Developing a BI Maturity Model – Towards More Complete Model

Author Tuomas Liimatainen		
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Thesis advisor(s) Yong Liu		
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Abstract

This thesis focuses on assisting organizations in performing an in-depth self-evaluation of their Business Intelligence (BI) competencies by developing a BI maturity model. Although numerous BI maturity models currently exist, many of them exhibit certain limitations, making it challenging to rely solely on a single model for evaluating and directing organizations. The primary goal is to advance towards a more comprehensive and complete BI maturity model while maintaining practical applicability.

The main research question revolved around creating a more comprehensive business intelligence maturity model to effectively evaluate the state of organization's BI. To address this main question, the study explored the BI-related areas that should be assessed by the new model and researched the types of methods that have been employed in developing new maturity models, ultimately identifying the most suitable method for this purpose. The research questions functioned as the foundation when the theoretical framework was developed. The developed framework was applied during the empirical stage of the study. In this stage, the developed model underwent testing using a single case company, which allowed for the validation of the model's practical applicability.

The primary end result of this study is a more complete BI maturity model created based on the established theoretical framework. The framework suggested that the most critical aspects of BI-related factors, essential for successful BI implementation, encompass organization, process, and technology. These three components serve as the main dimensions of BI. A review of the literature revealed that these dimensions should be further divided into relevant sub-dimensions, which represent their corresponding main dimensions. The conclusions of this study also indicate that by integrating elements from existing BI maturity models, the created model could be populated by utilizing a combination of findings from these pre-existing models allowing creating a new BI maturity model that would comprehensive, practical, and validated while allowing organizations to conduct an independent assessment of their current state of BI.

Keywords Business intelligence, BI maturity model, maturity model, maturity model development

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Tiivistelmä

Tässä työssä kehitettiin liiketoimintatiedon hallintajärjestelmän kypsyysmalli, joka ohjaa organisaatioita oman liiketoimintatietonsa hallintajärjestelmän syvälliseen analyysiin. Tällä hetkellä ei ole olemassa yhtä kaiken kattavaa kypsyysmallia, joka antaisi kattavan tuloksen organisaation liiketoimintatiedon hallintajärjestelmän tilasta. Tämän työn tavoite on kehittää kattavampi kypsyysmalli, jota voidaan soveltaa käytännön työssä.

Työn ensisijainen tutkimuskysymys pureutui siihen, kuinka luoda kattavampi ja tehokkaampi liiketoimintatiedon hallintajärjestelmän kypsyysmalli. Pääasiallisen tutkimuskysymyksen ratkaisemiseksi, tutkimuksessa selvitettiin liiketoimintatiedon hallintajärjestelmien osa-alueita, joita kypsyysmallissa tulisi arvioida kattavan kypsyysmallin tuottamiseksi. Lisäksi tutkittiin, millaisia menetelmiä kypsyysmallien kehitystyössä on hyödynnetty aiemmin. Tutkimuksessa löydettiin sopiva menetelmä kattavan kypsyysmallin tuottamiseksi. Tutkimuskysymykset antoivat pohjan teoreettisen viitekehyksen kehittämiselle. Kehitettyä viitekehystä sovellettiin tutkimuksen empiirisessä vaiheessa, jossa kehitetty malli testattiin yhdellä tapausyrityksellä. Tämä mahdollisti mallin käytännön soveltuvuuden validoinnin.

Tutkimuksen ensisijainen lopputulos on kokonaisvaltaisempi liiketoimintatiedon hallintajärjestelmän kypsyysmalli, joka rakennettiin kehitetyn teoreettisen viitekehyksen pohjalta. Viitekehyksen mukaan liiketoimintatiedon hallintajärjestelmien kriittisimmät alueet kattavat organisaation, prosessin sekä tekniikan. Nämä kolme aluetta toimivat liiketoimintatiedon hallintajärjestelmän pääulottuvuuksina. Kirjallisuustutkimus vahvisti, että nämä ulottuvuudet tulisi jakaa olennaisiin alaulottuvuuksiin kattavan kypsyysmallin varmistamiseksi. Tutkimuksen päätelmät osoittavat, että integroimalla elementtejä olemassa olevista liiketoimintatiedon hallintajärjestelmän kypsyysmalleista, voitiin luotu malli täyttää käyttämällä olemassa olevien mallien havaintojen yhdistelmää. Tämä mahdollisti sen, että voitiin luoda kattava, käytännöllinen sekä validoitu malli, joka mahdollistaa riippumattoman arvioinnin organisaatioiden nykyisestä liiketoimintatiedon hallintajärjestelmän tilasta.

Avainsanat liiketietotoimintajärjestelmä, liiketoimintatietojärjestelmän kypsyysmalli, kypsyysmalli, kypsyysmallin kehitys

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1 Introduction

The fundamental objective of business intelligence is to deliver accurate information to users of BI systems within the appropriate context and at the right time (Cardoso and Su, 2022). The literature on information systems has for long brought up that the information that business intelligence systems provide, bring positive impact on decision-making, especially in intensely competitive landscapes (Popovič et al. 2012). However, many organizations still continue to encounter challenges in realizing the complete advantages of business intelligence (Chuah and Wong, 2012). As a result, in response to this issue, organizations have begun employing maturity models to aid in evaluating the existing state of their business intelligence (Brooks, 2013).

BI maturity models can be used to guide their users in creating business intelligence development strategy by providing a systematic BI assessment method of the existing state of BI in the assessed organization (Chuah & Wong, 2011). Maturity models are commonly employed as instruments for self-evaluation with aim of recognizing the strengths and flaws of specific areas of interest within a company by evaluating the current maturity level of assessed dimensions (Cardoso and Su, 2022).

While there are several existing business intelligence maturity models, most of them suffer at least some certain drawbacks which makes it difficult to use just one existing model when assessing and guiding organizations (Shaaban et al., 2011). A significant number of the existing BI maturity models primarily emphasize data and information, while typically failing to consider the differences between the domains where the particular models are employed (Brooks et al., 2015). The majority of the existing BI maturity models have also not gone through empirical testing (Lahrmann et al., 2011), which questions their usability in practice. Therefore, it can be argued that for organizations to be capable to assess their current stage of business intelligence maturity, creating a more complete BI maturity model is justified. The intent of this thesis is to create a new more complete model that avoids the pitfalls of the existing models and thus allow the users of the new model to conduct a comprehensive self-assessment of the current situation of their organizations BI.

The empirical part of this thesis was conducted in a Finnish growth company where the thesis researcher is currently working. The study was done by following the design science methodology that has been a popular method in the prior research related to developing new business intelligence maturity models.

This thesis contributes to a practical problem of creating a BI maturity model that is comprehensive and still practical to use and thus may be of interest especially to managers interested in better understanding the current level of their company's business intelligence and how to assess it. Existing academic theories about business intelligence maturity models are also reinforced during the business intelligence maturity model creation process.

1.1 Research objectives and questions

The aim of this thesis is to create a more complete business intelligence maturity model that can assist organizations as a self-assessment tool to measure the existing state of companies' business intelligence systems. To summarize the objectives that have been set for the created BI maturity model, the model created should allow companies to:

- Identify the current BI maturity level of the company.
- Identify what are the BI-related dimensions that should be improved and thus support the development of a BI development roadmap.
- Communicate the need for investments to BI within the company.

To ensure practical relevance in the development of the model, three requirements were established to guide its design. The set requirements were aimed at enabling companies to perform a comprehensive yet cost-effective self-assessment of their existing BI systems.

- **Independency**: The model should be capable of serving as a self-assessment tool without external 3rd party bodies.
- **Compactness**: The model should allow assessment with limited resources, especially when it comes to time. This means that there shouldn't be too many assessed dimensions, as that would require a very long list of questions during the assessment.
- **Validity**: The model should be constructed by using prior research on BI maturity models to ensure the validity of the model.

The main research question of this thesis is:

How to create a more complete business intelligence maturity model that can be used to assess the state of organization's business intelligence?

In order to address the main research question, it is essential to answer supporting questions that are answered during the research:

- What are the BI-related areas that the new model should assess?
- What kinds of methods have been used when creating new maturity models and what method should be used?

Research questions are answered by first reviewing existing literature about business intelligence in general, BI maturity models, and maturity model development methods. A theoretical framework is created based on the insights of the examined literature and the framework is used, first to create a proposed BI maturity model and then in the empirical part of the study where the model is tested, and the model is evaluated against the set independency, compactness, and validity requirements.

2 Literature Review

2.1 Business Intelligence

Data volumes that organizations face have increased significantly in recent years – primarily because of cloud-based solutions which many companies have adopted. This has caused many companies to struggle with managing this data and harnessing it in a way that helps them to keep focus on the main drivers which enable business success and makes it possible to see if strategies they are executing give them desired results. (Cullen, 2021)

The utilization of business intelligence (BI) enables organizations to gather data from various structured and unstructured sources and transform it into valuable information, which can be leveraged to make well-informed decisions that enhance the effectiveness and productivity of companies (Niu et al., 2021). According to Yiu et al. (2020), adopting business intelligence systems successfully is a vital step for organizations to extract value from their data. Their results from analyzing high tech companies indicate that successful

adoption of business intelligence systems has led especially to notably better operational capabilities of the companies they analyzed. As organizations have acknowledged that there are clear benefits from business intelligence implementation, business intelligence development has seen the largest share of global investments in investments to information technology by businesses (Ransbotham & Kiron, 2017).

In this chapter, a definition of the term "Business intelligence" and the way it is used in this thesis is defined. Subsequently, the key components of BI systems are reviewed and the crucial elements contributing to the successful execution of BI are examined.

2.1.1 Definition of Business Intelligence

As discussed in the previous section, the volume and complexity of data that companies are dealing with nowadays has brought a clear need for business intelligence implementations across organizations. Within the context of this work, it is vital to address the meaning of business intelligence as the term is still quite novel and thus it does not have a universally standardized definition. As a result of this, there have been quite many definitions of what is included in the concept of BI (Shollo & Kautz, 2010).

Gaining popularity in the 1990s, the term "business intelligence" still remains a relatively new term (Chen et al, 2012). However, the term was used even before that, when Luhn (1958) used it in IBM Journal of Research and Development when describing it as a way to reach goals by understanding interrelationships between scanned documents. Chaudhuri et al. (2011) defined BI as an assemblage of technologies which support enterprises and their managers with faster and better decision making. This is similar to how Foley et al. (2010, p. 4) described it as *"a combination of processes, policies, culture, and technologies for gathering, manipulating, storing, and analyzing data collected from internal and external sources, in order to communicate information, create knowledge, and inform decision making."* and how Wixom and Watson (2010, p. 14) defined it as *"broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions."*

Business intelligence is defined in this work as an adoption of the descriptions mentioned above. The term BI is employed to involve a diverse collection of technologies, processes, and applications employed to collect, store, access, and examine data, with the goal of enabling users to make informed decisions.

2.1.2 Business Intelligence system components

According to recent research, business intelligence is recognized as a multidimensional concept encompassing three key components that are product, process, and a set of technologies utilized to produce information and knowledge with the aim of supporting decision-making (Shollo & Kautz, 2010). The key components are introduced below.

Product

A product in BI context can be defined as all relevant information and knowledge that organizations can use to predict their environment (Shollo & Kautz 2010). Shollo and Kautz (2010) defined data, information, knowledge, and decisions as typical products of BI systems. BI systems collect data from multiple sources which can be either internal or external. Typical data sources are for example operational databases that consist of transactions from ERP and CRM systems, but data sources can also be Excel files, Word documents, query logs from web sites, blog posts or even RFID keys that track inventory. Different data sources have often quite different kinds of data in inconsistent formats which can cause problems and make integrating and standardizing the data for BI tasks a challenge (Chaudhuri et al., 2011).

Process

BI systems use data for analysis and transfer it into information. When data is transferred into information it can then be further analyzed and transformed into knowledge. Information or knowledge can be used when an action such as a decision is needed (Shollo & Kautz, 2010). A good example of data transferred into information and knowledge in business intelligence systems is a report and/-or dashboard that is used to visualize and summarize data and lets the users explore the data for example by drilling data. Reports and dashboards are often described as the end-result of a BI system.

