implies an evolutionary progress from an initial to a desired stage, can maturity models be described “to represent phases of increasing quantitative or qualitative capability changes of a maturing element in order to assess capability advances with respect to defined focus areas” (Kohlegger et al. 2009, p. 59). Maturing subjects can be generally grouped into process maturity, object maturity, or people capability. A fundamental underlying assumption for maturity modeling is that a higher maturity level is related to higher performance, improved predictability, control and effectiveness.

It is observed that maturity models share common properties. These are usually a specific number of levels, a descriptor for each level, a generic description of the characteristics of each level, a specific number of dimensions, a specific number of elements for each dimensions, and a description of each activity as it might be performed at each level of maturity. However, maturity models can be distinguished on several factors, stemming from the decisions made during the model's development. Depending on the purpose of use, maturity models can be divided into descriptive, prescriptive and comparative models. While descriptive models focus on assessing the current situation, are prescriptive models giving out improvement activities and recommendations to achieve a higher maturity state. Comparative models are the most advanced form of maturity models and, in addition to descriptive-prescriptive functionality, provide benchmarking functionality for comparing results against industry standards and best practices. Whilst some maturity models have more of a general focus, do others focus on specific domains. Domain-specific models provide detailed information for mature domains like software engineering and information systems, but fall off when they are applied to new and niche fields of actions. Maturity models can be generally divided into three groups based on their composition and structure. Gird-like models are the simplest forms of maturity models, usually consisting of a frame of textual descriptions. Likert-like models have additionally an assessment part in the form of a questionnaire. CMM-like models are the most complex type of maturity models, defining key practices and target goals that support reaching an acceptable level of sophistication. CMM-like models are compared to the famous Capability Maturity Model, a pioneer of maturity modeling in the software development domain.

In the light of the benchmarking study, organizational Big Data maturity is considered as the collective level of all maturing subjects present in the Big Data program of an organization. In some definitions it is also considered as the evolution of an organization to integrate and leverage available data sources, as well as assessing progress and identifying relevant initiatives that improve progress. The maturing subjects of an organization can be anything from business users and processes to technical information systems, which together make up the whole Big Data internal ecosystem. Hence, Big Data maturity models are used to provide a tool for Big Data capability assessment and to help guide development milestones. Furthermore, they are useful in communicating the business goals and vision across the entire organization while at the same time measuring and managing the speed of progress and adoption. Big Data maturity models depict capability key areas as business dimensions. Dimensions differ slightly among the models but some common themes can be identified such as data management, technology, process, governance, people, and organization. However, Big Data maturity models have also been identified with weaknesses. Most of them are built on poor theoretical foundation and do not utilize standard and best practice methodologies. This results in poor documentation practices, lowering the reliability and applicability of the models. Also, reaching the highest level of Big Data maturity requires major investments over many years, which might not be realistic to smaller business organizations.

What are the best practices for generic development and classification of maturity models?

The research identified several unique approaches for developing theoretically sound maturity models. These proposals were selected through an extensive systematic literature review covering many articles from a variety of bibliographic databases. It was noticed that most of the proposals were influenced by the guidelines of design science research, a direction of research that focuses on building artefacts that support solving organizational problems. Slight saturation of content was detected when moving from the oldest to the newest paper, and later published proposals tended to reference the earlier ones. This however was not an issue, since every proposal provided a unique insight into the topic.

Analysis of the papers extracted two key problems that have existed in the maturity model development landscape. Firstly, the maturity model development methodology has not been fully standardized. Developers have difficulties to build reliable and generalizable models without consistent guidelines and thus a generic methodology is needed. Secondly, it was noted that maturity model developers have the tendency towards poor documentation practices. The development processes should always be documented in detail, considering each step of the process, the parties involved, the applied methods, and the testing results. This is to ensure that the model can be verified and validated. An answer to these two key problems was presented in the form of a generic maturity model development framework (figure 4.5), a consistent methodology for developing maturity models based on the practices found in the systematic review. The framework consists of four main phases, all split into several sub-phases. The four main phases “definition of scope”, “development of model”, “evaluation” and “deployment and maintenance” should be addressed in order, since previous decisions greatly influence the following ones. The framework favors and encourages iterative decisions by offering re-design paths for certain main phases. Iterative development is of great importance since it effectively supports error management as well making valuable adjustments in the later phases of development. Each sub-phase of the framework depicts the development decisions to be made. Maturity models should be built accordingly to the defined maturing elements, purpose, focus, target domain and audience. These facilitate the design activities including structuring the model as well as populating it with content. The model should be extensive, but still balanced to ensure the ease of application. Thus, when designing the assessment methodology, developing materials and tools for assistance should be considered. In order to develop a reliable model, it must be tested and evaluated either internally or externally. Evaluation should target both form and function of the model, meaning that evaluation addresses the model schema as well as the model's assessment method. Lastly, models should be under constant maintenance and refinement, to keep up with the changing environment and practices.

