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Risto Silvola

ONE PRODUCT DATA FOR INTEGRATED BUSINESS PROCESSES

UNIVERSITY OF OULU GRADUATE SCHOOL;
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ONE PRODUCT DATA FOR INTEGRATED BUSINESS PROCESSES

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Abstract

Master data describes business objects that are shared across an entire enterprise. Master data is a single source of information that should be used across the IT systems and business processes without changing. Definitions and understanding of common data and how well it is understood forms the basis for understanding the master data.

The main objective of this study is to clarify how one product data should be understood and defined and to identify the main challenges and the best practices for managing the one product data for business processes. This study approaches one product data for integrated business processes from several perspectives by focusing on one product master data, data ownership, and the importance of a governance model for managing the master data. The means also to determine business value of master data and to ensure that a company's success in reaching this business value is analysed.

The findings of this study reveal the need for balance between business processes, data, and IT systems. The study indicates that a governance model is necessary in conjunction with business processes, data, and IT systems to ensure that an adequate foundation is created for one product data. One product data is the sum of product-related business data and one product master data. One product master data is the "DNA" of a product that is created by the product portfolio management process and is stored and controlled by a Product Lifecycle Management IT-system that updates the receiving systems in business processes with the common product data.

One product data forms the basis for integrated business processes. In the product life cycle context, this means that data must be in place from the new product development phase to the maintenance phase, as well as across sales processes, supply chains, and care/service processes. Discontinuous data is harmful as it causes extra costs in management and slows down data analysis, as well as affects the reaction speed around changes on the business side. New business opportunities such as digitalisation may become very difficult if centralised one product data is not in place. It is important to keep in mind that if data integrity and quality are not in place in a company, adding new business models might be very challenging.

Keywords: business driver, business process, data, data owner network, digitalisation, enterprise resource planning, integrity, life cycle, master data, product, product portfolio, quality, sales, service, value

Silvola, Risto, Yhtenäinen harmonisoitu tuotedata integroitujen liiketoiminta prosessien tarpeeseen.
Oulun yliopiston tutkijakoulu; Oulun yliopisto, Teknillinen tiedekunta
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Tiivistelmä

Master data on informaatiota, joka on määritelty yksiselitteisesti ja sitä käytetään muuttumattomana ylitse eri IT- järjestelmien ja -prosessien. Datamäärityksillä tuetaan liiketoiminnan prosesseja. Datan määritelmät ja yleinen datan ymmärtämisen taso yrityksessä ovat tärkeitä elementtejä, muodostaen pohjan Master data -käsitteelle.

Tämän tutkimuksen päätarkoituksena on selkiyttää kuinka yksiselitteinen tuotetieto tulisi ymmärtää ja määritellä. Samalla identifioidaan suurimmat haasteet ja parhaat käytänteet yhdenmukaisen tuotetiedon hallinnalle. Tutkimuksessa keskitytään yhtenäisen master datan käsitteistön, datan omistajuuden, sekä hallinnointimallin tärkeiden näkökulmien kautta kokonaisuuden ymmärtämiseen useista eri näkökulmista. Tutkimuksessa perehdytään myös datan liiketoiminnallisen arvon tunnistamiseen. Sen kautta voidaan varmistaa yrityksen kyvykkyys saavuttaa asetetut tavoitteet, jotka johto on määritellyt esim. strategian kautta.

Tulokset kertovat, että on äärimmäisen tärkeää löytää oikea balanssi liiketoiminnan prosessien, datan ja tietojärjestelmien kesken. Yksikäsitteinen tuotetieto on summa, joka muodostuu tuotteeseen liittyvästä liiketoimintatiedosta sekä yhtenäisestä tuote master datasta. Yhtenäinen tuote master data on ikään kuin tuotteen DNA tietoa. Yhteenvetona voidaan todeta, että parhaimmillaan data määritellään kerran ja sitä käytetään muuttumattomana eri liiketoiminnan prosessissa hyödyksi.

Yhtenäinen tuote data muodostaa pohjan liiketoiminnan prosessien integroimiselle. Tuotteen elinkaaren sisällön osalta tämä tarkoittaa sitä, että data luodaan osana uuden tuotteen kehitysprosessia ottaen huomioon muiden liiketoiminta prosessien tarpeet kuten myynti, logistiikka ja valmistus, huolto jne.

On äärimmäisen tärkeää, että datalle ei synny epäjatkuvuuskohtia eri prosessien välille. Datan epäjatkuvuuskohdat voivat tuottaa ylimääräisinä kustannuksia ylläpidon, data analytiikan ja raportoinnin kautta. Yleinen reagointinopeus liiketoiminnan muutoksiin on yleensä hitaampaa. Uusien liiketoimintamahdollisuuksien kuten digitalisaation tai esineiden internetin (IoT) toteuttaminen voi olla haastavaa ja kallista mikäli keskitettyä ja yhtenäistettyä tuote data mallia ei ole. Yhtenäisen tuote master datan käsite ja parhaita käytänteistä toteuttava hallintamalli antavat pohjan tietokeskeiselle ajattelulle yrityksessä.

Asiasanat: arvo, data, datan omistajaverkosto, digitalisaatio, elinkaari, laatu, liiketoimintaprosessi, myynti, palvelu, päätiedot, tuote, tuotevalikoima, yhtenäinen, yritysajuri, yritysvarojen suunnittelu

Acknowledgements

I have had a rich experience working with data-related topics since 2003, before the term “master data” became known and used widely. When Professor Harri Haapasalo suggested I do a doctoral thesis on this subject, I was ready to take the challenge. This happened in 2007 in a conference organised at the same time as Neste Rally. I have always considered myself to be a practical person, and working in the academic world has thus been a rewarding experience for me. Explaining things in a scientific manner has taught me a lot.

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This academic work has been done outside of my normal work and family life.

Sometimes life really has felt too full and busy. One could say that feeling of stress has been present. Therefore, taking time off for hobbies has been a "must" to re-charge my batteries. I want to thank my masters swimming team friends in Hyvinkään Uimaseura.

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Finally, I want to thank my family, starting with my wife, Suvi. We have been together for over 25 amazing years. Ups and downs like in any marriage. Finding again the teenage spark for love has been 'cool'. To my children, Miika, Markus, Elias, Emmi, and Väinö, I thank each one of you. I am very proud of you all and impress my support to you. I should say it more often.

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Abbreviations and definitions

AI	Artificial Intelligence
BPM	Business Process Management
CAD	Computer Aided Design
CAE	Computer Aided Engineering
CAM	Computer Aided Manufacturing
CEO	Chief Executive Officer
CRM	Customer Relationship Management
ERP	Enterprise Resource Planning
e.g.	exempli gratia (for example)
etc.	et cetera (and the rest, and so on)
HR	Human Resources
i.e.	id est (that is)
IT	Information Technology
MES	Manufacturing Execution System
MDM	Master Data Management
PDM	Product Data Management
PDMA	Product Development & Management Association
PDO	Product Data Owner
PDON	Product Data Ownership Network
PLM	Product Lifecycle Management
PPM	Product Process Management
RPA	Robotics Process Automation

Business Process

A business process is a collection of related, structured activities or tasks that produce a specific service or product for a particular customer or customers.

Data

Data is digitally stored information (Encyclopedia Britannica 2009). Data occurs in forms such as symbols, images, and texts (Lawrence 1999, Williamson 1982).

Data Governance

Data governance is the data management of all the data which an organisation has to ensure that high data quality exists throughout the complete lifecycle of the data. The key focus areas of data governance include availability, usability, consistency, data integrity, and data security and includes establishing processes to ensure effective data management throughout the enterprise, such as accountability for the adverse effects of poor data quality and ensuring that the data which an enterprise has can be used by the entire organisation (https://dama.org/).