The Figure 1. shows how the business intelligence knowledge creation process turns the initial data into decisions that lead to improvement in competitiveness.
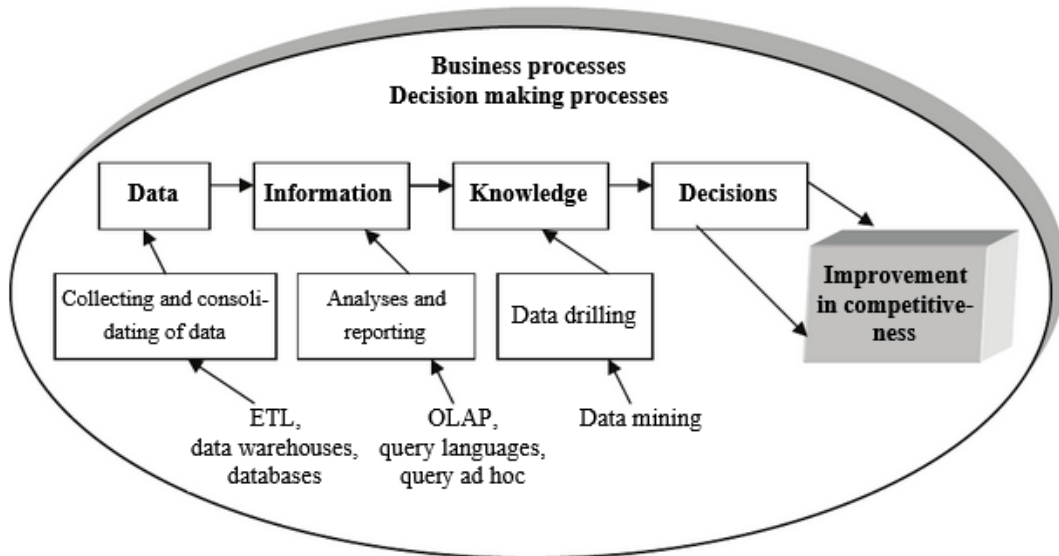
Figure 1. BI system knowledge creation process (Olszak & Ziemba 2007).

Technology

Technology is a key component of BI, as integrating different technologies enables facilitating business intelligence systems (Shollo & Kautz, 2010). According to Shollo and Kautz (2010) some authors even define business intelligence *only* as a combination of technologies. Because of how important role different technologies play in BI systems, it is important to describe the most commonly used and referred technologies and technology related techniques in BI context.

Data warehouse

Data warehouse constitutes as a vital part of BI that is used as a data storage that aggregates data from often multiple sources to a single location to support analytical and reporting needs of a company (Ranjan, 2009).

Data mart

Data marts are more focused sets of data, and they are often subsets of company-wide data warehouses, or they use other independent data sources or combination of these both (IBM, 2020). Data marts are usually created for specific need and therefore data marts usually include specifically selected data that is needed to support for example certain functions or departments data needs (Ranjan, 2009).

Online analytical processing (OLAP)

OLAP technologies enable faster creation of reports from data (Ranjan, 2009). Online analytic processing tools help to uncover a multidimensional visibility to data for users and enables common BI tasks such as aggregating, filtering, and drilling-down the data (Chaudhuri et al., 2011). OLAP tools are able to be used jointly with data warehouses and data marts to process queries with the aim of finding trends and analyzing critical factors from the data (Ranjan, 2009).

Extract, transform, load (ETL)

An effective and efficient data loading is vital for BI. The back-end technologies that are used to prepare the used data for the BI solution are called Extract, transform, load (ETL). ETL is used in BI context to integrate, clean, and standardize the used data. (Chaudhuri et al., 2011)

ETL is often used to clean the data to address specific BI needs such as monthly reporting and to help organizations with more advanced analytics. Common use cases for ETL are to help organizations to extract data from old legacy systems, clean data to improve the quality of used data, and to load the used data into a database (IBM, 2020).

Decision support systems (DSS)

Decision support systems can be defined as small-scale IT-systems that help managers with complex and difficult tasks. The term DSS is often used as a synonym to BI systems (Foley et al., 2010) and some researchers suggest that BI systems are only the newest progression in the ongoing development of decision support systems (Arnott & Pervan, 2014, as cited by Shollo & Galliers, 2016). BI systems and DSSs differ mainly in their scope – BI is a broader term that encompasses information technology, reporting, and analytics, and is commonly utilized throughout an organization, while DSSs typically concentrate on specific decisions and tasks that often relate to a single decision-maker (Arnott et al., 2019).

Knowledge management systems (KMS)

Knowledge management consists of activities such as extracting and distributing knowledge inside an organization (Weidong et al., 2010). KM systems are systems that are designed to deal with knowledge in the organizations by enabling capturing, storing, and distributing knowledge inside an organization. The key difference between the data in BI systems and knowledge management systems is that KM systems typically focus on non-structured data

such as text and visual information that can be quite subjective, whereas BI systems deal usually with actual objective information and turn this information to structured resources. Typical KM systems consist of document management and text mining technologies. (Cheng & P. Cheng, 2011)

Data mining

Data mining is a process that is used to discover patterns and insights from large datasets through methods including decision trees, regression analysis, neural networks, and cluster analysis (Maheshwari, 2014). Data mining can be regarded as a crucial step in the entire process of discovering knowledge, where knowledge is discovered from data that has been cleaned and thus data mining is often used as a synonym for discovering knowledge from data (Han, et al., 2012). Business intelligence is commonly thought to be a good example of a successful usage of data mining, and as BI related technologies such as data warehouses and OLP-tools greatly relay on multidimensional data mining – data mining is in a way the core of business intelligence (Han, et al., 2012). Figure 2. illustrates technologies and techniques adopted by data mining.
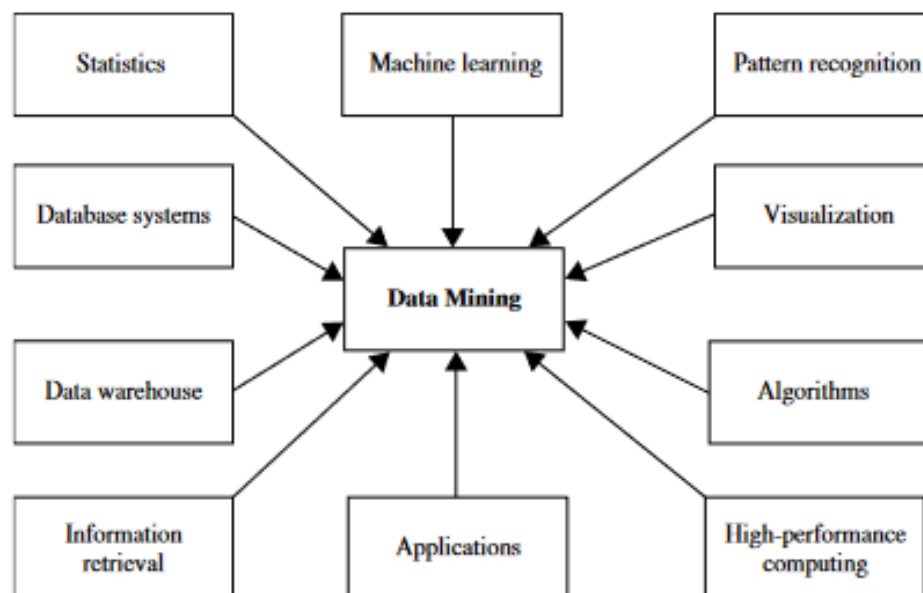
Figure 2. Tecnquies and technologies adopted by data mining (Han, et al., 2012).

Business intelligence tools

When it comes to business intelligence is it easy to misunderstand the difference between the terms *BI system* and *BI tool*. For the context of this thesis, it is important to describe the difference between these two terms as even though they can easily be understood to be synonyms they mean slightly different things.

BI tools can be described as software products that are deployed in the organization which are BI related software such as data warehouse, data mining software, and dashboards. On the other hand, a BI system comprises a combination of BI tools and BI associated technologies utilized to assist the organization's BI efforts (Wieder et al., 2012).

2.1.3 Critical success factors for business intelligence

To understand what components of business intelligence a company should develop and thus would therefore want to assess, it is important to examine the critical factors leading into success in execution of BI.

Critical success factors (CSF) refer to the specific areas or elements that, if achieved successfully, ensure overall success in a particular project or organization. (Gaardboe & Jonasen, 2018). A failure to implement an effective business intelligence can be attributed to an organization's insufficient knowledge of the CSFs for BI (Farzaneh et al., 2018).

A commonly used framework for determining the crucial success factors of BI is the framework created by Yeoh and Koronios (2010), which is also basis for many newer frameworks of the subject. Organization, process, and technology are the three distinct areas of CSF's that Yeoh and Koronios (2010) identified as impacting the success of business intelligence. Their framework also includes two dimensions which consists of infrastructure performance and process performance.

Table 1. illustrates that there are common factors identified by previous studies as vital to the success in BI. An analysis of the most mentioned areas of critical success factors shows that especially management support, data quality, technology, data sources organizational culture, change management, personnel skills, vision and strategic alignment, and end-user involvement have been widely mentioned as being critical for BI success. The most frequently cited areas establish a strong framework for incorporating essential elements into a comprehensive BI assessment model.

Critical Success Factors	References
Management support	(Adamala & Cidrin, 2011; Dawson & Van Belle, 2013; Farzaneh et al., 2018; Kulkarni & Robles-Flores, 2013; Olszak, 2016; Thamir & Poulis, 2015; Villamarín-García, 2020; Watson & Wixom 2007; Yeoh et al., 2008; Yeoh & Koronios, 2010; Yeoh & Popovič, 2016)
Data quality	(Dawson & Van Belle, 2013; Geiger, 2009; Kulkarni & Robles-Flores, 2013; Olszak & Ziemba, 2012; Thamir & Poulis, 2015; Villamarín-García, 2020; Watson & Wixom 2007; Yeoh et al., 2008; Yeoh & Koronios, 2010; Yeoh & Popovič, 2016)
Organizational culture	(Adamala & Cidrin, 2011; Kulkarni & Robles-Flores, 2013; Geiger, 2009; Olszak & Ziemba, 2012; Olszak, 2016; Thamir & Poulis, 2015; Villamarín-García, 2020; Villamarín-García & Pinzón, 2017; Watson & Wixom 2007)
Change management	(Olszak & Ziemba, 2012; Yeoh & Popovič, 2016; Villamarín-García, 2020; Yeoh et al., 2008; Yeoh & Koronios, 2010)
Personnel skills	(Adamala & Cidrin, 2011; Geiger, 2009; Olszak, 2016; Olszak & Ziemba, 2012; Villamarín-García, 2020; Watson & Wixom 2007; Yeoh et al., 2008; Yeoh & Koronios, 2010)

Technology and data sources	(Adamala & Cidrin, 2011; Geiger, 2009; Olszak & Ziemba, 2012; Olszak, 2016; Watson & Wixom 2007; Yeoh et al., 2008; Yeoh & Koronios, 2010)
Project management	(Adamala & Cidrin, 2011; Olszak & Ziemba, 2012; Villamarín-García, 2020; Yeoh et al., 2008)
Vision and strategic alignment	(Dawson & Van Belle, 2013; Olszak & Ziemba, 2012; Olszak, 2016; Thamir & Poulis, 2015; Villamarín-García, 2020; Watson & Wixom 2007; Yeoh & Koronios, 2010; Yeoh et al., 2008; Yeoh & Popovič, 2016)
Resources	(Olszak & Ziemba, 2012; Olszak, 2016; Villamarín-García, 2020; Watson & Wixom 2007; Yeoh et al., 2008)
End-user involvement	(Dawson & Van Belle, 2013; Kulkarni & Robles-Flores, 2013; Olszak & Ziemba, 2012; Olszak, 2016; Villamarín-García, 2020; Yeoh & Koronios, 2010; Yeoh & Popovič, 2016)

Table 1. Critical success factors for BI.

2.2 Business intelligence maturity

The definition of maturity is "*The state of being complete, perfect, or ready*" (OED Online, 2023, 4b). The maturity in business intelligence context can be defined as "BI successfully deployed" and "organizational impact fully realized" (Lahrmann et al., 2011).