To ensure the maturity models reliability and validity, the framework emphasizes on the importance of documenting the decisions made within each sub-phase (as seen on the left side of figure 4.5). Documentation practices provide evidence for testers and evaluators to use, that might later turn into user acceptance. The decisions attributes and their characteristics were later used to construct the classification system framework (figure 4.6). The classification system framework offers developers the possibility to classify their models on the decision attributes. These attributes can then be searched by the end users, resulting in greater retrievability and generalizability. While the majority of papers focused on development activities only, did the paper of Mettler et al. (2010) specifically focus on the classification of maturity models. The proposal of Mettler et al. thus formed the basis of the framework, and was later on enhanced by decision attributes extracted from the development framework.

How can maturity models be evaluated and compared effectively?

To show that a maturity model is effective and usable to a good effect, it can be evaluated comparatively against other models. One form of comparison is normative comparison that highlights the best models among the alternatives in terms of defined criteria. A method that fits the normative element of comparison is benchmarking. Thus benchmarking was selected as the tool for measuring and comparing specific performance indicators of the models. The benchmarking framework of Vezzetti et al. (2014) was utilized in designing the benchmarking process for Big Data maturity model evaluation. The selected framework highlights the strengths as well as the weaknesses of maturity models by focusing on different model features such as general, design, and usage.

To align the benchmarking process with the objective of this research, variables for evaluation had to be selected. Variables such as actuality, completeness, consistency, relevancy, trustworthiness, comprehensibility, ease of use, performance and stability complemented the research objectives and were used to create four distinct criteria groups. The first three groups, namely "completeness of the model structure", "the quality of model development and evaluation" and "ease of application", all evaluated different aspects of good practices of maturity modeling. The fourth group "Big Data value creation" evaluated how well Big Data business value creation ways were addressed. After establishing the criteria groups, they were assigned accordingly with decision attributes of the classification system framework. As a result, each attribute could then be assigned with a numeric value, enabling quantitative benchmarking. The highly systematic and quantitative procedures of the benchmarking process ensure that the process is reliable and that it can be replicated at any time.

What kinds of existing models measure organizational Big Data maturity and what differences are there between them in terms of good practices of maturity modeling and Big Data business value creation?

As a result of a strict screening process, eight Big Data maturity models were selected to be included in the benchmarking process. The selection was made based on the availability meaning that evaluation targeted commercial-free models only, leaving out third party assisted maturity assessment services. All selected models were developed independently from each other, originating from distinct sources. One of the models originated from an educational background and was developed by TDWI (Halper & Krishnan 2013), while the rest were developed by business organizations and consultancies. These business organizations included big names such as IBM, IDC and Strategy&, as well as smaller players such as Infotech, Radcliffe Advisory Services, TNO and Knowledgent group Inc.

The eight selected maturity models differed in terms of naming practices describing themselves as tools, models, frameworks or assessments, but all represented an artefact for assessing an organization's Big Data maturity level. The eight Big Data maturity models were classified with the help of the classification system framework. This included analyzing the models one by one and filling in characteristical information for each decision attribute. As a result, the maturity models could be compared in terms of characteristical differences. These decision attributes were later aggregated into four distinct criteria groups. Thus, maturity model characteristics could be evaluated against specific evaluation criteria. The four criteria groups that maturity models evaluated in were ”completeness of the model structure”, ”quality of model development and evaluation”, ”ease of application”, and ”Big Data business value creation.” The benchmarking study experienced major differences in the first three criteria groups regarding good practices of maturity modeling. For example, the quality of model development and evaluation was almost non-existing in the majority of the evaluated models. Big Data value creation ways on the other hand were addressed in a more balanced manner. On the basis of the total benchmarking scores, three performance groups could be identified. In terms of good practices of maturity modeling and addressing Big Data business value creation opportunities, maturity models were categorized as top-performers (2 models), mid-performers (2 models) and low-performers (4 models).