Deoxyribonucleic acid (DNA)
: This is a thread-like chain of nucleotides carrying the genetic instructions used in the growth, development, functioning, and reproduction of all known living organisms and many viruses.

IT System
: An IT system is any organised system for the collection, organisation, storage, and communication of information.

Master Data
: Master data represents the business objects that are agreed on and shared across the enterprise. It can cover relatively static reference data, transactional, unstructured, analytical, and hierarchical data, as well as metadata.

One Master Data
: One master data is a set of disciplines over the business processes, master data management, and IT systems that represent the concept of creating data once and sharing it across the IT systems and business processes without changing it.

One Product Data
: One product data is the sum of product-related business data and one product master data.

One Product Master Data
: One product master data is the unique DNA of the product that is created by the product portfolio management process and is stored and controlled by a PLM/PDM system that updates the receiving systems with the common product data.

Process

A process is series of actions or steps taken in order to achieve a particular end result.

Product

A product is an item that has been made to be sold. It can be hardware, software, service or a combination thereof. A product may also contain documentation.

Product Data

Product data broadly covers all the data related to a product. Product data ensures that a company manufactures, delivers, sells, and maintains the correct products.

Product master data

Product master data entails the data that is produced during the NPD phase. Data that is then released to be used in other corporate functions and business processes. This data is validated in different development phase milestones and steering group meetings to ensure the deliverable content meets the use phase expectations of the business processes. Product master data is often stored in PDM/PLM systems. The quality of the product master data should not be compromised, and the data should be commonly understandable.

Product-Related Business Data

This includes product-related marketing and sales data, product-related supply chain data, and product-related service and care data in business processes.

Original publications

This thesis is based on the following publications, which are referred to throughout the text by their Roman numerals:

I Silvola, R., Jaaskelainen, O., Kropsu-Vehkapera, H. & Haapasalo, H. (2011). Managing one master data - Challenges and preconditions. *Industrial Management & Data Systems, Vol. 111*, No. 1, pp. 146–162.

II Silvola, R., Kemppainen, T., Haapasalo, H., Kropsu-Vehkapera, H. & Jaaskelainen, O. (2011). Elements and implementation of product data ownership network. *Proceedings of TIIM2011 Conference*, 28–30 June, 2011 Oulu, Finland, pp. 735–752.

III Silvola, R., Harkonen, J., Vilppola, O., Kropsu-Vehkapera, H. & Haapasalo, H. (2016). Data quality assessment and improvement. *International Journal of Business Information Systems, Vol. 22*, No. 1, pp. 62–81.

IV Silvola, R., Tolonen, A., Harkonen, J., Haapasalo, H. & Männistö, T. (In press). Defining one product data for a Product. *International Journal of Business Information Systems*.

V Silvola, R., Kauhanen, J., Collin, J., Haapasalo, H. & Kropsu-Vehkapera, H. (2011). A framework for improving the launch concept of new services. *Proceedings of TIIM2011 Conference*, 28–30 June, 2011 Oulu, Finland, pp. 692–706.

Two of the articles have been published in journals, one has been accepted to be published in a journal, and two have been published in conference proceedings. All five articles have undergone a double blind review process. The author of this dissertation is the primary author of all the original publications. The researcher has been responsible for formulating the research problems, collecting the relevant literature, collecting or coordinating the collection of empirical material, analysing the material, drawing conclusions, and acting as the primary author in all five articles. The role of the co-authors included reviewing and commenting on the article manuscripts by the primary author and supporting the writing process.

Contents

1 Introduction

1.1 Background and research environment

Today's businesses face several challenges, such as price competition and pressures to be fast with new product launches. The technological revolution demands rapid changes where the fastest can make better profits and the laggards barely survive (Lehto et al., 2011; Belt, Haapasalo, Harkonen, Mottonen, & Kess, 2009; Helo, 2004; Moore, 1999; D'Aveni, 1995). The solutions offered to businesses increasingly involve high-end technologies. Also, the current large product portfolios contain an increasing number of product variations while the internal product complexity contributes to the surrounding business atmosphere. Continuous product changes caused by shortened technology life cycles have made the product data management process challenging.

Product management and data management must be organised efficiently across the company and throughout the product life cycle. In fact, this has become a foundational requirement for companies (Buffington, 2011; Ouertani, Baïna, Gzara, & Moreld, 2011). This foundation covers the collaboration with partners in the supply chain where data is shared between different parties (Gerritsen, Gielingh, Nowacki, Anderl, & Dankwort, 2008). Data is used to ensure the quality of products, services, and different types of support activities. Business drivers contribute to the overall efficiency of a company's value-creation process, and data is an essential part of making it happen (Terzi, Bouras, Dutta, Garetti, & Kiritsis, 2010).

The internal operational models of companies can be designed and manufactured anywhere because of modern IT systems. All decisions made in the operational environment are based on the availability of data. Data is a requirement, an asset, and the foundation that enables different internal operational models. However, data quality is a new issue as a topic in the daily operations of business management (e.g. Redman, 2008). Data quality issues are very common in today's companies as they have typically not invested sufficiently in data management, even though their data volumes have increased (Breuer, 2009; Lee, Ahn, Kim, & Park, 2006; Knolmayer & Röthlin, 2006). This situation is complicated by the increasing amounts of data involved in modern IT solutions. Thus, data management has become extremely challenging in today's business environment.

Direct data errors and inconsistencies between data attributes are often the cause of these data quality issues, which can lead to management mistakes, lost business opportunities, wrong or failed deliveries, and invoicing problems. The list of the impacts to businesses from data issues is very long (as stated by Redman, 2008). Calculations by experts have estimated that 15–25% of operating profit is lost because of data quality issues (Olson, 2003). Of all the different data types, product data is seen to cause 43% of all data problems in organisations (Russom, 2006).

Modern IT systems and product technologies are providing more software along with the physical product, which adds a vast amount of product data, causing further challenges in the product life cycle. There is no limit to the increase of data when it comes to IT technology and the digitalisation of products, which emphasises the need for companies to track the data in their business processes (e.g. Saaksvuori & Immonen, 2008; Ameri & Dutta, 2005; Crnkovic, Asklund, & Persson-Dahlqvist, 2003). Most managers believe that IT systems take care of data and related challenges automatically (Redman, 2008). Hence, there is a strong motivation to study product data in the context of integrated business processes.

1.2 Objectives and scope

Today, new buzzwords such as the Internet of Things (IoT), big data, and digitalisation are in every CEO's and leadership team's vocabulary and agenda. Individual nations have started initiatives to drive concepts such as Industry 4.0 further in their countries in order to gain business momentum. The new developments are welcome, but the readiness of companies from the data perspective remains a big question. Even extensive experience in IT and business transformations may not be enough to answer this question. In many instances, data has not been maintained well in the past, and thus challenges have become daily issues. The best practices are also somewhere out there in daily business operations as success stories go hand in hand with failures.