BI is often seen only as an IT artifact but assessing only the technical maturity is not comprehensive enough view and therefore does not lead by its own to success in BI (Lahrmann et al., 2011). As outlined in previously in this chapter, BI could be defined as follows: "*a combination of processes, policies, culture, and technologies*" as described by

Foley et al. (2010, p. 4). This highlights the need of much more comprehensive context for BI maturity than simply the technological aspect. Lahrmann et al. (2011) conceptualized BI maturity to three concepts, "deployment", "use", and "impact" (Figure 3.) that are part of organizational BI maturity as their own concepts, but which are also dependent on each other. The dependency relationship between BI maturity concepts can be for example explained understandable way by pointing out that even if an organization has deployed the best possible BI architecture, it might not bring the overall BI maturity to high level if the deployed BI technologies and applications are not *used* on individual and organizational level and thus the BI *deployment* does not bring positive *impact* to organizations performance (Lahrmann et al., 2011).
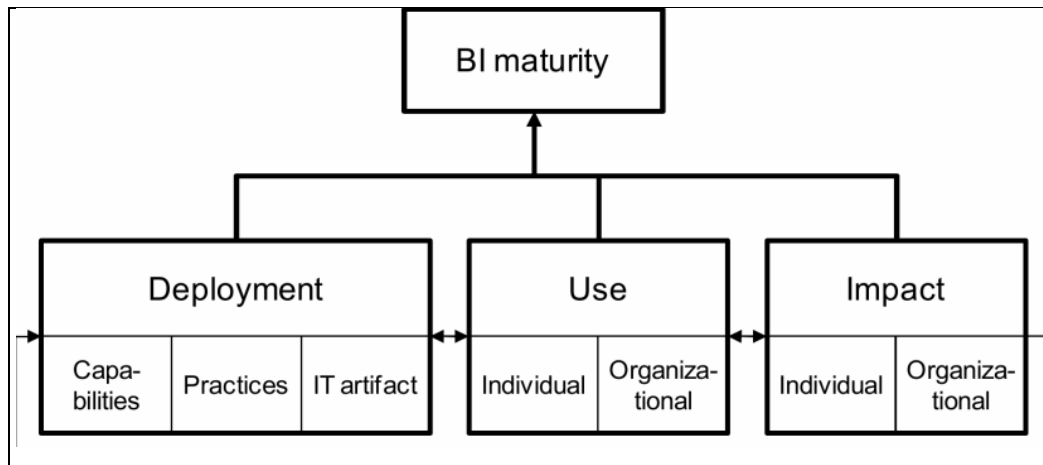
Figure 3. Theoretical conceptualization of BI maturity (Lahrmann et al., 2011).

2.2.1 Business intelligence maturity model concept

Maturity models help their users to get from existing state of maturity to the desired state of maturity (Fraser & Gregory, 2002). Maturity models have become widely accepted tools to help organizations to document and find best practices during development processes within the organization (Paulk et al., 1993), and as a result, the information systems domain has witnessed more than a hundred distinct maturity model variations (Mettler & Rohner, 2009).

Typical maturity models consist of levels that run-in order for different classes of objects such as "organization" and "processes" (Becker et al., 2009). These levels represent an evolutionary path for these objects staring from the bottom level which is the initial starting maturity level and lead to the highest level that represents a total maturity that organizations should aim to reach (Becker et al., 2009). Each level in the maturity model

context requires that the measured object reaches certain requirements (Raber et al., 2012). The main characteristics of maturity models can be summarized to include *maturity concept*, *dimension*, *level, maturity principle*, and *assessment* (Lahrmann & Marx 2010). The descriptions for the main characters of maturity models written below.

Maturity concept

According to Mettler and Rohner (2009) the concept of maturity comprises three distinct components, namely object, process, and people, which are regarded as separate concepts of maturity. When it comes objects, technologies and systems are the most commonly evaluated objects (Popovic et al., 2009). The capability of people can be referred to the knowledge, skills that are available within the people of organization to carry out the business activities (Curtis et al., 2007). When it comes to process in maturity model context, it may be described to be the degree to which a particular process is clearly specified, effectively regulated, evaluated, and efficient (Paulk et al., 1993).

Dimension

When it comes to the context of a maturity models, dimensions refer to distinct areas that describe different characteristics of the object under evaluation (Mettler & Rohner, 2009). All maturity models have a common feature of defining multiple dimensions at various maturity stages and providing a description of typical execution across different levels of maturity (Fraser & Gregory, 2002).

Level

Levels represent common stages of development for a specific domain or dimension, and each level is distinguished by a unique description that expresses its purpose and a comprehensive explanation. (Lahrmann et al., 2010).

Maturity principle

Continuous or staged models can be used to measure maturity. Continuous models are capable of quantifying maturity by attributing scores to activities dispersed among distinct levels. This can be achieved through the consolidation of particular scores or by examining individual levels through different dimensions. In contrast, staged models necessitate the fulfillment of every component within a specific level. (Fraser et al., 2002).

Assessment

Assessing the maturity can be carried out through quantitative means, such as the use of questionnaires with a Likert scale, or qualitative methods, such as conducting interviews (Fraser et al., 2002).

2.2.2 Existing business intelligence maturity models

BI maturity models have become recognized means of an evaluation of both the positive and negative aspects of BI initiatives (Cardoso & Su, 2022), and according to Chuah and Wong (2011), BI maturity models can serve as an evaluative tool for developing BI strategies and enabling organizations to acquire a more comprehensive understanding of their current BI maturity. Business intelligence maturity models consist typically of features that can be especially identified to have a role in assessing BI maturity (Muller & Hart, 2016). Several maturity models in BI context have been created of which some have their origins in academia, but most of the models have their origins in practice (Raber et al., 2012). This segment provides a comparison of the key features of pre-existing business intelligence maturity models to support the development process of new more complete BI maturity model. Table 2. presents an overview of existing BI maturity models.

No.	Model	Reference	Description
1	Gartner's BI and Project management maturity model	(Rayner & Schlegel, 2008)	Gartner's BI and PM maturity model evaluates the level of maturity of organizations in terms of BI and PM and determines the requisite level of maturity to achieve company objectives. There are five levels in Gartner's BI maturity model called *unaware, tactical focused*, *strategic*, and *pervasive* which are defined textually. Gartner's MM was criticized by Lahrmann et al. (2010) for not having defined dimensions and for lack of

			documentation of reliability of the model.
2	The HP Business Intelligence Maturity Model	(Hewlett-Packard, 2007)	HP created a BI maturity model that describes the evolution of their client's business intelligence capabilities. HP's MM has five levels: *operation, improvement, alignment, empowerment, excellence*, and three dimensions *business enablement, information management*, and *strategy and program management*. HP sells the model as a service to its clients.
3	Capability Maturity Model for Business Intelligence	(Raber et al., 2012)	Capability MM for BI created by Raber et al. (2012), focuses on business intelligence capabilities of organizations. The model comprises of five levels: *initiate, harmonize, integrate, optimize,* and *perpetuate,* and five dimensions: *strategy, organization, IT systems, quality of service,* and *use/ impact of BI.*
4	BI maturity model for ISMETT hospital	(Gastaldi et al., 2018)	Gastaldi et al. (2018) created a healthcare specific BI MM for ISMETT hospital. The model was created by researchers and practitioners that had knowledge of BI use in healthcare. The model consists of 4 levels: *initial, managed, systematic,* and *disrupted.* This model differs from most other MMs with the number

			of dimensions, as it has 23 different dimensions that allow it to measure healthcare specific BI maturity with enough detail for that domain specific need.
5	Enterprise business intelligence maturity model (EBIMM)	(Chuah, 2010)	Chuah (2010) developed the enterprise business intelligence maturity model that they constructed on the principles of capability maturity model. The model was created to help companies to elevate their BI maturity level to higher level. The model has five levels: *initial, managed, defined, qualitative managed,* and *optimizing.* This model has only three quite high-level dimensions: *Data Warehouse, information quality,* and *knowledge process.*
6	EBI2M	(Chuah & Wong, 2012)	Enterprise Business Intelligence Maturity Model (EBI2M) proposed by Chuah and Wong (2012) uses a structure borrowed from capability Maturity Model Integration (CMMI) model. The model has five levels: *initial, managed, defined, qualitative managed,* and *optimizing* and thirteen different dimensions. EBI2M allows its users to use staged representation or continuous representation when measuring maturity levels.

7	The Business Intelligence Development Mode (BIDM)	(Sacu & Spruit, 2010)	Sacu and Spruit (2010) devised a model to aid organizations in recognizing their current stage of business intelligence and help them in understanding of how to enhance the BI function within the company. The model was created by comparing the characteristics of existing BI MMs. BIDM consists of six dimensions: *temporal, data, decision insights, output insights, BI-process, and "other"-* dimensions, which each have several sub-dimensions. BDIM has six stages: *predefined reporting, data marts, enterprise wide DW. Predictive analytics, operational BI,* and *business performance management,* which describe the level of BI implementation in the organization.
8	Service-Oriented Business Intelligence Maturity Model (SOBIMM)	(Shaaban et al., 2011)	Service oriented BI MM was created by Shaaban et al. (2011) to help companies find barriers of proper BI adaptation such as lack of information integration and poor planning. The model has five levels of maturity: *initial, immature, controlled,* and *mature* and has three dimensions: *technology, organization,* and business *expertise* which all have sub-

9	TDWI Analytics Maturity Model	(Halper & Stodder, 2014)	TDWI Analytics Maturity Model defines analytics as a higher-level concept that includes also BI in their analytics maturity model. The model has five maturity levels: *Nascent, pre-adoption, early-adoption, corporate adoption, mature* and five dimensions: *infrastructure*, *data management*, *analytics, governance,* and organization which all have sub-dimensions. TDWI 's maturity assessment is done with online assessment that consists of questionnaire about the five dimensions mentioned above.
			dimensions. The model has also a checklist that consists of questions regarding service orientation which is used to provide a rating for each maturity level.
10	The Ladder of Business Intelligence (LOBI)	(Cates et al., 2005)	The Ladder of Business intelligence (LOBI) framework allows measuring the effectiveness of business intelligence utilization. The model has six levels: *facts, data, information, knowledge, understanding, enabled.* The model comprises of three dimensions: *people, process,* and *technology* that are not explained in detail. LOBI framework also includes a balanced scorecard framework

			which consists of financial, customer, business, and organization learning perspectives.
11	HE-BIA Maturity Model	(Cardoso & Su, 2022)	Business Intelligence and Analytics Maturity Model for Higher Education (HE-BIA Maturity Model) is a BI and analytics maturity model that was created by Cardoso and Su (2022) to aid higher education institutions comprehending the current level of their BI and analytics landscape. The model has five levels called *pre-adoption, initial, managed, systematic,* and *optimized.* The model evaluates dimensions classified into technology and organizational categories, each with multiple sub-dimensions.

Table 2. Description of existing BI maturity models

A review of existing BI maturity models revealed that even though the used dimensions vary widely between the reviewed maturity models, there are several distinct dimensions that emerged. The dimensions were analyzed following Lahrmann et al. (2010) in their overview of BI maturity models, meaning that dimensions and sub-dimensions that were named differently but in essence addressed similar aspects of maturity were considered as synonyms e.g., "IT" and "technology".

Table 3. represents the most frequently emerged dimensions in the eleven BI maturity models studied, using dimensions and their description's defined by Lahrmann et al. (2010).

Dimension	Description	1	2	3	4	5	6	7	8	9	10	11	#
Applications	Analytical applications in use.	■	■	■	■	■				■			6
Architecture	Source systems, platforms, and integrations.				■	■		■	■	■		■	6
Behavior	Fact-based decision-making culture.	■			■		■			■		■	5
Change	Controlling and tracking changes.						■					■	2
Data	Used data models, data quality, and data quantity.	■			■	■	■	■	■		■	■	8
Impact	Individual and organizational impact.	■	■	■									3
Infrastructure	Databases and application servers.	■	■	■	■						■	■	6
Org. structure	Structure and placement of BI in organization.				■					■			2
Processes	BI related activities.				■		■			■		■	4
Staff	BI related experience and skills of staff.	■	■	■			■			■		■	6
Strategy	BI strategy alignment on business and IT strategy	■	■	■	■	■				■		■	7
Users	Types and number of BI users in organization.				■						■	■	3

Table 3. Dimensions in BIMM's studied, based on (Lahrmann et al., 2010).