Main research question: *What maturity models are the most useful to organizations for determining and improving Big Data capabilities and ultimately creating business value?*

In the light of the research results, there are clear differences in the overall performance of the evaluated Big Data maturity models. Two models were clearly overshadowing the rest, scoring relatively high in all criteria groups. The top-performing models included Halper and Krishnan’s (2013) “Big Data maturity model and assessment tool” acquiring a total benchmarking score of 17.26, and IDC's (2013) "CSC Big Data maturity tool" acquiring a total benchmarking score of 16.11 (out of the maximum of 23.00). They represent the models that the benchmarking process identified as the most useful for organizational Big Data maturity assessment in terms of quality and business value creation. Thus, it is logical to focus in more detail on the common features these models share.

Both models scored high in the group "completeness of the model structure", demonstrating high quality of model structure, extensiveness and detail level. They are developed as descriptive-prescriptive-comparative models, assessing the current situation, providing recommendations for improvement, and benchmarking the assessment results across industry standards. However, industries are addressed on a more general level and the industry benchmarks strictly depend on whether there is enough respondent generated sampling available. The models share a common feature in composition in that they are built as Likert-like questionnaires, providing assessment in forms of questions. These ca. 80 questions are asked across five primary business dimensions, covering a wide area of Big Data capabilities. In addition to the five primary business dimensions, Halper and Krishnan (2013) embed five additional dimensions/factors within the questionnaire that consider BI, cloud and outsourcing related activities. Big Data maturity is presented at five distinct levels, presenting a progress from the lowest level of organizational Big Data capabilities to the highest. In addition, Halper and Krishnan add a sixth "non-existing" level between the third and fourth primary level. Adding a non-existing level to a maturity model demonstrates deepening understanding of the situation as it can identify crucial time-consuming phases and assist in smoothly transitioning over problematic barriers. It is important to keep the structure of a maturity model balanced, comprising of both simple and complex features. This ensures that a sufficient coverage of content is provided, but in a timely manner.

The overall poor results for the criteria group "quality of development and evaluation" confirm the statements found in the systematic review, namely that maturity model developers document their development practices in a dissatisfactory manner. In most cases, information for development quality characteristics was simply not available. However, the top-performers Halper and Krishnan (2013) and IDC (2013) redeem themselves by having documentation available for the ways in which the maturity model was designed, tested and maintained. As suggested by the generic development framework, model development should be conducted iteratively. This is the case for Halper and Krishnan, them stating that best practices are iteratively added to the maturity model as practitioners learn more about what companies are doing to succeed in their Big Data efforts. To ensure the reliability and generalizability of the model, it has to be tested internally and evaluated externally. As the assessment for both models is conducted via a web interface, the maturity model reaches a wide number of end users. As of 2014, a total of 600 respondents have tested the model of Halper and Krishnan, moving it closer towards public acceptance. For IDC, the total number of respondents is even higher providing benchmarks against a sampling of 2000 respondents. However, there was no clear indicator on whether the model has ownership of an official verification, validation or certification status. The maintenance of the models is designed in the way that evolution is continuous. This means that the maturity models are constantly evaluated and refined to keep up with the changing Big Data environment and practices. Maintenance of a model should be targeted to both form and functioning of the model, focusing on the maintenance of both model schematic content and the assessment instrument.

To ensure that the Big Data maturity model is easy to use, the end user has to be guided and provided with assistance throughout the whole assessment process. The Likert-like composition of the models indicates that there is a clear assessment instrument to measure the maturity level. In both models, the assessment instrument was in the form of a software assisted questionnaire. Having designed the assessment as software assisted is advantageous to the end user, since a software tool is intuitive and provides assistance throughout the assessment process. In both cases maturity assessment is perceived as evolutionary, letting the assessing organization to adjust its answers as changes in capabilities are occurring. Software assessment tools are efficient as they can be published to a large number of end users, gathering and analyzing assessment data for benchmarking purposes. In addition to the software assessment tool, end users were supported with virtual handbooks to better interpret the assessment scores. Another aspect of easy application is the way results are presented. Visualizing the scores as interactive charts increases understandability and comprehensibility. Furthermore, when prescriptive models give out recommendation, the practicality of these recommendations should be explicit rather than implicit and give out detailed information about improving the current level of Big Data capabilities.