The main motivation for this research has arisen from the practical challenges in data management, especially the problems that are due to narrow thinking and deficient competence in understanding the big picture. Similar to the need to understand and explain the way other things are done in companies, there must be a way to explain why data management, and, specifically, master data management, is needed in a company. Hence, this study aims to define the meaning of one product master data for integrated business processes as a concept. The concept needs to be a composition of business process related drivers that can be translated into the practical master data. The concept also needs to be linked to the IT systems so that the main business processes are supported. Also, business and IT cooperation plays a very important role. Master data quality is a way to measure how well the concept works in practice. Therefore, the research problem of this dissertation is formulated as:

> *Understanding the current best practices and pitfalls relating to product master data, and understanding the type of high-level product master data concept necessary for creating data once, and then using the data across the IT systems through the life-cycle of the product are needed to tackle practical challenges in data management.*

The research problem has been approached from five complementary perspectives, which can be framed as questions:

1. What are the challenges and preconditions for one product master data?
2. How can product master data ownership be implemented?
3. How can data quality be ensured?
4. What is the role of PDM in the launch phase?
5. What are the business process requirements for product data?

Each of these five viewpoints corresponds to an individual original publication. The research problem is hence narrowed into five research questions (RQs), as presented in Table 1. Each of the journal articles aims to answer one of the research questions, and each research question contributes to the whole formed by the thesis. Three of the individual publications are journal articles, and two papers have been published in conference proceedings. The main contribution of each individual article and the sum of the formed whole are presented in this dissertation.

Each of the five research questions provides an individual contribution to the whole research problem, and they are all related. Figure 1 depicts the positioning of the articles and the research questions in the context of the logic of this dissertation. Each article can be seen to fill its own research gap, and together they answer the central research question of this dissertation.

Table 1. Research questions and articles overview.

Article	RQ#	Research question	Article title	Publication
I	RQ1	What are the challenges and preconditions for one product master data?	Managing one master data - Challenges and preconditions	Industrial Management & Data Systems
II	RQ2	How can a product data ownership network be implemented and what are its elements?	Elements and implementation of product data ownership network	Proceedings of TIIM2011 Conference
III	RQ3	How can data quality for product data management be ensured?	Data quality assessment and improvement	International Journal of Business Information Systems
IV	RQ4	What are the business process requirements for product master data?	Defining one product data for a product	International Journal of Business Information Systems
V	RQ5	What is the role of PDM in product launching?	A framework for improving the launch concept of new services	Proceedings of TIIM2011 Conference

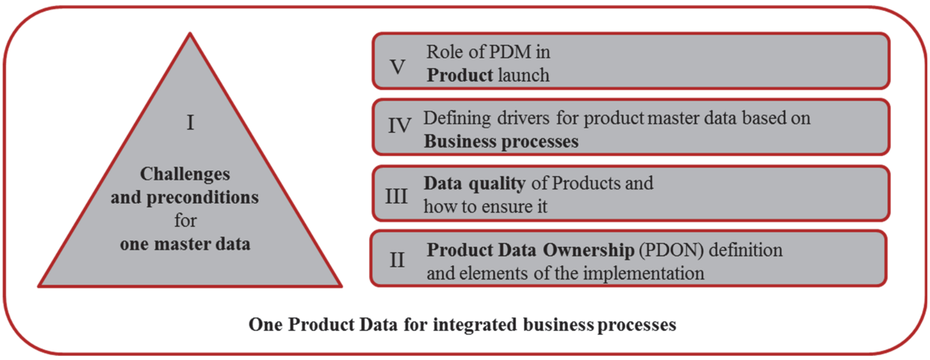

Fig. 1. Epistemological and ontological basis.

Article I describes the current state of the master data literature and the challenges and preconditions for master data management in companies. Article II considers the elements of product data and clarifies the essential roles in companies, such as the data owner. Article III focuses on data quality analysis by introducing a model for operationalising data quality assessment and improvement. Article IV maps one product master data, the product DNA, in the context of business processes. Article V deals with the elements and implementation of product data ownerships in the service launch process. The overall contribution of the articles is to develop a framework for one product data for integrated business processes.

1.3 Research process and dissertation structure

Researchers who approach scientific research from a philosophical viewpoint face epistemological, ontological, and ethical questions. In other words, how can one believe and know reality based on scientific research (Lancaster, 2005), how can one trust and know scientific reality, and how is the knowledge that is obtained scientific? It is also vital to consider when the researcher abuses his or her research object or acts unethically against the scientific community (Lancaster, 2005).

Epistemology is a theory that explains what is understood as appropriate knowledge regarding the social world. A very important aspect is the question of whether a natural science model of the research process, including principles, procedures, and philosophy, is suitable when studying the social world (Bryman & Bell, 2003). Epistemology can be viewed as having two sides: positivism and interpretivism. Positivism holds that phenomena can be explained through causal relationships and regularities. The natural science nature of positivism, however, makes it rather challenging to outline it precisely. Interpretivism seeks to understand phenomena through those who are involved. Interpretivism views people, institutions, and social science differently than the natural sciences do (Saunders & Pearlson, 2009). In terms of the epistemological positioning of this study, interpretivism is closer to its aims than positivism, hence the philosophical choice. This even if a purely positivistic approach might not be unfruitful or inappropriate should the researcher have idea and means to measure precisely as the essence of positivistic approach would justify the question of “can this be measured by using a thermometer?”. Interpretivism was selected as understanding phenomena through the involved was seen focal for this study, instead that of assuring the phenomena through senses as positivistic approach would entail. The research approaches one product master data as a strategic issue for companies, one that has not had enough focus to standardise it across the business processes and IT systems. Hence, the study’s main goal is to analyse and interpret company-wide, nonstandard organisational practices that are not possible to observe through the senses, as the natural sciences would necessitate. Overall, product-related master data and practices such as PLM are rather new and not well studied (e.g. Kärkkäinen, Myllärniemi, Okkonen, & Silventoinen, 2009), indicating that master data management and its links to the strategy are loose, with numerous open points. Interpretivism is hence the more correct epistemological positioning. The purpose of the research is to increase the understanding of the subject and the analysed topics. In order to understand the studied phenomena, one must first understand the people involved and then analyse how they perceive product data and its management.

Ontology explains the reality in which studied phenomena are understood to exist and how they relate to this reality. In scientific research, ontological pre-conceptions on the nature of the studied topics are typical. Ontology guides one to answer the question of whether the reality is objective or subjective. Ontology looks into the selection of theory and concepts and what has influenced the selection (Harisalo, 2008; Anttila, 2005). The two sides of ontology are objectivism and subjectivism. Objectivism is a position that implies that research is based on facts instead of subjective analysis. Objectivism views phenomena as independent of social actors, and a company or organisation is seen as a machine-like entity that functions based on standards, guidelines, rules, and legislation. In contrast, subjectivism views people as operators who realise processes and values. According to subjectivism, social actors create events based on their observations, thus highlighting an individual's experiences. Operations in companies are based on the interactions of people (Saunders & Pearlson, 2009; Bryman & Bell, 2003). The ontological positioning of this study resides somewhere in the middle of the ontological scale and is closer to the approach of pragmatism. From this standpoint, contextual understanding with knowledge creates the basis for practical working solutions. The researcher can choose viewpoints from both approaches based on their suitability to the study (Saunders & Pearlson, 2009). Figure 2 illustrates the epistemological and ontological basis for this research.