The analysis uncovered that out of the eleven existing maturity models studied the most used dimensions were: *applications, architecture, data, infrastructure, staff, and strategy.* This is quite parallel to the analysis of most common dimensions in BI maturity models conducted by Lahrmann et al. (2010) and Muller and Hart (2016). It is worth noting that none of the reviewed models encompassed all of the identified dimensions, and only one of them evaluated all of the commonly mentioned dimensions (BI MM for ISMETT hospital). This review emphasizes the need for a new model, as none of the existing models were comprehensive enough to enable a comprehensive assessment while meeting the established requirements for the model as set out in this study.

2.3 Maturity model development

Even though there are several existing maturity models, many organizations have found out that of the current maturity models adequately meet the specific requirements of their company (Patas et al., 2013).

Developing completely new maturity model from scratch is not always the most effective way to help organizations with the problem of not finding a maturity model that meets their needs, and thus the more effective approach is often to configurate an existing maturity model according to the specific needs of an organization (Mettler & Rohner 2009, as cited in Patas et al., 2013).

Maturity model development processes can be divided to two different approaches: new model development and model extension (Lahrmann & Marx, 2010). When a new model developed, initiating the model's development is started from scratch and is often created by combining aspects of pre-existing models whereas in model extension process, an already existing model is updated or modified by for example adding a new level or sub-dimension without challenging the fundamentals of the existing model, and thus in this case the previous characteristics such as the scope of the model restrict the content of the extended model (Lahrmann & Marx, 2010). Lahrmann and Marx (2010) outlined the primary distinctions between creating a new maturity model from scratch and expanding an existing one, which are as follows:

New model
- Developed from scratch.
- Often a combination of existing BI maturity models towards new and improved model.
- Structures and contents from existing maturity models transferred towards new areas.

Model extensions
- Re-defining/ updating existing maturity model.
- Adding additional levels/ dimensions to existing maturity model.
- Formalizing existing maturity model to be suitable for use in practice.

As observed above, there are notable differences between creating a new model and expanding an existing one. As this thesis focuses on developing a more complete model, it is evident that simply extending an existing model is not a feasible option. Doing so would limit the model's content and scope, preventing combining existing models in a manner that would enable the creation of a genuinely new and more comprehensive maturity model.

2.3.1 Maturity model development methods

The process for developing maturity models differs slightly depending on literature examined, but most of the maturity model development process models have quite similar basic design (Lahrmann et al., 2011). In this section, maturity model development process methods found from literature are covered to support establishing a framework to create a new more complete BI maturity model.

A solution to the lack of widely accepted and theoretically sound guidelines for creating maturity models was presented by De Bruin et al. (2005) through the introduction of a generic process for developing maturity models. The methodology proposed by De Bruin et al. (2005) consists of six phases where the first phase consists of determining the model's scope and culminating in the final phase, where the deployed model is maintained.

The process of creating maturity models by Becker et al. (2009) follows similar process than the one suggested by De Bruin et al. (2005) utilizing slightly varied phases. Becker et al. (2009) recommended a development methodology that particularly emphasizes evaluating pre-existing maturity models prior to formulating the strategy for development and highlights the importance of documentation on each phase of the process. The model comprises several phases, starting from problem definition, and ending in evaluation of the developed model, which are the phases before initial deployment of the model. Maier et al. (2009) introduced a roadmap to assist developing maturity grids, which consists of four phases where the development is started by planning phase and leads to the maintenance of the model. Steenbergen et al. (2010) introduced a development approach tailored to focus area maturity models to support domain specific information systems improvement. Their model has four process phases starting initially from scoping and ending to the last phase where the model is implemented and used. Each of the phases in the method suggested by Steenbergen et al. (2010) have additional sub-phases.

All the maturity model development models presented above share at least some common elements. However, there are also some clear differences between them. Table 4. summarizes the main steps of each presented maturity model development method.

Process steps	Reference
1. Scope 2. Design 3. Populate 4. Test 5. Deploy 6. Maintain	(De Bruin et al., 2005)
1. Problem definition 2. Comparison of existing maturity models 3. Determination of development strategy 4. Iterative maturity model development 5. Conception of transfer and evaluation 6. Implementation of transfer media 7. Evaluation	(Becker et al., 2009)
1. Planning 2. Development 3. Evaluation 4. Maintenance	(Maier et al., 2009)
1. Scope 2. Design model 3. Develop instrument 4. Implement and exploit	(Steenbergen et al., 2010)

Table 4. Summary of maturity model development steps.

3 Methodology and theoretical framework

This section presents the theoretical framework which was developed by combining finding from the literature review conducted in chapter two and justifies the chosen research methodology. The data collection method is also discussed, along with an introduction to the case company utilized in this thesis.

3.1 Design science research

Given the noteworthy influence that design science has had on prior studies involving developing business intelligence maturity models, it was considered an appropriate research methodology for this thesis.

Design science research is used to design new or better solutions to an already existing problem (Peffers et al., 2007). This is done by creating artifacts that may include models or methods, as outlined by Hevner et al. (2004). In this particular scenario, the maturity model which is developed can be viewed as the artifact utilized for addressing the problem of not having comprehensive BI maturity assessment model that is independent, compact, and validated. Peffers et al. (2007) recognized six action steps in their design science research methodology: 1) identify the problem and motivation, 2) define objectives of the solution, 3) design and develop, 4) demonstrate, 5) evaluate, and 6) communicate.

The creation of the BI maturity model followed the design science methodology. The process started with understanding the problem and requirements and concluded with demonstrating the practical applicability of the model in a real-life setting.

3.2 Theoretical framework

The theoretical framework proposed in this work combines theories regarding BI success, BI maturity, approaches for developing BI maturity models, and a summary of existing models in the field, which were utilized to construct the new more complete BI maturity model.

The development of the BI maturity model is, to some extent, the core of the proposed theoretical framework presented in this thesis. This development process follows the development methodology suggested by De Bruin et al. (2005), with small modifications. Their process uses similar steps than general design science process which was proposed by Peffers et al. (2007).

Phases in the generic maturity model development process, as they were described by De Bruin et al. (2005) are written below.

Phase 1: Scope: First phase during the process is determining the scope of the developed maturity model. The decision will have a far-reaching impact on all subsequent phases, and it will set constraints on the application and execution of the maturity model. The primary determinations during this stage include identifying the model's focus and stakeholders. Focus on this context means, what is the domain that the model is targeted and used in. This usually means deciding if the model in domain specific or general. Choosing the development stakeholders means choosing who are the stakeholders that are used to assist with development of the model.

Phase 2: Design: Designing is the second phase of maturity model development process. During this stage the structure of the developed model is established. This design functions as a foundation for the following model development. During this phase the concept of maturity, used maturity levels and their structure, dimensions and sub-dimensions are determined. In a design process, either a top-down or bottom-up methodology may be utilized. In a top-down method attention is directed towards specifying the levels of maturity as well as the corresponding descriptions. If a bottom-up method is used, the dimensions and characteristics that are used to represent maturity are first defined, after which the descriptions of the maturity levels are defined.

Phase 3: Populate: Once determining the scope and design, the following step entails outlining the model's content. In populate-phase, the measured domain components whose maturity is assessed need to be identified. It is also important in this phase to determine how the maturity of these components can be assessed.

Phase 4: Test: After the developed maturity model is populated, it is tested during the testing phase. During this phase, the model's construct and the utilized instruments are tested for both reliability and validity.

Phase 5: Deploy: The deployment stage consists of making the maturity model accessible for use. Deployment of the model is often issued to application by using the stakeholders that assisted during the design phase as respondents.

Phase 6: Maintain: Maintaining the model is the last phase of development process. In this phase, the model is maintained by making sure that the knowledge and understanding of the model broadens and deepens, and thus the models continue its evolution and development to ensure that the model continues to be relevant.

Since the scope was already established at the opening chapter where the objectives and requirements for the new model were set, the actual development process starts from the design phase. During the conducted review of existing literature, it was seen that understanding what the critical areas for success in BI are, constitutes a crucial element for the effective application of an organizational BI system (Farzaneh et al., 2018). Therefore, the critical success factors for BI framework created by Yeoh and Koronios (2010) displayed in Figure 4., that recognizes organization, process, and technology as the three key areas for successful BI is used as a base case as areas that the developed maturity model should assess. An overview of the most frequently mentioned CSF's that was conducted in the literature review is also used as a source to determine the areas that should be integrated in a comprehensive BI assessment model.
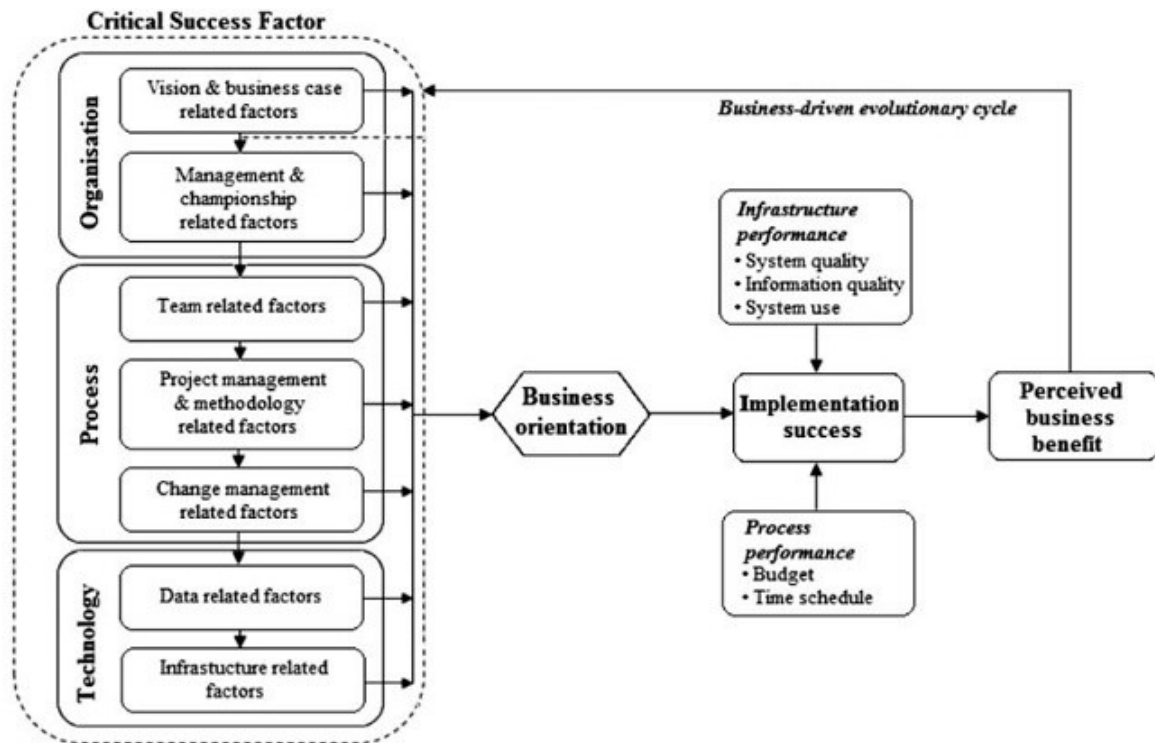
Figure 4. Framework for critical success factors of BI systems (Yeoh and Koronios, 2010).

The design and populate phases where the dimensions, levels, and the assessment model are defined are constructed with the assistance of a review of pre-existing BI maturity models in chapter 2. Existing models are used to help "cherry pick" suitable components from existing BI maturity models by combining structures and components to create a BI maturity model that allows comprehensive BI assessment while fulfilling the requirements of independency, compactness, and validity set in the first chapter of this study.