The focus of the models is domain-specific, addressing Big Data essential themes and topics. While more generic models can be generalized to multiple domains, are these not prepared to capture domain-specific issues. In the case of Big Data, issues include poorly managed competences and talent as well as data governance in terms of privacy and security concerns. Halper and Krishnan (2013), and IDC (2013) clearly state that their model's intention is to serve the needs of both managerial and technical people. This is important since a Big Data ecosystem can only be operated efficiently in cooperation of both technicians and management. Technology enables business goals and visions, and vice versa. Maturing subjects in Big Data include all three generally acknowledged groups including people capabilities (eg. technical and managerial competences), process maturity (eg. analytics, data management, data governance) as well as object maturity (eg. infrastructure, data stores). All these subjects are addressed well in both models and they are distributed across the business dimensions. Halper and Krishnan (2013) present dimensions as organization, infrastructure, data management, analytics and governance, while DC (2013) group dimensions into intent, data, technology, people and process. This research identified 24 different domain capabilities for an organizational Big Data program, including Big Data business value creation opportunities as well as technological and organizational components. Big Data maturity models are required to include these capabilities in the their assessment, since they represent the current means of achieving a Big Data maturity level that contributes to increased competiveness and business value creation. Both Halper and Krishnan (2013), and IDC (2013) sufficiently address the main Big Data value creation ways including data transparency, customer segmentation, advanced data-driven analytics, and business model innovation. Data transparency is achieved through Big Data management, aligned with aspect such as data quality, data governance and data automation. Customer segmentation enables analyzing the behaviors of customers and targeting adverts towards micro segmented groups. The value of customer segmentation ultimately comes from utilizing data from Big Data type networks. Social networking data was in both models addressed well, but there is still room for improvement in terms of including an IoT focus. Data-driven analytics positively impact the decision making process, support BI/DW related functions, and are achieved by data mining and data visualization tools. Lastly, business model innovation enables innovating completely new products and services, also regarding the optimization of current business practices.

In addition to value creation ways, trending Big Data technological solutions including Hadoop, NoSQL and cloud computing as well as organizational solutions such as proper talent management and cost-effectiveness strategies contribute to the increase of organizational Big Data maturity. Technological components were especially well-addressed in the model of Halper and Krishnan, involving several Hadoop and cloud centric assessment questions. On the other hand, IDC achieved high quality assessment for organizational components, broadly addressing the degree of skill and qualification possession.

6.2 Critical evaluation of the research

To ensure the trustworthiness and quality of the results, the research is critically evaluated in terms of reliability and validity. Fundamentally, reliability "concerns the extent to which an experiment, test, or any measuring procedures yields the same results on repeated trials" (Carmines & Zeller 1979, p. 11). In other words, reliability is the tendency towards consistency found in repeated measurements of the same phenomenon (ibid). Kirk and Miller (in Saaranen-Kauppinen & Puusniekka 2006, pp. 25-26) divide reliability into three categories: quixotic, diachronic and synchronic reliability. Quixotic reliability measures whether a research method is trustworthy and consistent, diachronic reliability measures whether research results will remain stable over time, and synchronic reliability measures whether research results are logical and consistent when collecting them at the same point of time but using a different instrument (ibid). Validity on the other hand concerns the degree to which obtained research arguments, interpretations and results measure what they are intended to measure. Validity ensures that the results of the research can be utilized effectively and credibly in further scenarios. Variables that may threaten validity should be controlled as much as possible. (Saaranen-Kauppinen & Puusniekka 2006, p. 25.) Validity can be generally divided into internal and external validity. Internal validity evaluates the internal logic and possible contradictions of the research, while external validity ensures that the research findings are generalizable and applicable outside the confines of the selected study. Furthermore, a third form of validity, namely construct validity, is often addressed. Construct validity measures whether the research data collection is based on a logical process that maintains consistency from the research question to conclusions. (Yin 2009.) The evaluation of reliability and validity supports understanding the complex issues of measurement in both theoretical and applied research settings. Reliability is generally more of an empirical issue focusing on the performance of empirical measures, while validity focuses on theoretically oriented issues. These two factors are independent from each other and therefore it is possible that a research can be reliable without being valid, or vice versa. However, a research is said to be complete and successful only when it meets both criteria. (Carmines & Zeller 1979, pp. 9-13.)