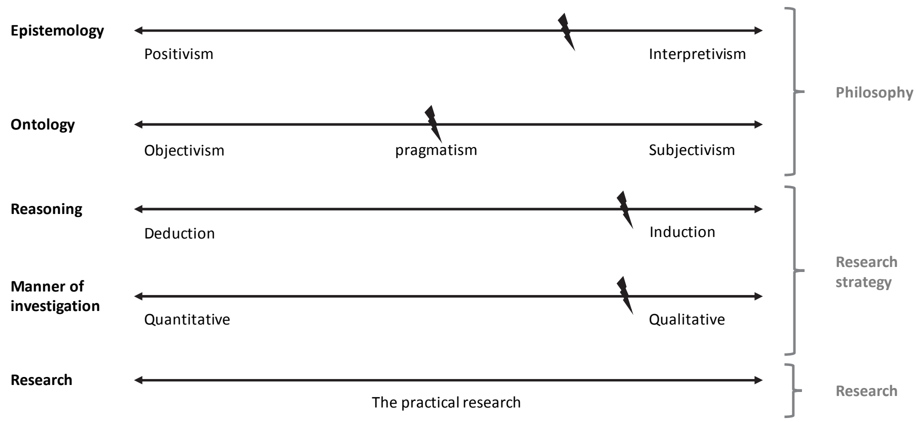

Fig. 2. Epistemological and ontological orientations for this study.

As the research topic approaches product master data as a unified company-wide issue across the business processes and IT systems, and it is not standardised, the qualitative method was selected as it was believed to best match the nature and goals of this study. The purpose of the study is to create in-depth knowledge and understanding of product master data challenges and preconditions and the elements necessary to manage it. The experiences of industry managers, different subject matter experts, and other practitioners were found to be the key way to collect input in order to reach the goals set for this research.

In this study, inductive reasoning is used as part of the research strategy. A dialogue of theory and observations provides valuable benefit for the inductive logic approach. It is much more than a one-way approach from observations to theories in a practical study (Bryman & Bell, 2003). This study used earlier studies to collect background for the qualitative investigations. This was done to ensure that, in the research phase, the relevant concepts needed are clearly defined. The essence of the research focuses on creating new knowledge based on the research findings. The study is based on interviews and the researcher's and other key stakeholders' understanding about the relevant topics presented in each journal article.

Qualitative research is a tool used to gain deeper understanding of a phenomenon, which is why it fits the purpose of this research. Qualitative research provides a certain freedom to the researcher, but it is strongly linked to his or her own values, strengths and deficiencies in describing the realities. Hence, complete research objectivity is questionable as the researcher and the studied phenomenon are interlinked. Analysing cases allows the researcher to utilise different techniques for the data collection and to have a strong empirical emphasis. The analysed cases are often linked to a fuzzy phenomenon, while the attempt is to increase understanding (e.g. Yin, 2003).

Very importantly, research needs to meet the quality set for the work, and thus meet the criteria of reliability and validity. This can be ensured in three key stages of the research: research design, data collection, and data analysis, which together set the necessary criteria (Yin, 2003). In this study, the validity and reliability of the research is managed through two key approaches: 1) using retrospectives with the informants to validate the study reports, and 2) using multiple sources of data as evidence in order to manage triangulation.

In addition, as the research consists of individual publications, the number of researchers cooperating in the study has given different perspectives to the analyses. The research process has been well described and the data repositories and research database have been well utilised. These are introduced and further discussed in the following description of the research process (Figure 3).

This research was conducted in five separate studies involving industrial companies and university researchers. This researcher was the main planner for all five individual studies, labelled I, II III, IV, and V. In each of the studies, there were cooperating researchers who took on the roles of data collection and analysis. The main researcher's role was in planning the study and providing guidance on its theoretical and practical implementation, thus setting the reliability and validity criteria for the study. The role of the cooperating researchers was mainly one of data collection, thus serving to reduce the bias in the data. The main researcher was also responsible for selecting relevant informants in all cases. For the studies I, IV, and V, however, the researcher had a major role in the data collection phases. It is important to mention that the researcher was responsible for all analyses and for drawing the conclusions in all of the studies that comprise this dissertation. This responsibility included selecting the different approaches towards data and definitions for data, the background information, and the included and excluded topics.

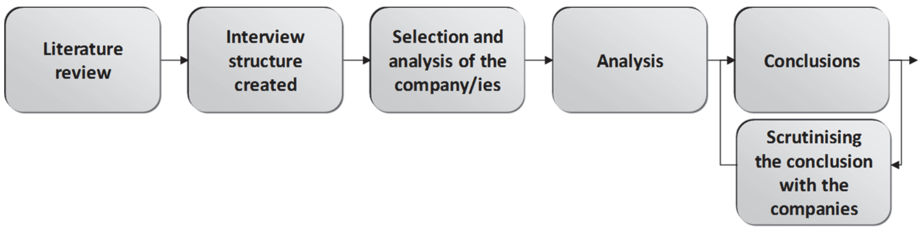

Fig. 3. Typical research process in the original article studies.

Each individual study was initiated with a literature review that ensured an adequate understanding of the previous literature on the topic and provided a basis for the analyses. The literature review provided the necessary understanding of the topics related to business processes, master data, data quality, and product data management. An interview questionnaire was created for each individual study based on this understanding. The studied journals, conference papers, and books formed the basis for developing the necessary interview questionnaires. The data collection typically took place through interviews in selected companies. The companies included in the studies consisted of good quality cases for the respective analysis purposes. The main selection criteria were the companies' interests and development aims with respect to the analysed topics. In addition, the possibility of gaining research data from companies with different data management maturity level played important role in the company selection. The company selection was aimed at gathering the best possible information to gain the understanding sought by the study. The qualitative research data were collected by implementing semi-structured interviews and by analysing the companies' documentation. Qualitative researchers understand the need to comprehend the role of the interviewer (Hollway & Jefferson, 2000) to discover meaningful patterns and to clarify a phenomenon. Rich data is particularly highlighted as essential for qualitative studies (Miles & Huberman, 1994). In total, interviews were conducted with 42 specialists, who were selected based on their interests and professional background and expertise. Ensuring the right number of interviewees and good understanding of research topics were among the main considerations. The interviews were mostly conducted face-to-face with the informants. The selected companies' characteristics and settings for the interviews are presented in Table 2.

Table 2. Characteristics of the analysed companies.

Case	Company type and size (according to EU definition)	Product type	Business type	Interview sessions and informants	Role of the interviewees (examples)
A	Manufacture of basic metals Large	Tangible	B2B	3 sessions, 5 informants	• Head of product development • Product development manager • Product manager
B	Manufacture of communication equipment Large	Tangible & intangible	B2B B2C	3 sessions, 6 informants	• Head of product development • Head of product engineering • Product manager • Supply chain manager
C	Manufacture of irradiation, electromedical, and electrotherapeutic equipment Large	Tangible	B2B	3 sessions, 5 informants	• Chief technical officer • Project management director • Product manager • Supply chain manager

Case	Company type and size (according to EU definition)	Product type	Business type	Interview sessions and informants	Role of the interviewees (examples)
D	Manufacture of construction installation equipment. Medium	Tangible & intangible	B2B	2 sessions, 8 informants	• CEO and Vice CEO • Head of R&D • R&D project manager • Program manager • Product manager • Quality consultant • Head of operations
E	Manufacture of machinery and equipment Large	Tangible & intangible	B2B	2 sessions, 13 informants	• Product owner • Product manager • Supply chain manager • Sourcing manager • Product development manager
F	Manufacture of electronic products Medium	Tangible & intangible	B2C B2B	2 sessions, 4 informants	• R&D manager • SM specialist • After-sales manager • Supporting tasks manager
G	Manufacture of chemical products Large	Tangible	B2B	1 session, 2 informants	• R&D, global processes and projects director • Supply chain manager
H	Manufacture of medical instruments & supplies Medium	Tangible	B2B	2 sessions, 3 informants	• Chief operations officer • Logistics manager • Supply chain manager
I	Manufacture of medical instruments & supplies Large	Tangible & intangible	B2B	2 sessions, 3 informants	• R&D manager • Logistics manager • Production manager
J	Manufacture of consumer electronics Large	Tangible & intangible	B2C	2 sessions, 4 informants	• Logistics manager • Demand/supply manager • R&D director • SM director
K	Manufacture of communication equipment Small	Tangible & intangible	B2C	2 sessions, 3 informants	• SM specialist • R&D manager • Board member

The analysis and conclusion are linked to the interviews and the analysis of company materials. The possibilities of access and interests of potential interviewees had an influence on the realisation of interviews, but the sample was seen adequate to facilitate the research. The analysis took place according to the respective research focus of each individual study. The interviewees had the opportunity to review interview notes. Each individual study and the respective publication contains the details specific to the respective interviews and research process. The analyses followed the qualitative approach. Necessary follow-up questions or scrutinising the results with the analysed companies took place before the final conclusions were reached. The companies were always given the possibility of providing feedback and confirming the outcomes. The cooperating researchers took part in verifying the results to reduce the possibility of unnecessary misinterpretations.