Figure 5. Illustrates the application of the proposed theoretical framework within the empirical section of this study.
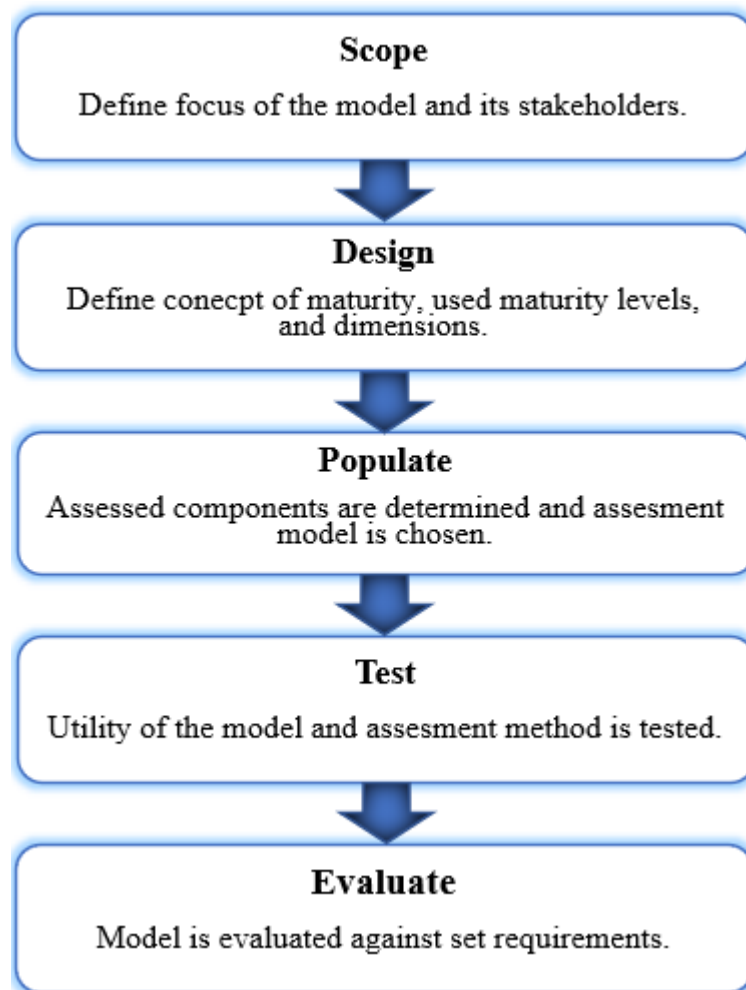
Figure 5. Maturity model development steps (Based on De Bruin et al.,
2005; Peffers et al., 2007).

3.3 Data collection

The thesis contains a twofold data collection approach, which comprises of two distinct phases. The initial phase was to collect existing secondary data, and the second step was to gather new primary data.

In first phase, details from existing business intelligence maturity models were collected and compared by conducting a literature review to compare the characteristics of the models so that they could be used in the maturity model development phase of this study. Findings from literature of critical success factors were also reviewed to assess the areas that should be assessed. This kind of data that is collected from other sources and has not been created specifically for the researchers' needs is called secondary data (Juneja, n.d.).

Primary data was collected during the second phase of data collection in this study. The data was collected and analyzed using quantitative methods. Quantitative research methods focus on collecting and analyzing structured numerical data to create dependable measurements for statistical analysis (Goertzen, 2017). As the primary data was collected in the BI maturity model testing phase of this study, the most cost-effective way to collect numeric answers to structured questions, was seen as a questionnaire which was sent to chosen employees of the case company.

3.4 Case company

The case company is a Finnish healthcare technology company that specializes in medical devices. The company has experienced remarkable growth in recent years, expanding its operations to all Nordic countries. To support this expansion, the company has made significant investments in its IT systems, including the implementation of an ERP system that manages the entire order to cash process that replaced numerous Excel documents.

However, due to the company's rapid growth, there is a considerable amount of technical debt that impacts both the BI system and other related IT systems and processes. Despite the company's relatively modest size, it relies heavily on data for internal and customer reporting, utilizing a great deal of BI and analytics. However, the presence of technical debt and unclear processes for many BI-related tasks has resulted in challenges that need to be addressed.

Therefore, the case company is an excellent candidate for testing the developed BI maturity model. The model will help assess the company's current BI maturity level, identify gaps and opportunities for improvement to enhance the overall BI capabilities of the company. By implementing the model, the case company can improve its BI related processes and enhance data-driven decision-making.

4   Results

4.1   Development of the model

This chapter presents the process of developing the BI maturity model. First, the model is designed by defining the used dimensions and sub-dimensions. Subsequently, the model is populated by specifying the descriptions associated with each level of the evaluated BI-related sub-dimensions. Following the construction of the proposed model, an empirical evaluation is conducted by developing a BI maturity assessment tool. This tool is initially employed to test the model in the case company. Later, the model is evaluated against the requirements outlined in the initial chapter of the study.

The objective of this chapter is two-fold: validate the developed theoretical framework while simultaneously offering a solution to the practical issue of not having a comprehensive BI maturity assessment model that is independent, compact, and validated.

4.1.1   Design

Because the newly developed maturity model draws heavily upon existing models, the decision was made to adopt a five-level framework to assess the maturity of the assessed objects. The selection of this number of levels was based in the fact that it is the most commonly utilized number of levels among the models reviewed in Chapter 2.

As revealed through the comprehensive review of existing BI maturity models in Chapter 2, the assessment of BI maturity encompasses several dimensions. Furthermore, the detection of the factors critical for BI adds to the complexity of the assessment, which highlights the need for a structured approach that can comprehensively cover all the critical areas. In this regard, Yeoh and Koronios (2010) suggested a CSF framework that recognizes three crucial dimensions - organization, process, and technology - as vital to success in BI. The utilization of these dimensions in the development of a comprehensive BI MM appeared to be a practical approach when assessing BI maturity.

To construct a BI maturity model that considers all critical aspects related to BI success, multiple sources were used, including existing maturity models and literature on CSFs for BI. These sources were used to break down the main dimensions into related sub-dimensions, which were then incorporated into the model. The selection of sub-dimensions

was based on their occurrence in existing literature and their ability to cover a wide enough range of the corresponding main dimension. This approach ensured that the resulting model was comprehensive and able to provide valuable insights into the specific areas that require improvement within the assessed organization where the model is used. The selection of sub-dimensions was performed considering the compactness requirement set for the developed model. In other words, the number of sub-dimensions was kept at a moderate level, ensuring that the resulting model was not overly complicated or time-consuming to use.

Table 5. presents the selected main dimensions and sub-dimensions for the suggested BI maturity model, along with the definitions of the sub-dimensions, which can be found in Appendix A.

Dimension	Sub-dimension
Organization	BI vision and strategic alignment
	Fact-based decision-making culture
	Management support
	User capabilities
Process	Change management
	Project management
	Personnel BI competence development

Technology	IT infrastructure
	Data architecture
	Data quality

Table 5. Main dimensions and related sub-dimensions of the proposed BI maturity model.

4.1.2 Populate

Following the choice of the main dimensions and sub-dimensions of the developed maturity model, the next step involved populating the model with attributes to define the five distinct levels of each dimension. The characteristics designated for each level were derived from features and descriptions of equivalent dimensions as identified from existing BI maturity models. This approach was chosen to ensure that the model's attributes would satisfy the requirement for validity which was one of the requirements set to direct the model development.

The utilization of existing BI maturity models for reference, as a starting point for the formulation of the dimensions and sub-dimensions, represented a pragmatic approach to building a reliable and comprehensive model. By drawing on the knowledge and experience gained from previous research, the resulting model was better able to capture the essential attributes of each dimension and sub-dimension accurately. The development of the model in this way ensured that it met the requirement for validity and was able to produce reliable results.

Organizational dimension leveling

Dimension	Maturity level					Source
Organization	1	2	3	4	5	
BI vision and strategic alignment	BI is decentralized and IT driven, there is no defined BI strategy in place.	Centralized IT driven BI. Only local departmental BI strategies in place that are only somewhat united with organizations strategy.	Initial BI strategy and roadmap in place. BI strategy aligned with different departmental strategies within the company.	Managed BI portfolio and use in business cases. BI portfolio management is integrated with wider organization strategy.	Fully implemented and continuously improved BI strategy that is integrated with organizational goals.	(Cardoso & Su, 2022; Hewlett-Packard, 2007; Raber et al., 2012)
Fact-based decision-making culture	No defined process for analytics on decision making. Culture is not based on data, and judgments are founded on intuition rather than evidence.	Analytics discussions started in the company. Individual BI or analytics projects to support tactical decision making.	Company has started determining business problems to solve with analytics and has started to utilize analytics in its decision-making processes in individual departments.	Company has realized the importance of analytics and implemented successful BI projects. Use of data and analytics is a core value in the company. Company uses performance metrics that are linked to	Analytics is seen as a competitive asset. Analytics is used in day-to-day activities within the company to generate revenue and make operations more efficient. Performance metrics might	(Halper & Stodder, 2014; Rayner & Schlegel, 2008)

			company's goals and uses them to guide organizations strategy. BI applications support cross-functional decision processes and are used by managers and senior executives.	have been extended to include customers and partners.	
Management support	Most executives unaware of the benefits of analytics. Only limited management interest in data and analytics.	An executive sponsorship for BI has stepped up to bring forth further discussions of BI and analytics. C-level involvement in BI decisions still very limited.	Executives are committed to analytics by aligning resources and establishing timeframes for the development of company's analytical capabilities. C-level management has started to be involved in	Advanced BI governance model is set up and strong C-level sponsorship ensures that BI is integrated into all of company's critical activities.	Executives view analytics as a critical part of the company and use BI in their strategic efforts. Strong support from CEO and roles such as chief analytics officer or chief data officer have been established in the company.	(Halper & Stodder, 2014; Hewlett-Packard, 2007; Rayner & Schlegel, 2008; Tan et al., 2011)

			BI related decisions.			
User capabilities	Users do not have BI or analytical capabilities.	Users have basic BI skills and management position users are able to interpret static reports.	Users have average level understanding of BI and analytics. Management position users that have a technical background are capable to use dynamic reports.	Self-service BI users are capable to build reports themselves. Management position users are able to use sophisticated reports and use "pull" analysis.	Very good basic skill level and initial use of advanced analytics by management position users. All non-management users able to use static reports.	(Gastaldi et al., 2018)

Table 6. Organizational dimension leveling.

Process dimension leveling

Dimension	Maturity level					Source
Process	**1**	**2**	**3**	**4**	**5**	
Change management	No change management process for BI system.	The need for BI change management process is known but no proper process defined yet.	An initial change management process in place and changes	A standardized change management process in place and	BI related changes fully documented and communicated to internal and	(Cardoso & Su, 2022)

| | | | partially documented. | used by BI team.

BI related changes are fully documented. | external BI system users. | |
|---|---|---|---|---|---|---|
| **Project management** | Project management is limited and BI related projects mostly intra-departmental with no real collaboration between departments. | Project based skills and roles within departments identified and BI project managers have responsibilities outside their department.

Each project still has its own tools and performance measures, and projects are done in silos without much collaboration between departments. | Project- and IT managers monitor BI projects across departments and business processes.

A BI program management that follows BI roadmap in place.

BI projects still mostly led by single departments or individuals. | Business and IT work as a team and have experience working together in BI projects successfully.

BI projects are completed with sophisticated processes such as agile development and prototyping, and clear requirements are defined. | All BI projects use a standardized processes that are customized based on specific needs of each project.

Advanced BI portfolio management is established. | (Halper & Stodder, 2014; Hewlett-Packard, 2007; Rayner & Schlegel, 2008) |
| **Personnel BI competence development** | There are no BI or analytics related trainings in | There is awareness of the need of BI and analytics related training | BI trainings in place but mostly focused on the importance | Ad hoc BI trainings that focus on specific issues. | Constant BI and analytics training courses in place with the aim of | (Cardoso & Su, 2022) |

| | place for users. | programs for users. | and benefits of BI and analytics. | | creating more autonomous users that contribute on improving the overall competence of the BI system. | |

Table 7. Process dimension leveling.