The total reliability of this research is perceived as very good. The quixotic reliability of this research is good due to the systematic and highly structured data collection and analysis methods. The concepts and definitions introduced in the theoretical background stem from a wide range of literature sources, resulting in little or no reference bias. As the research advances to the systematic literature review part in chapter 4, all methods from selecting the bibliographic databases to synthesizing the results are strictly and precisely documented. This also includes documenting the point of time when the collection process was conducted. Documenting the systematic review procedures ensures that the review can be repeated, with the same information sources and restrictions. The benchmarking process in chapter 5 is also highly reliable, since it employees quantitative means against pre-defined criteria. The diachronic reliability of this study is a little lower. New maturity models are constantly published and existing ones are refined according to domain changes. Thus, the selection of maturity models for the benchmarking process and benchmarking results may be completely different in a few years. Achieving high diachronic reliability would require conducting the benchmarking process every few years. However, it can be argued that all research can be associated with lower diachronic reliability since change is natural and it will always happen in every examined subject. Synchronic reliability for this research can be predicted as good. The systematic review was conducted with the procedure model of Fink (2005), a highly cited and broadly accepted tool for systematic literature reviews. Fink's process employs good practices for gathering information from valuable sources as well as other aspects that must be present in a systematic review.

The internal validity of this research is somewhat difficult to evaluate, since arguments are always presented form the perspective of an individual researcher. However, this research does not employ an empirical data collection part, and all arguments are based on existing high quality information sources. Thus, internal validity can be viewed as the strongest in the literature review parts of the research. Some internal validity issues can be identified relating to the quality of presented arguments and possible contradictions in the benchmarking part. The Big Data maturity models are evaluated on textual descriptions only, not relying on a practical assessment. The assumptions made for the attributes related to practicality and application may thus have a connection to decreased internal validity. Furthermore, the attribute scoring process for every Big Data maturity model is prone to errors. Valuable aspects could be missed by the evaluator due to misconceptions or biased opinions.

The external validity of this research as a whole can be considered good. The intent of the systematic review was to cover as many relevant papers as possible to establish a generic maturity model development and classification system framework. To ensure external validity throughout the systematic review, every step of the review, including the data collection and screening process, were explicitly defined. Nevertheless, it is very likely that some valuable articles have been left out. This is related to the loosely based inclusion criteria “cited over 0 times.” The criteria was chosen for practical reasons to conduct the systematic review in a timely manner, but ultimately resulted in the exclusion of newer and lesser-known papers. Hence, this research cannot guarantee completeness of the results but can still be trusted to give a good overview of best practices of maturity modeling. Furthermore, the maturity model development framework and the classification system framework are designed as generic methodologies. This means, that the generalizability of these methodologies is high and they can be applied in any possible domain. In addition, using a broad classification system framework helps the developer to document the development procedures of the maturity model as well as reduce the irretrievability issues that occur for end users. However, Mettler et al. (2010) have argued that there should be as few attributes as possible present in a classification system. The classification system framework for this research consists of a much greater number of attributes than the proposal of Mettler and his team. This is because the classification system framework was constructed in the light of utilizing it for benchmarking purposes. Thus, it suffers a bit in external validity when applying it to pure classification purposes only. The benchmarking framework can be adapted for different maturity model evaluation scenarios by just applying different evaluation criteria. This argument is backed up by the fact that the first iteration of the benchmarking framework stems from the PLM research of Vezzetti et al. (2014), but was here successfully applied to the Big Data domain. Benchmarking results for the Big Data maturity models are intended to support organizations to choose the most appropriate ones for maturity assessment in terms of good maturity modeling practices and Big Data business value creation. This is ultimately done by examining the top performers of the benchmarking process and especially their characteristics in general. Thus, external validity qualifies as good due for benchmarking results.

The construct validity of this research meets the standard research requirements. The research is structured logically so that objectives, limitations and scope guide the selection of methodological assumptions. The methodology consists of first selecting the appropriate philosophical assumptions that support selecting the right research strategy. The strategic choices ultimately guide in choosing the data collection and analysis methods. The research employs a deductive approach, meaning that the benchmarking process is built on existing theoretical assumptions found in literature sources. The research sub-questions are designed so that as they unfold one by one, enough information is gathered to ultimately provide an answer to the main research question.

6.3 Suggestions for future research

The field of Big Data and Big Data maturity models is constantly changing. Old models are under constant refinement and new models are developed in a rapid manner. This opens up further research opportunities.

One key research opportunity regards the ways Big Data can be utilized in business value creation. The Big Data domain as of today is still fairly new, but acceptance will without a doubt increase during the following years. As Big Data becomes part of everyday business activities, are business and technological solutions also evolving and improving. The evolution of Big Data will present new ways of creating business value. These new business value creation opportunities can be, for example in the frame of benchmarking studies, be used in defining benchmarking evaluation criteria. Thus, future research should focus on the changes in ways of Big Data business value creation.