2 Theoretical foundation

2.1 Theoretical framework

Three literature dimensions are relevant to this study and important to understand. These are the literature pertaining to: business processes and how they are managed, the main IT system business processes that provide the capability to store and share data, and the data itself. In this study, the data was approached from many perspectives, but the main categories were master data management and data quality as these are understood as the foundations for effective data management. Figure 4 illustrates the theoretical foundation of this study.

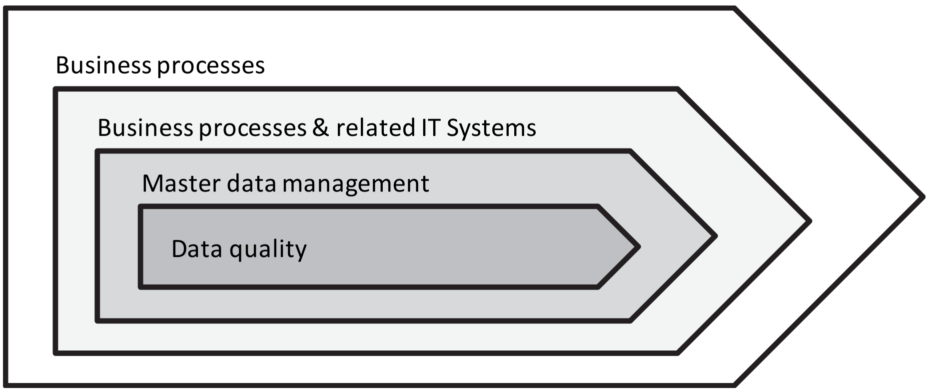

Fig. 4. Theoretical framework of the study.

Business processes as a literature dimension opens the discussion of the need for one product master data, which would ensure that all the integrated business processes are based on the common product data and any added business process related data (Gunyung, 2010; Lindfors, 2002; Laamanen & Wallin, 2009). The literature covers the business processes and how they are managed, what kind of classification models exist, and how they link to continuous improvement and corporate strategy (Laamanen & Wallin, 2009). The literature also focuses on organising business processes and the conditions necessary for them to be successful in a company, together with the best practices to structure the processes (Kock, 2005). In addition, the literature covers the business process value to companies. Laamanen and Wallin (2009) and Hannus (1994) discussed business process management (BPM) and how to set up a relevant framework. Hannus (1994) presents BPM as part of a company's management framework, emphasising it as an integrated entity and not a separate thing. Wisner and Stanley (2008) discuss how to ensure that BPM delivers the expected outcomes and how it should be set up correctly. All these considerations are relevant for the focus of this study. As the operative business processes are the foundation of organisational activities, it is reasonable to base the literature review on these processes.

The connection of business processes and IT systems is also an important consideration for this study. Genaroro and Lourero (2015) and Tian and Quan (2008) define the link between business processes and IT systems. They discuss the data collection within business processes and describe how IT systems play an important role in capturing data. The main business processes require specific support from IT systems, and the most important of these systems are the Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), PLM/Computer Aided Design (CAD), and service systems. The literature covers the CRM system (Alter, 1999), the ERP system (Madu & Kuei, 2005), and the PLM system, including CAD systems (Stark, 2005). The service/care system and the workflow and business process use cases are also covered (Chang, 2010). All these considerations have relevance for this study.

Master data and master data management also have particular significance for this study. The basics, including a framework, have been discussed in the previous literature (Loshin, 2009; Dayton, 2007; Berson & Dubov, 2007; White & Genovese, 2006; Moss, 2007). Also, the different data areas and classification of the data in a company have been covered (Loshin, 2009; White & Genovese, 2006; Dyche & Levy, 2006). Snow (2008) acknowledges different domains while discussing the master data in companies by explaining customer, vendor, product, and people data as well as the relevant differences. Otto and Huner (2009) point out how master data differs from other data in companies and why master data is so important. Without master data, there cannot be transactions that are the basis of daily business. Hence, these perspectives are essential.

Master data management (MDM) is also logically a relevant perspective for this study. MDM and the key criteria for its successful implementation have been discussed (Loshin & Dayton, 2007; Moss, 2007). Certain cornerstones can be seen for successful MDM, linking BPM and MDM. Joshi (2007) observed the dependencies between IT systems and MDM, such as logical data models and integration between IT systems. Understanding the basic cornerstones can support the successful MDM implementation and operations of a company.

In addition, data quality is a highly relevant consideration for this study. The roots of data quality research and studies go back to the 1950s (e.g. Deming & Edwards, 1982). The data quality depends on the actual usage of the data, and the usability of the data is linked to the quality (Wand & Wang, 1996; Gustafsson, Lindstrom, Jagerlind, & Tsoi, 2006). Eppler (2006) has discussed the meaningfulness of data quality where some of the data attributes has more business value than some other data attributes. The data quality can also be seen to have multidimensional dependencies (Ofner, Otto, & Österle, 2012). The main dimensions of data quality were described by Ballou and Pazer (1985), but later additions have also been made (Shanks et al., 2000; Wang & Strong, 1996; Kahn, Strong, & Wang, 2002). The practical dimensions of data quality have significance. Loshin (2006) explored how data quality can be linked to the operational value creation for business. Data quality can also have an impact on an entire enterprise (Haug, Zachariassen, & van Liempd, 2011; Redman, 1998). Based on some studies, the total cost of poor data quality has been estimated to be in the range of 8–12% of a company's revenue (Redman, 1998), or even more (Olson, 2003). Hence, data quality is an extremely important consideration.

Aside from the key theoretical perspectives, there are some concepts that are outside the scope and focus of the study. The out-of-scope concepts, however, have linkages to the studied topics, and are therefore of importance. One product master data is a multidimensional topic, and thus some elements of the out-of-scope concepts form the basis for the theoretical framework. For example, enterprise architecture (EA) is one of these framework elements (e.g. Bradley, Pratt, Byrd, Outlay, & Wynn, 2012; Ross et al., 2006, Schekkerman, 2003; Winter & Fischer, 2006). Enterprise architecture applies architecture principles and practices to guide organisations through the business, information, process, and technology changes necessary to execute their strategies. However, since the purpose of this study is to look deeper into the practical challenges, the architecture level would raise the topics to a level that is too high for the purposes of the study, without the relevant practical application.

In addition, data science and analytics are important parts of data management practices, but are outside the scope of this study. Data science and analytics, however, provide value to data quality improvement and to the overall master data management (Agarwal & Dhar, 2014; Amirian, van Loggerenberg, & Lang, 2017; Banerjee, Bandyopadhyay, & Acharya, 2014; Dhar, 2013). However, they are not part of the theoretical framework for this study due to their high IT technology dependencies and also because the main purpose of the study is to highlight business processes, IT systems, and master data.