Technology dimension leveling

Dimension	Maturity level					Source
Technology	1	2	3	4	5	
IT infrastructure	There is no IT infrastructure or integrations between systems in place. No BI solution in use.	IT infrastructure mainly decentralized and very limited integrations between IT systems. Multiple different BI applications used by different teams across the company.	Centralized organizational BI system that is set up according to organizational structure. Integrations between more than half of the main IT systems. Technology standards started to emerge for IT	IT infrastructure enables company to develop full spectrum of BI and analytical products such as repositories for data (e.g., data warehouses), data marts, and AI and machine learning enhanced BI	IT infrastructure enables and supports development of all BI and analytics related products in a secure, reliable, scalable, and cost-effective manner. Integrations between systems work	(Cardoso & Su, 2022; Raber et al., 2012; Rayner & Schlegel, 2008; Hewlett-Packard, 2007)

			infrastructure, data warehouses, and BI system ensuring BI systems reliability and security.	reports when required. Bi-directional integrations between most of the main IT systems.	seamlessly no matter what IT system or integration technology is used.	
Data architecture	Data is housed in departmental or functional data marts within specific applications, spreadsheets, or desktop databases and no cross-functional integration of data.	Non-integrated data marts/ data warehouses in use that might be shared by more than one department but are still mostly focused on single subjects.	Consolidated data marts/ data warehouses, in place, but usually only for structured data.	Enterprise data warehouse in place, that reconciles organizations all major data to help organization achieve a single version of truth.	New data sources can be integrated seamlessly into the comprehensive enterprise data warehouse.	(Cardoso & Su, 2022; Halper & Stodder, 2014; Hewlett-Packard, 2007; Tan et al., 2011)
Data quality	No data quality controls. The quality of data depends on individual developers,	Organization has documented process for data quality controls, but it has not been fully	Organizations views data quality management as a core activity and has implemented	Metrics for data quality have been established and used for evaluating the quality of data.	Systematic data quality controls for all managed data. Issues with data quality have been	(Chuah, 2010; Halper & Stodder, 2014; Raber et al., 2012;

					identified and effect of inadequate data quality has been assessed. Data quality processes are assessed and improved continuously.	Tan et al., 2011)
systems users, or analysts and organization acts on data quality issues only when data quality issues occur.	implemented across the organization.	data quality controls across the organization.	The organization has allocated sufficient resources for data quality management activities.			

Table 8. Technology dimension leveling.

4.1.3 Test

In order to assist companies in understanding their level of BI maturity, a BI maturity model should be practical and applicable in real-world scenarios (Brooks et al., 2013). The testing phase of the BI maturity model development process consisted of testing the constructed maturity model in a case company in a real-life situation. Developing a quantitative BI maturity assessment tool was seen as a viable approach for testing the developed maturity model, as this seemed the most time-efficient way of reaching multiple stakeholders from the company in a limited amount of time.

The tool for assessing BI maturity level was developed by generating statements for each maturity level of every evaluated sub-dimension based on the maturity model developed during the populate and design phases of the development process. The statements for each level of each sub-dimension were written to support a questionnaire that allowed the stakeholders in the case company to answer a questionnaire by giving a Likert scale rating from one to five for each of the statements. Likert scale was decided as the answer format because of its simplicity that allowed creating a questionnaire that was easily completed and read. Likert scale has also been used widely as a measurement technique in the existing maturity models reviewed earlier in this study. The results from the

questionnaire were utilized to define a BI maturity level rating for the company, and for each separate main dimension and sub-dimension.

The questionnaire that was created comprised 10 sets of statements, each containing a statement for every maturity level of the BI maturity related sub-dimensions which were derived from the descriptions provided for each level. The assessment tool consisted of 50 statements in total that covered the three main dimensions. Each of the statements was answered in Likert scale from 1 to 5, (1) *strongly disagree* (2) *disagree* (3) *undecided* (4) *agree* (5) *strongly agree.*

Seven employees with varying roles within the case company were selected to receive the questionnaire. Participants were chosen based on their familiarity with the organization, ability to answer the statements, and willingness to participate. It was also considered important that at least one of the participants had immediate contribution in the development of the BI system within the company. The respondents consisted of the higher management of the organization including the CEO and CFO of the case company where the assessment was tested. This ensured that all functions and main users of the BI system were given an opportunity to give input about their view of the current state of the company's BI related factors.

The online questionnaire was created using Google Forms - a free tool which enables creation of questionnaires and forms with different question types. On December 5th, 2022, a link to the questionnaire was sent to the respondents through email, who were then provided a two-week timeframe to complete the questionnaire before the responses were analyzed. Out of the seven employees, six answered the questionnaire. Appendix B contains the created questionnaire. Once the participants finished filling out the questionnaire, the gathered data was examined by creating a table (Table 9.), where the results of the questionnaire are presented by showing number and percentage of answers to each Likert scale item of each statement.

Dimension	Sub-dimension	Statement	(1)	(1) %	(2)	(2) %	(3)	(3) %	(4)	(4) %	(5)	(5) %	#
Organization	BI vision and strategic alignment	1	2	33,3	0	0	2	33,3	1	16,7	1	16,7	6
		2	1	16,7	1	16,7	2	33,3	2	33,3	0	0	6
		3	1	16,7	2	33,3	2	33,3	1	16,7	0	0	6
		4	1	16,7	0	0	3	50	1	16,7	1	16,7	6
		5	1	16,7	0	0	3	50	2	33,3	0	0	6
	Fact-based decision-making culture	1	2	33,3	3	50	0	0	1	16,7	0	0	6
		2	0	0	1	16,7	0	0	3	50	2	33,3	6
		3	0	0	0	0	1	16,7	3	50	2	33,3	6
		4	1	16,7	0	0	2	33,3	2	33,3	1	16,7	6
		5	1	16,7	0	0	1	16,7	3	50	1	16,7	6
	Management support	1	3	50	2	33,3	1	16,7	0	0	0	0	6
		2	1	16,7	2	33,3	1	16,7	2	33,3	0	0	6
		3	0	0	2	33,3	3	50	1	16,7	0	0	6
		4	1	16,7	0	0	2	33,3	2	33,3	1	16,7	6
		5	1	16,7	2	33,3	1	16,7	2	33,3	0	0	6
	User capabilities	1	3	50	1	16,7	2	33,3	0	0	0	0	6
		2	0	0	2	33,3	0	0	3	50	1	16,7	6
		3	0	0	2	33,3	2	33,3	1	16,7	1	16,7	6
		4	0	0	1	16,7	4	66,7	1	16,7	0	0	6
		5	2	33,3	1	16,7	3	50	0	0	0	0	6
Process	Change management	1	0	0	1	16,7	0	0	1	16,7	4	66,7	6
		2	0	0	3	50	1	16,7	1	16,7	1	16,7	6
		3	1	16,7	2	33,3	1	16,7	2	33,3	0	0	6
		4	4	66,7	0	0	2	33,3	0	0	0	0	6
		5	4	66,7	1	16,7	1	16,7	0	0	0	0	6
	Project management	1	1	16,7	1	16,7	2	33,3	1	16,7	1	16,7	6
		2	3	50	1	16,7	2	33,3	0	0	0	0	6
		3	2	33,3	2	33,3	0	0	1	16,7	1	16,7	6
		4	2	33,3	2	33,3	2	33,3	0	0	0	0	6
		5	2	33,3	2	33,3	2	33,3	0	0	0	0	6
	Personnel BI competence development	1	1	16,7	3	50	1	16,7	1	16,7	0	0	6
		2	1	16,7	1	16,7	3	50	1	16,7	0	0	6
		3	1	16,7	1	16,7	4	66,7	0	0	0	0	6
		4	0	0	5	83,3	1	16,7	0	0	0	0	6

		5	4	66,7	2	33,3	0	0	0	0	0	0	6

Technology	IT infrastructure	1	4	66,7	1	16,7	0	0	1	16,7	0	0	6
		2	2	33,3	2	33,3	0	0	1	16,7	1	16,7	6
		3	2	33,3	0	0	1	16,7	3	50	0	0	6
		4	1	16,7	0	0	5	83,3	0	0	0	0	6
		5	1	16,7	2	33,3	3	50	0	0	0	0	6
	Data architecture	1	1	16,7	1	16,7	2	33,3	1	16,7	1	16,7	6
		2	1	16,7	1	16,7	3	50	1	16,7	0	0	6
		3	1	16,7	1	16,7	3	50	1	16,7	0	0	6
		4	2	33,3	2	33,3	1	16,7	1	16,7	0	0	6
		5	2	33,3	1	16,7	3	50	0	0	0	0	6
	Data quality	1	0	0	1	16,7	2	33,3	2	33,3	1	16,7	6
		2	3	50	1	16,7	2	33,3	0	0	0	0	6
		3	3	50	1	16,7	2	33,3	0	0	0	0	6
		4	4	80	0	0	1	20	0	0	0	0	5
		5	3	50	1	16,7	2	33,3	0	0	0	0	6

Table 9. Number of answers and percentages for statements in Likert scale.

The very last step in analyzing the collected data was to establish the BI maturity levels for the sub-dimensions, main dimensions, and the entire organization. Each sub-dimension comprised five Likert scale statements that collectively represented the sub-dimension. The main dimensions were comprised of a combination of sub-dimensions, while the organization was comprised of a combination of the main dimensions.

As one of the use cases for the developed BI maturity model was to help organizations develop their BI capabilities further by using the assessment for creating for example a BI development roadmap it was seen fit to use a staged approach when determining the BI maturity level based on the assessment. In staged approach, an organization must meet all of the determined requirements of a particular level before reaching it, as well as satisfying the requirements of the preceding levels (Fraser et al., 2002). This means that for company to reach for example level 4 maturity in a certain dimension or sub-dimension, it has to also achieve the requirements set for levels 1, 2, and 3. This means that when a BI maturity level is determined for a company, the maturity level for a main dimension, sub-dimension, or organization is the highest rating of the entire area as long as the requirements for lower levels of each dimension are satisfied.

The maturity rating for each sub-dimension was calculated by multiplying the count of answers to each statement with the responding level. The responses to each of the statements were then totaled and the total was divided with the count of responses. This way, an average rating for each statement was determined. After average rating for each statement was determined, the sum of the averages within each sub-dimension were totaled and the maturity rating for each sub-dimension was determined by dividing the sum by the total number of responses. The answers to statements and initial ratings for each statement are presented in Table 10.

		Statement	1	2	3	4	5	Statement rating
Organization	BI vision and strategic alignment	1	2	0	2	1	1	2,83
		2	1	1	2	2	0	2,83
		3	1	2	2	1	0	2,50
		4	1	0	3	1	1	3,17
		5	1	0	3	2	0	3,00
	Fact-based decision-making culture	1	2	3	0	1	0	2,00
		2	0	1	0	3	2	4,00
		3	0	0	1	3	2	4,17
		4	1	0	2	2	1	3,33
		5	1	0	1	3	1	3,50
	Management support	1	3	2	1	0	0	1,67
		2	1	2	1	2	0	2,67
		3	0	2	3	1	0	2,83
		4	1	0	2	2	1	3,33
		5	1	2	1	2	0	2,67
	User capabilities	1	3	1	2	0	0	1,83
		2	0	2	0	3	1	3,50
		3	0	2	2	1	1	3,17
		4	0	1	4	1	0	3,00
		5	2	1	3	0	0	2,17
Process	Change management	1	0	1	0	1	4	4,33
		2	0	3	1	1	1	3,00
		3	1	2	1	2	0	2,67
		4	4	0	2	0	0	1,67
		5	4	1	1	0	0	1,50
	Project management	1	1	1	2	1	1	3,00
		2	3	1	2	0	0	1,83
		3	2	2	0	1	1	2,50