It would be also meaningful to conduct a new benchmarking study for Big Data maturity models during the following years to evaluate the newcomer models, as well as reevaluate the old models in respect to evolutionary changes. This would give insight on how maturity modeling practices change in the domain of Big Data. The target of evaluation could also be how well maturity model developers have improved their documentation practices or whether standard and consistent development methodologies are used.

Maturity between two segments may vary greatly. For example, Big Data maturity capabilities in the core organization may be vastly different than their partner organizations. It was noted, that current Big Data maturity models did not focus on this issue and mostly treated Big Data maturity as the internal capabilities of an organization. Future research is thus required keep track on models that consider the relationships between different capability levels, and how to integrate the Big Data landscape between all relevant organizational segments and third party vendors.

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APPENDICIES (2 PIECES)

APPENDIX A: The selection of papers for the systematic literature review
APPENDIX B: Questionnaire regarding the development of the maturity models

APPENDIX A: THE SELECTION OF PAPERS FOR THE SYSTEMATIC LITERATURE REVIEW

#	Author(s), Year, Title	Publication info	Summary
1.	De Bruin, T. Freeze, R. Kaulkarni, U. & Rosemann, M. 2005. "Understanding the main phases of developing a maturity assessment model."	Proceedings of the 13th European Conference on Information Systems, Regensburg.	Proposal of a new generic methodology for developing maturity models.
2.	Becker, J. Knackstedt, R. & Pöppelbuß, J. 2009. "Developing maturity models for IT management. "	Business & Information Systems Engineering. Vol. 1, No. 3, pp. 213-222.	Proposal of a procedure model for developing maturity models based on a design science approach.
3.	Kohlegger, M. Maier, R. & Thalmann, S. 2009. "Understanding Maturity Models. Results of a Structured Content Analysis."	Proceedings of I-KNOW '09 and I-SEMANTICS '09, Graz. pp. 51-61.	Proposal of a maturity assessment questionnaire based on an exhaustive structure content analysis of 16 existing maturity models.
4.	Mettler, T. 2009. "A design science research perspective on maturity models in information systems."	Technical Report BE IWI/HNE/03. Universität St. Gallen, St. Gallen.	Proposal for developing maturity models from both the perspective of a developer and a user, using a design science research approach.
5.	Mettler, T. Rohner, P. & Winter, R. 2010. "Towards a classification of maturity models in information systems."	In Management of the Interconnected World, Physica-Verlag HD, Berlin. pp. 333-340.	Proposal of a classification system for maturity models.
6.	van Steenbergen, M. Bos, R. Brinkkemper, S. van de Weerd, I. & Bekkers, W. 2010. "The design of focus area maturity models."	In Global perspectives on design science research, Springer, Berlin.	Proposal of a methodology for developing focus area maturity models, extending the current methodologies.
7.	Lahrmann, G. Marx, F. Mettler, T. Winter, R. & Wortmann, F. 2011. "Inductive design of maturity models: applying the Rasch algorithm for design science research."	In Service-Oriented Perspectives in Design Science Research, Springer, Berlin. pp. 176-191.	Proposal of a methodology for developing maturity models, focusing on the design phase and the appliance of quantitative methods such as the Rasch algorithm.

8.	Pöppelbuß, J. & Röglinger, M. 2011. “What makes a useful maturity model? A framework of general design principles for maturity models and its demonstration in business process management.”	Proceedings of the European Conference on Information Systems 2011.	Proposal of a framework of general design principles for maturity models, extending the current methodologies.

APPENDIX B: QUESTIONNAIRE REGARDING THE DEVELOPMENT OF THE MATURITY MODELS

1. Is the maturity model a new original model, an enhancement of an existing model, or a hybrid of these?

2. Did you develop the maturity model using a top-down or a bottom-up approach?
    a. *Top-down:* Defining maturing entities, then structuring the model around the defined elements.
    b. *Bottom-up:* Building the model structure first, then defining the maturing entities

3. Was the development process done more iteratively or cyclically?

4. How was the model tested and evaluated?
    a. Is this model validated, verified or certified by a third party?
    b. How many respondents have tested/used your model as of 2015?

5. Is the model being maintained?
    a. Is evolution non-recurring or continuous
    b. If continuous, are you addressing:
        i. Form = reflecting the change of meta-model/model schema
        ii. Functioning = reflecting the change of the assessment instrument
        iii. Both