This is also the reason why PDM is not introduced as a separate topic. PDM is a practical way to collect and maintain data, but, first, the definition for the data itself needs to be determined (e.g. Gao, Aziz, Maropoulos, & Cheung, 2003; Hameri & Nihtila, 1998; Kropsu-Vehkapera, Haapasalo, Harkonen, & Silvola, 2009; Philpotts, 1996; Peltonen, Pitkanen, & Sulonen, 1996; Weber & Werner, 2003). In this study, PDM is looked at from the business process perspective as one of the main business processes, and the whole study focuses on the product master data.

Finally, business change management (Guimaraes & Armstrong, 1998; Hiatt & Creasey, 2003; Kettinger & Grover, 1995; Kramer & Magee; 1990) is out of the scope of this study in order to retain focus on the three cornerstones i.e. business processes, IT systems, and data. However, changing the organisation's behaviour and helping it see the value of the data are important and increasingly valuable goals. The connecting concepts that are excluded from the focus of this study are not discussed further. A more thorough literature review of the selected key concepts is presented in the following sub-sections.

2.2 Business processes

Business processes explain the way a company works to meet its organisational goals. In other words, business process is a collection of activities in sequence that provides a product or service for a specific customer (Davenport, 1993; McKeen & Smith, 2007). As businesses need to keep up with their environment and competitors, continuous change must take place in their business processes. Predicting what will happen in the near future is very difficult; it is a challenge that has an impact on process-oriented businesses that aim to respond quickly to changes from the process management perspective (Gunyung, 2010). The way the processes are organised in a company gives a framework for process integration between that different functions (Lindfors, 2002). According to Laamanen and Wallin (2009), describing processes is actually basic requirement from company perspesctive.

Processes are used to bring clarity and to provide organisations a way not only to meet current needs but also to satisfy customers' future needs. If a company is successful, it typically collaborates with its partners. Thinking differently may break some boundaries and help in finding the most effective solutions to manage process issues (Wisner & Stanley, 2008). In simple terms, the purpose of process thinking is to create a simple and understandable way of working.

According to Hannus (2004), it is possible to divide business processes into two main groups: core processes that are strategically important and processes that support internally important processes. Examples of the supports and activities include firm infrastructure, human resources management, technology development, and procurement. One way to recognise these internal support processes is that they have only internal customers (Karvonen, 1999). Core activities are also recognisable as business processes. They are seen by the customer and thus are easy to recognise, e.g. logistics, operations, marketing and sales, and services offered to customers. How well processes are described and how well different tasks are coordinated have an impact on how the company can succeed in meeting the organisational goals set by the management (Sandhu & Gunasekaran, 2010). One of the key considerations is that business processes produce value for external customers and thus are critical for a company's success. These processes may stretch across organisational boundaries and can be connected to all areas of the company (Kock, 2005).

Processes can be classified generally as core, key, and business processes. They all mean and refer to the same topic. However, definition of the process structure requires attention to the classification when the processes are created for the first time. Communication of the classification is also important to ensure common understanding and thus to avoid misunderstandings. Classification is agreed upon first through agreeing to the terms and then carrying out the process design (Laamanen & Wallin, 2009). In this dissertation, processes that create value for customers are called core processes, and they may include key processes. Core processes are higher in the process hierarchy than key processes. It is common practice within some industries for processes to have a similar outlook, and there is much room for major change. However, there are many things that create variety within a certain business sector based on the customers' needs (Hannus, 1994). Process mapping can easily generate 100–200 processes within all organisations. As the management of such a large number of processes is far too complex, it is recommended to map only the most important processes and focus on managing only those (Laamanen & Wallin, 2009). There can also be several sub-processes and flowcharts that are connected to the most important processes that are being managed.

2.2.1 Business process management

The management of processes is vital for all business areas and thus needs to be part of company's overall management system. Companies must be able to describe all their major activities from a process perspective and to have process management in place. Understanding company processes is a basic requirement for companies to develop activities in an economically efficient way. Understanding the processes also enables the management of them. Process management further enables a focus on quality (e.g. Hannus, 1994; Kettinger et al., 1995). In addition, IT systems and their implementation play an important role in the business process execution (Neubauer, 2009).

If a company is renewing and redesigning its core business processes, it is actually doing process management (Wisner & Stanley, 2008). Improving the organisation's performance and increasing the efficiency of its processes is the main reason for business process management (BPM). The role of BPM is to capture the organisational targets and present them in such a manner that people from different levels of the organisation can understand the changes that are needed to meet those targets. Organisational targets are part of a company's strategy, and thus it is necessary that senior management understands the role of BPM as a holistic management system, including the IT systems (Doebeli, Fisher, Gapp, & Sanzogni, 2011). BPM is not a clear-cut topic, however, as company needs and the use of BPM varies due to practicalities and common sense (Doebeli et al., 2011). Companies should question their traditional, functional ways of thinking in order to reach their continuous improvement capability. Merely thinking about process change might produce goals that are too narrow, and a lot of bureaucracy is often linked to this type of thinking. The main reason for core process renewal is to ensure maximum value for the customers, which can only be reached if non-value adding steps are removed from the process (Hannus, 1994).

2.2.2 Objectives for process management

The purpose of process management is to ensure the expected outcomes from the processes. This is done through measuring the performance with a scale that shows the effectiveness of the processes. Based on a study by Wisner and Stanley (2008), several things have to be measured to get the right and effective results:

1. Link measurements to the company's vision and goals.
2. Understand and measure the customers' needs.
3. See the big picture besides the output, i.e. monitor the quality, cost, and timeliness.
4. Keep in mind that effectiveness exceeds efficiency. This means that key performance indicators (KPIs) that give the wrong signal should not be used. An example of such a KPI is where it might refer to solutions that are not finalised and thus result in problems to close customer defects in time.
5. Have as few as possible extra measurements in order to gain a complete picture about the process performance.

The main objectives of process thinking, and process management are to clarify the operational activities and to increase their effectiveness throughout the organisation. The goal of the management system is to collect different process management areas under the management practice. Employees know how their inputs fit into the next process and thus the contribution of these inputs towards the end product. The best opportunities to increase efficiency, if the process thinking method is used, involve those spots where the task execution is moved on to the next department. Within the departments, it is essential to have clear departmental boundaries to ensure efficient, flexible, and supportive ways of cooperation (e.g. Lehtinen, 2003; Doebeli et al., 2011).

2.2.3 Continuous improvement and process life cycle

Continuous improvement as a method is often used with process management. It is important that improvements are based on an understanding of the customers' needs. The desired changes need to be understood and resourced properly as the possibilities for change are in many cases tied to the nature of the change and how challenging it is to carry out. The most critical improvements may need to be prioritised (e.g. Jeston & Nelis 2008; Doebeli et al., 2011).

Business process management is based on process leadership, process governance, process performance, strategic alignment, people capability, project execution, and technology (e.g. Jeston & Nelis, 2008). BPM is also based on the four basic components of process hierarchies: process strategy, process model, process execution, and process performance (Margherita, 2013). There are also eight process management knowledge areas that can be evaluated further by the five criteria of completeness, extendibility, understandability, application, and utility (e.g. Bandara, Harmon, & Rosemann, 2010).

Cross-functional processes are run by the employees to deliver the desired business results. Important to keep in mind is that it is not the organisation itself that delivers the business results, but the people (Rummler & Brache, 1990; Womack & Jones, 1996). According to (Neubauer 2009), there are only a few companies that have reached the status of a process-focused organisation (PFO). Those companies focus on reaching the end-to-end process performance targets instead of focusing on individual tasks (Harmon, 2006; Madison, 2005; Gardner, 2004; Green, 2004; Kersten & Verhoef, 2003; Hammer, 2002; Lee & Dale, 1998).