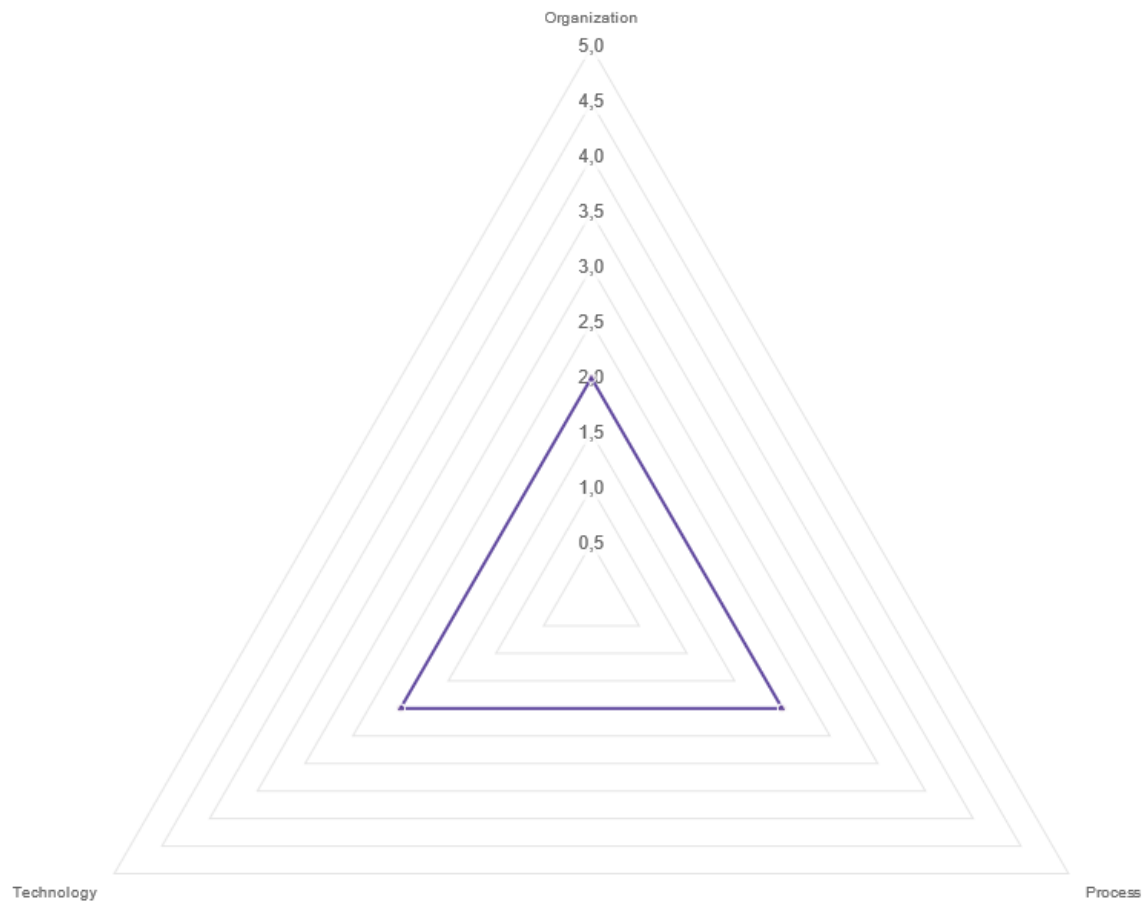| Dimension	Sub-dimension							
		4	2	2	2	0	0	2,00
		5	2	2	2	0	0	2,00
	Personnel BI competence development	1	1	3	1	1	0	2,33
		2	1	1	3	1	0	2,67
		3	1	1	4	0	0	2,50
		4	0	1	5	0	0	2,83
		5	4	2	0	0	0	1,33
Technology	IT infrastructure	1	4	1	0	1	0	1,67
		2	2	2	0	1	1	2,50
		3	2	0	1	3	0	2,83
		4	1	0	5	0	0	2,67
		5	1	2	3	0	0	2,33
	Data architecture	1	1	1	2	1	1	3,00
		2	1	1	3	1	0	2,67
		3	1	1	3	1	0	2,67
		4	2	2	1	1	0	2,17
		5	2	1	3	0	0	2,17
	Data quality	1	0	1	2	2	1	3,50
		2	3	1	2	0	0	1,83
		3	3	1	2	0	0	1,83
		4	4	0	1	0	0	1,40
		5	3	1	2	0	0	1,83

Table 10. Answers for statements and statement ratings.

The findings of the calculated statement ratings were used to calculate the sub-dimension specific BI maturity scores for the case company. The results of the calculated BI maturity scores for each sub-dimension are displayed in a radar chart form in Figure 6. The results show that fact-based decision-making culture (3,4) and BI vision and strategic alignment (2,87) have the highest and data quality (2,08) and project management (2,27) the lowest sub-dimension maturity scores of the assessed sub-dimensions in the case company.

Figure 6. Case company's BI maturity scores for each sub-dimension.

After the sub-dimension scores were calculated, the outcomes were subsequently utilized to determine the BI maturity ratings for the main dimensions: *organization*, *process*, and *technology*. As described earlier in this chapter, the main dimensions maturity ratings are determined by the highest scores of the entire areas on the condition that all of the corresponding sub-dimensions also reach that level. In the case company's case, the highest complete level that was reached in any main dimension was 2. Since 2 was the highest BI maturity rating that was reached by all of the assessed main dimensions, the overall BI maturity rating on the scale of 1 to 5 for the case organization was determined as 2. Therefore, it can be concluded that the case organization under consideration had a moderate level of BI maturity. Even though the company had some successful implementations of BI related factors especially when it comes to the organization dimension, the company did not attain the same level of success across all its dimensions and sub-dimensions, which prevented it from reaching a higher level of maturity.

Figure 7. Case company's BI maturity ratings for main dimensions.

The results of the assessment of BI maturity carried out in the case company indicate that the company has made significant progress in fostering an environment of data-driven decision-making and is aligning its BI vision with overall organizational strategy. However, the same level of progress has not been observed in the areas of project management and data quality that are especially responsible for lower maturity ratings of technology and process main dimensions, which indicates that these areas require attention to improve the overall BI maturity of the case company.

4.1.4 Evaluate

In this section, the BI maturity model developed in this study is evaluated against the requirements outlined in the initial chapter. The objective of this evaluation is to verify if the model successfully meets the goals of independency, compactness, and validity. To achieve

this, the model's structure, and design, as well as the developed BI maturity assessment tool are discussed. The evaluation provides insight into the usefulness of the model as a practical and reliable way for organizations to self-assess their BI maturity level.

The BI maturity model developed in this study successfully met the goal of independency by functioning as a self-assessment tool without the need for external third-party entities. This was achieved by creating a questionnaire that was distributed to selected employees working in the case company, enabling the company to calculate organization's BI maturity level independently. The questionnaire included questions covering the three dimensions and their sub-dimensions of the model, and selected persons of the case company were asked to rate each sub-dimension's level on a Likert scale. The resulting data was analyzed to determine the company's overall BI maturity level as well as the maturity level of each main dimension and sub-dimension. By fulfilling the independency requirement, the model provided a cost-effective and accessible method for case organization to assess its BI maturity level without relying on external resources.

Success in achieving the goal of compactness set for the model in this study was measured by the number of assessed dimensions and time that the employees had to use to answer the assessment. The case company's employees were offered the option to skip questions during the assessment. This allowed for the assessment's compactness to be evaluated by examining the number of questions answered by the employees by determining whether the employees had completed all of the questions during the assessment.

The model only included three main dimensions and ten sub-dimensions, which were assessed using a questionnaire with a total of 50 questions answered on a Likert scale. This approach ensured that the assessment could be conducted with limited resources, particularly with regards to time, as the questionnaire could be completed in approximately 15 minutes. By avoiding an excessive number of assessed dimensions, the model was able to provide a focused and concise assessment of an organization's BI maturity level, without the need for extensive resources or time-consuming evaluations. As can be seen from table 9 in chapter 4.1.3, only one of the respondents did not answer all the questions and the respondent in question left only one question unanswered. This indicates that the model was compact enough so that the respondents had patience to answer the survey. Overall, the model's compactness allowed for an efficient method of assessing BI maturity and it can be concluded that the compactness requirement was successfully achieved by the developed BI maturity model.

The BI maturity model developed in this study successfully met the goal of validity by leveraging prior research on existing BI maturity models. The model was constructed by analyzing and incorporating elements from existing BI maturity models to ensure that its dimensions, levels, and assessment model were all valid. This approach allowed for the development of a model that was rooted in established research and could provide organizations with a reliable and accurate assessment of their BI maturity level.

All in all, the BI maturity model developed in this study successfully met all three requirements. The independency goal was met by creating a self-assessment questionnaire that enabled the company to determine its BI maturity level independently, without the need for external resources. The compactness goal was met by limiting the number of assessed dimensions and questions, making the questionnaire compact and efficient to use. Finally, the validity goal was met by leveraging prior research on existing BI maturity models. In conclusion, the developed BI maturity model proved to be compact and practical tool for organizations seeking to evaluate their BI related capabilities.

5 Conclusions

The focus of this thesis was to aid organizations in conducting a comprehensive self-assessment of their Business Intelligence capabilities by creating a BI maturity model. The ultimate objective was to progress towards more complete and comprehensive BI maturity model that would still be feasible to use in practice.

In order to guarantee the model's intended use, criteria of independency, compactness, and validity were established and followed as a guideline when developing the model. The primary research question of the study was "How to create a more complete business intelligence maturity model that can be used to assess the state of organization's business intelligence?" which was answered by the assistance of supporting questions "*What are the BI related areas that the new model should assess?*" and "*What kinds of methods have been used when creating new maturity models and what method should be used?*". To answer the research questions a theoretical framework was created by combining findings from literature regarding critical success factories of BI, BI maturity, BI maturity model development methods, and a summary of existing BI maturity models. Next, the responses to the supporting questions and how the developed theoretical framework addressed them will be discussed.

Question 1: *What are the BI related areas that the new model should assess?*

The CSF framework created by Yeoh and Koronios (2010) was used as a baseline as factors that the developed maturity model should assess. In addition, an overview of literature review of most cited BI success factors was conducted to determine a combination of assessed areas to be included in the model. This method ensured that the most significant areas essential for successful BI implementation were considered when the determining included areas to the maturity assessment.

Questions 2: *What kinds of methods have been used when creating new maturity models and what method should be used?*

Numerous maturity model development methods found from literature were examined and general process for developing a maturity model as proposed by De Bruin et al. (2005) was seen as a suitable method to be applied as a guideline during the maturity model development phase of the study. The process was used in conjunction with Peffers et al.'s (2007) general design science process, leading to a clear, step-by-step process that begins with determining the scope of the model and concludes with evaluating the proposed model. To ensure the proposed model met the validity requirement, the model was populated by conducting a review of established business intelligence maturity models in the literature. The results of this analysis were then utilized to populate the model.

The following sections will cover theoretical contributions and practical implications. Additionally, the limitations of this study will be discussed, and suggestions for subsequent studies will be proposed.

5.1 Theoretical contribution

This study made contribution to the existing academic literature on BI maturity model development. Literature of existing BI maturity models, maturity model development methods, and critical success factors of BI were used to create a theoretical framework and empirically testing the framework in real-life setting. Despite the presence of multiple BI maturity models, Shaaban et al. (2011) have suggested that none of them provide a complete assessment of BI maturity when used in isolation. Additionally, Lahrmann et al. (2011) have pointed out that the majority of current models lack empirical testing and validation. To

address shortcoming of previous BI maturity models, attention was especially paid to the comprehensiveness and practicality of the developed model to ensure that the developed model could be used alone to assess organizational BI maturity comprehensively.

The theoretical framework suggests that most critical areas of BI related factors crucial for the effective implementation of BI are organization, process, and technology. These three areas can be seen as main dimensions of BI. Studied literature reviled that these dimensions should be broke-down into related sub-dimensions that represent the related main dimension. The study broke-down the three main dimensions into 10 related sub-dimensions to create a comprehensive assessment model which was then tested empirically.

In the context of creating maturity models, this thesis contributes to research of maturity development especially on the BI maturity model context. Through a literature review of maturity model development processes, it was found that the general maturity model development process proposed by De Bruin et al. (2005), which closely aligns with the general design science process, continues to be relevant and useful for developing new maturity models today.

The study also gives a contribution of research of BI maturity models. Several existing BI maturity models were examined and referenced when creating a new more comprehensive BI maturity model. It was found that even though there was not a single existing maturity model that could be used, the developed model could be populated by utilizing a combination of existing models. By populating the developed model using existing BI maturity models, the study supports finding of previous studies of BI maturity models and confirms findings of requirements of the assessed sub-dimensions that should be met for the corresponding stages of maturity. Moreover, the thesis enhances the research of BI maturity models by conducting empirical testing, filling in the gap of insufficient empirical testing in many existing BI maturity models.

5.2 Practical implications

This research has three specific practical implications. Firstly, it provides insights into the process for developing a BI maturity model. Secondly, it identifies the areas that a comprehensive BI maturity model should assess. Thirdly, the outcome of the study is a model that organizations can utilize as-is or modify to suit their unique organizational needs.