2.3 Business process related IT systems

All business processes require data collection and the maintenance of the data that is stored in the IT systems. There can be several IT systems, normally integrated, in a specific company. This means that business processes are integrated via the information systems, which can be used to obtain information for process control, performance management, and reporting to the internal and external stakeholders (Genaroro & Lourero, 2015; Tian & Quan, 2008).

The main IT systems used include CRM, ERP, CAD, PDM, PLM, and Service IT systems.

CRM solutions allow companies to know who their customers are and their specific requirements. Specifically, CRM solutions collect information about customers and evaluate the information. The IT system normally has a database where all the data is collected. The system can have a data master role such as customer, contact, and contract master data. CRM solutions also provide the capacity to interact with consumers through any medium, and they select and distribute information to consumers in real-time. Along with fulfilling the above goals, effective CRM systems examine and provide an overall view of customers' behaviour patterns, including their past and present dealings with sales executives, in order to suggest the best available product or solution to the customer (Alter, 1999; Bradley et al., 2012).

ERP is intended to support all of the company business processes. Ideally, the ERP system has a single database that contains IT system support for all the data collected in the company. However, many times ERP system usage covers mainly some of the business process areas and as a single business IT solution ERP might not meet all of the business processes specialities. The ERP system is the central place for the data storing of the software modules such as Product Lifecycle Management, Supply Chain Management (e.g. Purchasing, Manufacturing, and Distribution), Warehouse Management, CRM, Sales Order Processing, Online Sales, Financials, Human Resources, and the Decision Support System. The typical implementation of an ERP system covers Sales Order Processing, Supply Chain Management, Financials, and some parts of the decision making. For CRM and PLM, there are systems that focus only on those areas (Madu & Kuei, 2005; Bradley et al., 2012).

Computer Aided Design (CAD) means the use of information technology (IT) in the design process. A CAD system typically consists of IT hardware and specialised software. Also, peripherals are used which can be very specific. The core of a CAD system is the software that enables the use of graphics for product representation, contains the databases for storing the product model, and drives the peripherals for product presentation. The use of a CAD system does not change the nature of the design process, but, as the name indicates, it serves as an aid to the product designer (Finger & Dixon, 1989; Weber & Werner, 2003).

PDM is the use of software or other tools to control and track all data related to a particular product. The data details are usually tracked according to the technical specifications of the product, the specifications for manufacture and development, and the types of materials needed to produce the goods. The use of product data management also allows a company to track the various costs associated with the creation and launch of a particular product. PDM is part of Product Lifecycle Management (PLM) and configuration management, and is primarily used by engineers (Stark, 2005; Hameri & Nihtila, 1998). PDM is normally one part of the PLM strategy and content (Stark, 2005; Hameri & Nihtila, 1998).

PLM is an integrated, information-driven strategy that speeds the innovation and launch of successful products. It is built on the common access to a single repository of all product-related knowledge, data, and processes. As a business strategy, PLM lets distributed organisations innovate, develop, support, and retire products throughout their life cycles as a single company. It captures best practices and lessons learned, creating a storehouse of valuable intellectual capital for re-use.

Service IT systems are part of the after-sales business models or complete life cycle care models. They relate to service products that involve maintenance tasks, spare parts, and related labour, and include data collected remotely using online technologies. The core functionalities of these systems are: service workflow management, service product pricing, installed base data collection, and maintenance and reporting (Chapman, Soosay, & Kandampully, 2003; Chapman et al., 2003; Chang, 2010).

Based on the enterprise architecture integration policy, these business applications can be very tight or very loose. Loose integrations may be used if there are no re-usable data between business processes or for other reasons, for example, problems in managing the business processes in the company. Especially if the process management system is not described or managed properly, challenges are likely to be present. In practical terms, business process management and IT system management need to have linkages from the design perspective. Many times, this means that processes, data, and IT systems form together the enterprise architecture of the company (Bradley et al., 2012; Kaisler, Armour, & Valivullah, 2005).

2.4 Master data

Master data defines the properties of the data that are linked deeply to the business goals. Master data is used across different IT systems and organisations. Metadata links to the master data, describing the meaningfulness of the specific master data group. The definition of metadata includes its attributes, definitions, roles, connections, and taxonomies (Loshin, 2009; Dayton, 2007). Master data has a specification of values and needs to be harmonised and integrated with other enterprise-wide IT systems. With the necessary integration, master data can be used across multiple business processes (Berson & Dubov, 2007).

The core master data entities are parties (organisations, customers, prospects, people, citizens, employees, vendors, suppliers, or trading partners), places (locations, offices, regional alignments, or geographies) and things (accounts, assets, policies, products, or services) (White & Genovese, 2006; Moss, 2007). All the data in a company is not master data, only the well-selected data elements that are required for data sharing and standardisation. Master data objects are the key business elements that matter the most from the business process goal perspective (Loshin, 2009; White & Genovese, 2006).

It can be said that master data provides "the single version of truth" when it has been properly described, communicated, and understood in the company. According to Berson and Dubov (2007), master data enables an organisation to understand the factors and trends that could have an effect on the business. This single version of the truth characteristic is a key enabler in supporting business transformations from old business models to new models. Other layman terms that are used with the same meaning include “golden record”, “critical business data”, “the best record”, or “the best version of truth” (Dyche & Levy, 2006).

MDM can have a wide scope that may cover customer data, supplier data, parts data, product data, location data, and contracts. Most common MDM activities focus on customer or product data, but any business data can be master data (Berson & Dubov, 2007). Often the customer master data is the starting point for many organisations’ MDM as it has limited and easy-to-define data attributes. Typical customer master data elements are marketed to, sold to, and billed to account-related addresses, contact names, and hierarchies. Product data is more challenging as it is widely scattered across the organisation and managing it is a cross-functional responsibility. Product data also has many more master data attributes than customer master data. For example, product master data contains part numbers, descriptions, specifications, and stock codes (Snow, 2008).

According to Otto and Huner (2009), master data differs from other types of data in four ways:

1. As a comparison to transaction data (e.g. invoices, orders, and delivery notes) and inventory data (e.g. stock on hand and account data), master data always describes the basic characteristics (e.g. the age, height, and weight) of an object in the real world.
2. Master data has a longer life cycle than transactional data, i.e. once it has been created, it remains largely unaltered. For example, as the characteristic features of a certain material are always the same, there is no need or value to the business to change respective master data. However, data can be enriched during the life cycle of a product. Various attribute values can be added over time, but the basic data remains the same (e.g. dimensions, weight, and replenishment times).
3. Transaction volumes do not directly impact the amount of master data. (e.g. customer data).
4. Without master data, there cannot be transactional data, but not vice versa. While a purchase order always involves the respective material and supplier master data, the latter does not need any transaction data in order to exist.

MDM governance is a collection of the best data management practices that organise key data stakeholders and participants over the different organisations and business clients (Loshin, 2009). It is a workflow-driven process where business units and experts in information systems cooperate to describe, harmonise, cleanse, publish, and protect mutual information assets that must be shared across the organisations (White & Genovese, 2006). The focus of MDM is to create an integrated, accurate, timely, and complete set of data needed to manage and grow the business (Berson & Dubov, 2007). MDM is a disciplined governance model to define and standardise key business data and manage changes to those definitions over time (e.g. Dayton, 2007; Moss, 2007). The model that makes the master data possible needs a single data location where data is guaranteed to be valid and up-to-date. This place where the data is stored is referred to as the master data system of record (SOR) (White, 2007). From the MDM perspective, there should be only a single SOR where the controlling of the data takes place. Therefore, changes to the data can be replicated across all related IT systems in an automated and timely fashion (Dayton, 2007).