This study presents a theoretical framework that provides a practical and systematic approach for creating a BI maturity model. The framework proposes combining elements

from existing models to produce a comprehensive model. The primary objective was to establish a well-defined methodology for the development of BI maturity models. By utilizing multiple existing BI maturity models during the construction phase, the proposed framework aimed to avoid the drawbacks of relying on a single substandard model that fails to assess BI maturity adequately.

Some organizations hold the misconception that a successful implementation of BI can be accomplished solely by producing visually appealing and precise reports, without acknowledging the multitude of diverse elements that must function in harmony for a BI implementation to thrive (Brooks et al., 2015). Through a review of relevant literature on critical success factors, the theoretical framework developed in this research clarified the crucial elements of BI that organizations should prioritize to achieve a successful implementation. The framework subsequently established a set of dimensions that were utilized in creating the assessment model, enabling organizations to effectively identify and address the essential components necessary for BI success and thus giving organizations seeking a successful BI implementation a good understanding of the areas to be developed to ensure successful BI implementation.

Finally, the study concludes in the developed BI maturity model that aims to be comprehensive, practical, and universally applicable for assessing the BI maturity of any organization. The BI maturity model created in this research aims to be a cost-effective assessment tool which enables organizations to evaluate their present level of BI maturity, making it useful for example in creating a BI development roadmap.

5.3 Limitations of the study

It's important to acknowledge that all research has limitations that can impact the results. Therefore, discussing these limitations is necessary, including in this study where there are specific limitations affecting the results and thus which should be mentioned.

It should be acknowledged that the conclusions of this research should be interpreted cautiously due to the fact that the testing phase of the model's development process was carried out in only one case company. With more time and resources, the study could have enhanced its value by increasing the number of companies from different industries to test the assessment model, thereby further validating its usability in practice.

The developed BI maturity model in this research is significantly influenced by existing BI maturity models to ensure the validity of the assessment. Descriptions for each

maturity stages of assessed dimensions were a combination existing models which limited the scope of the new model to the descriptions of existing models. Additionally, the descriptions of different models used might not be in all cases consistent with each other as some of the existing models were specifically developed to be used in specific context or industry. Even though dimensions which were chosen to be assessed were somewhat generally applicable in any context or industry, it is important to understand that the descriptions might not therefore be relevant to all contexts or industries and might need modifying to be used so that misinterpretations of the descriptions for the maturity stages can be avoided.

Furthermore, it is also important to acknowledge that the dimensions and their descriptions selected for this thesis were based on the latest and most relevant information available, reflecting the continuously evolving nature of the BI environment and thus they might not all be relevant as the BI field evolves over time.

5.4 Suggestions for future research

The BI maturity model was created to evaluate an organization's maturity level using a quantitative approach, specifically a questionnaire. However, using a questionnaire that requires independent responses from respondents, as opposed to a qualitative assessment like an interview where a researcher can provide guidance, may require a higher level of knowledge from the respondents. Therefore, conducting the assessment through an interview may provide more precise results, as respondents can ask for clarification on each question and term. Even though a qualitative assessment would take more time, it would be a useful method especially when respondents are not familiar with more technical oriented questions.

It is also important to acknowledge that even though the proposed BI maturity model outlines the assessed dimensions and their characteristics for each stage of maturity, the model does not provide a quantitative approach to measure the statements associated with these dimensions when responding to the questionnaire. Hence, the responses obtained are likely to be subjective and may vary significantly based on the respondent's individual perspectives and knowledge regarding the given question of each dimension while answering the assessment. Considering future research, exploring methods to quantify the requirements for each stage of assessed dimensions would be beneficial. Doing so would enable companies to utilize the model even with a limited number of individuals possessing

comprehensive knowledge of BI terminology and BI related technologies by giving them clear quantitatively measurable requirements for each statement in the questionnaire.

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Appendix A: Definitions of used sub-dimensions

Table A1: Definitions of used sub-dimensions

Organization	
BI vision and strategic alignment	One of the most commons reasons for BI initiatives to fail is their lack of alignment with organizations overall strategy, and as a result they do not satisfy the business needs of organizations (Yeoh & Koronios, 2010). The objective of this sub-dimension is to measure the level of BI development planning and its compatibility with organizations wider strategy.
Fact-based decision-making culture	A fact-based organization culture means an organization culture that encourages use of quantitative evidence when making decisions and has a clear fact-based decision-processes in place (Kulkarni & Robles-Flores, 2013). This sub-dimension measures the level of organizations use of BI and analytics when making decisions.
Management support	It is widely acknowledged that committed management support is among the most crucial factors in successfully implementing a BI system, as consistent support from top executives within the organization is a crucial factor for BI initiatives to secure the needed funding and resources (Yeoh & Koronios, 2010). This sub-dimension is used to measure the involvement and support of management e.g., the decision makers of the company for BI development initiatives.
User capabilities	BI user capabilities are an important part of ensuring that organizations get the full technical potential of the used BI system (Cardoso & Su, 2022). This sub-dimension assesses the BI user capabilities within the assessed organization.
Process	
Change management	Changes that impact BI solutions scope, budget or schedule can be considered a change that should be documented and

	communicated to involved stakeholders to support the development and use of the system (Nakayama et al., 2020). This sub-dimension measure how the assessed organization processes and documents changes regarding the BI system.
Project management	A proper project management is pivotal for planning and managing business intelligence initiatives (Bach et al., 2017). BI project teams should be cross-functional and include members from technical and business side of the organization (Yeoh & Koronios, 2010). This sub-dimension assesses how BI projects are managed and the level of BI related project management processes within the organization.
Personnel BI competence development	To fully benefit from a BI system, it is crucial for an organization to ensure that end-users can effectively utilize the system and even perform more complex analytical tasks, and thus it is important to improve BI competence of the BI system users (Cardoso & Su, 2022). This sub-dimension assesses how well the organization ensures sufficient BI related trainings for the users.
Technology	
IT infrastructure	A lack of IT infrastructures flexibility to for example give access to the needed data often leads to BI projects slowing down or needing to use unreliable workarounds (Cardoso & Su, 2022). The success of a business intelligence system is heavily reliant on the ability to accommodate new data sources based on the evolving needs of an organization, which can be achieved through a scalable IT infrastructure (Yeoh & Koronios, 2010). This sub-dimension assesses organizations IT infrastructures capabilities to enable flexible BI development. The assessment also measures the level of integrations between the main systems used by the organization.

Data architecture	Well centralized central data repositories often lead to fewer potential data problems and maintenance and give more flexibility when answering to emerging data and ad-hod reporting needs (Cardoso & Su, 2022). Data architecture sub-dimension assesses how well data is stored and organized within the organization.
Data quality	One of the critical elements that determine the success of a BI system is the quality of data especially when it comes to the source systems, as the data quality significantly impacts the accuracy and dependability of the BI reports using the data (Yeoh & Koronios, 2010). Data quality governance ensures the precision and reliability of the data used by the BI solution (Cardoso & Su, 2022). This sub-dimension assesses the level of data quality management in the organization.

Appendix B: BI maturity assessment tool

Table A2: BI maturity assessment tool

BI vision and strategic alignment	1	2	3	4	5
1. BI is decentralized and driven by IT – no defined BI strategy in place.					
2. BI is centralized but driven by IT. There are local departmental BI strategies in place, but they are only partially aligned with wider organization strategy.					
3. Our company has an initial BI strategy and roadmap in place. BI strategy is aligned with different departmental strategies within the company.					
4. BI is used in business cases and BI portfolio is managed and integrated with wider organization strategy.					
5. We have implemented and continuously improve our BI strategy that is fully integrated with our organizational strategy and goals.					
Fact-based decision-making culture	1	2	3	4	5
1. Our culture is not driven by data and decisions are mostly made on instinct instead of facts.					
2. We have individual BI and analytics projects to support tactical decision making.					

	1	2	3	4	5
3. We use BI and analytics in our decision-making process in individual departments.					
4. Use of data and analytics is a core value in our company. BI metrics are linked to company goals and are used to guide strategic decisions.					
5. BI and analytics are used in day-to-day activities to generate revenue and make operations more efficient. BI performance metrics have been extended to include customers and partners.					
Management support	**1**	**2**	**3**	**4**	**5**
1. Our management has only very limited interest in BI and analytics.					
2. There is some executive level sponsorship for BI initiatives, but C-level involvement in BI related decisions still very limited.					
3. Our executives align resources to BI and analytics development and C-level management is involved in BI related decisions.					
4. We have clear BI governance and strong C-level support for BI, which ensures BI's integration to company's critical activities.					
5. Our executives view BI as critical for company and roles such as chief analytics officer or chief data officer have been established in the company.					
User capabilities	**1**	**2**	**3**	**4**	**5**
1. Our users do not have any BI or analytical capabilities.					
2. Our users have very basic BI system skills and management position users are able to read static reports.					
3. Our users have average skill level and understanding of BI and analytics. Management position users with more technical background are able to use dynamic BI reports.					
4. We have self-service BI users who are able to build their own BI reports and management position users are able to use sophisticated BI reports that require a good understanding of the system.					
5. All of our BI users have very good basic skill level and management position users have started initial use of advanced analytics.					
Change management	**1**	**2**	**3**	**4**	**5**
1. There is no change management process for our BI.					
2. The need for change management process is known, but no defined process in place yet.					
3. We have an initial change management process and changes to BI system are partially documented.					
4. We have a standardized change management process in place and used by our BI team. BI related changes are fully documented.					
5. All BI related changes are fully documented and communicated to internal and external users of our BI system.					
Project management	**1**	**2**	**3**	**4**	**5**
1. Our BI related projects are mostly intra departmental without real collaboration between departments.					
2. Our BI related projects have project managers, but projects are done in silos without much collaboration between departments.					

	1	2	3	4	5
3. We have project- and/ or IT managers that monitor BI projects across departments and business processes.					
4. Our business and IT work as a team and BI related projects have clear pre-defined requirements and use processes such as agile development and prototyping.					
5. All of our BI projects follow standardized process that is customized based on the specific needs of each project.					
Personnel BI competence development	**1**	**2**	**3**	**4**	**5**
1. We have no BI related user trainings in place.					
2. We have plans to implement BI related trainings for users.					
3. There are BI related trainings in place that are mostly focused on the importance and benefits of BI and analytics.					
4. We have ad-hoc trainings that are focused on specific issues and the use of self-service BI.					
5. We have continuous BI related training programs in place.					
IT infrastructure	**1**	**2**	**3**	**4**	**5**
1. We have no BI solution in use and there are no integrations between our IT systems.					
2. Our IT infrastructure is mainly decentralized and integrations between IT systems very limited. There are multiple different BI systems in use by different teams across the company.					
3. We have centralized BI system in use that is set up according to our organizational structure. There are integrations between some of our main IT systems.					
4. Our IT infrastructure allows us to develop BI related products such as data warehouse and data marts. We have bi-directional integrations between most of our main IT systems.					
5. Our IT infrastructure enables us to develop all BI related products in a secure, reliable, cost-effective, and scalable manner. Needed integrations between all of our main systems work seamlessly no matter what system or integration technology is used.					
Data architecture	**1**	**2**	**3**	**4**	**5**
1. Our data is housed in departmental or functional data marts within specific applications or spreadsheets and there is no cross-functional integration of data.					
2. We have non-integrated data marts/ data warehouses that are shared by more than one department, but which are still mostly focused on single subjects.					
3. We have consolidated data marts/ data warehouses in place for structured data.					
4. We have an enterprise data warehouse in place that reconciles our major data to help us create a single version of truth.					
5. New data sources can be integrated seamlessly into our comprehensive enterprise data warehouse.					
Data quality	**1**	**2**	**3**	**4**	**5**
1. We don't have any data quality controls and the quality of used data depends on individual system users. As an organization we only act on data quality issues when issues occur.					

2. We have a documented process for data quality controls, but it has not been fully implemented across the organization.					
3. Data quality management is a core activity for us, and we have implemented data quality controls across our organization.					
4. We have data quality metrics which are used to evaluate quality of our data. We have also allocated sufficient resources for data quality management activities.					
5. We use systematic data quality controls for all managed data, and effect of inadequate data quality has been assessed. Our data quality processes are assessed and improved continuously.					