Implementing MDM requires a collection of disciplines, policies, procedures, methods, infrastructure, and individuals. The individuals involved are expected to have authority and ownership over the data (Moss, 2007). All the different technologies and applications that are used to create, maintain, and distribute the master data belong to the MDM IT system context (White, 2007).

MDM has two focus areas: operational and analytic. In operational MDM, different IT systems are integrated, such as ERP, CRM, and supply-chain management, in an upstream data flow. In analytical MDM, there are working practices that cover data warehousing (DW), data analytics, and reporting. Together, they form the enterprise MDM (Apostol, 2007). The enterprise MDM system is used for maintaining and publishing all the organisation's master data. The main components of an enterprise MDM system are MDM applications, i.e. a master data store, a master metadata store, and a set of integration services for master data (White, 2007).

Different applications have their own specific master data to manage. The PDM or PLM system is used to manage all product-related data and also product master data. The CRM system is used to control customer data and the life cycle of the customer data.

According to Loser, Legner and Gizanis (2004), the basis of business processes is the master data. The master data describes business objects and how they are represented in different information systems (McKeen & Smith, 2007). There are four basic pre-requisites for successful MDM: an enterprise information policy, a definition of the data ownership, implementation of a data governance model, and a definition of the role of the IT systems.

Loshin (2009) and Brunner et al. (2007) studied the creation of an enterprise-wide master data model and how it integrates the different master data, and they considered it the most crucial aspect of a company's success. White and Genovese (2006) state that a successful MDM system is dependent on data quality, governance, stewardship, and change management. In other words, MDM needs an appropriate level of organisational commitment to work effectively.

According to Loshin (2009), a successful MDM solution relies heavily on the following:

1. a collection of data objects used across the enterprise landscape and guidance on how that is maintained,
2. existing practices to identify data objects for integrated master data,
3. descriptions of the definitions used in different scenarios, and the intentions, meanings, and semantics for these entities, and
4. data hierarchies and object relationships have been collected, documented, and shared between individuals and the organisation as a whole.

Some researchers (Guimaraes & Armstrong, 1998; Wailgum, 2007; Stark, 2005) explain the master data quality directed migration process, which utilises "best practices" for the master data asset. In this model, the data creators, maintainers, and users have enterprise-level services available to make their work efficient from a data asset perspective. Such a best practice is an essential part of the governance model for managing the master data assets in the enterprise.

IT technologies are a necessary part of a fully functioning MDM, but without a defined logical model for the data entities and data maintenance processes, including ownership, it will not work (Joshi, 2007). According to Snow (2008), the MDM process needs to describe how business people manage the master data and how IT staff support the business efforts. Data knowledge in a company means how data has been defined, how it flows, and how data change impacts the systems. This data knowledge resides in the organisation and business units, and can exist in the form of silent knowledge that is not easily available. According to Joshi (2007), the following steps are needed for a successful MDM process:

1. master data flow has been defined,
2. master data source and consumers have been defined,
3. metadata for business has been collected,
4. master data model has been described,
5. functional and operational characteristics of the MDM tool have been described,

6. collection and maintenance of the technical and business rules for metadata have been described, and
7. publishing the master data or modifying the consuming applications has been defined.

According to Loshin (2009), MDM is about integrating the methods for managing access to a consistent and unified view of enterprise data objects. Too often, the basic information management principles are forgotten in MDM, and the practices become technology-focused such that different IT systems are viewed from a data management perspective in silos, and thus corporate level MDM is not reached (Moss, 2007).

2.5 Data quality

The roots of research and study on data quality go back to the 1950s when different studies of product data were done in relation to data issues. The first data quality definitions were worded as: quality is "the degree to which a set of inherent characteristics fulfil the requirements" (e.g. Deming & Edwards, 1982). Since then, other researchers have stated that data quality means "fitness for use" (Wang & Strong, 1996) and "conformance to requirements" (Crosby, 1988). Rapid development in IT systems technology has further increased the need for data quality definitions and studies.

According to Wand and Wang (1996), data quality is dependent on the actual usage of the data. The same data can simultaneously have multiple users (e.g. Tayi & Ballou, 1998; Shankaranarayanan & Cai, 2006). As the use of data is linked to its quality, there can be people in the organisation who see data quality as important while for some people (who are not using the specific data), the quality of the data is of low interest or even without meaning (e.g. Gustafsson et al., 2006). Based on Eppler's study (2006), data quality has two meanings and can be either:

1. subjective, which means that the expectations for quality are met, or
2. objective, which means that the data specifications are met.

This means that data quality (DQ) has contextual and multidimensional dependencies (e.g. Ofner et al., 2012). According to Tayi and Ballou (1998), data quality should be looked at beyond the traditional concerns with the accuracy of the data.

2.5.1 Data quality dimensions

The concept of dimensions gives a description and a reference frame for data quality measurement. Different dimensions describe and classify measurable aspects of data quality, which can be used later in the MDM process to monitor data quality against defined organisational DQ targets. The reason for representing the DQ targets as values is to quantify the data quality assessment and thus avoid the misinterpretation of measurements. This is important to avoid a view that is too narrow, for example, one that is provided by qualitative measurements only. However, some researchers (Loshin, 2011; White & Genovese, 2006) stress that it is important for organisations to take subjective data quality assessment needs into account and thus the capabilities of different stakeholders to highlight the "fitness-for-use" definition of data quality (e.g. Pipino, Lee, & Wang, 2002).

According to Ballou and Pazer (1985), there are four main dimensions to data quality: accuracy, timeliness, completeness, and consistency. However, there have been many add-ons to the list of dimensions since their initial definition. Table 3 lists the various studies and additions to the dimensions.

Table 3. Additional dimensions of data quality.

Source	Additions to dimensions
Wang & Strong (1996) A Conceptual Framework for Information Quality	Believability, Accuracy, Objectivity, Reputation, Value-added, Relevancy, Timeliness, Completeness, Appropriate amount of data interpretability, Ease of understanding, Representational consistency, Concise representation, Accessibility, Access security
Shanks et al. (2000) Semiotic-Based Framework for IQ	Well defined/format syntax, comprehensive, unambiguous, meaningful, correct, timely, concise, easily accessed, reputable, understood, awareness of bias
Neumann & Rolker (2000) Classification of IQ Metadata Criteria	Believability, Concise representation, Interpretability, Relevancy, Reputation, Understandability, Value added, Completeness, Customer Support, Documentation, Objectivity, Price, Reliability, Security, Timeliness, Verifiability, Accuracy, Amount of data, Availability, Consistent representation, Latency, Response time
Kahn et al. (2002) Mapping IQ Dimensions into the PSP/IQ Model	Product Quality: Free-of-error, Concise representation, Completeness, Consistent representation, Appropriate amount, Relevancy, Understandability, Interpretability, Objectivity Service Quality, Timeliness, Security, Believability, Accessibility, Ease of manipulation, Reputation, Value added

According to Wang (1998), intrinsic data quality means that information has quality in its own right. Similarly, Loshin (2011) believes that intrinsic data quality dimensions are related to the data value itself, out of a specific context. On the other hand, contextual data quality highlights the consideration of the context of the task at hand (Wang, 1998). Representational DQ dimensions are dependent on the format and meaningfulness of the data. Data should be easily understandable, clearly presented, and interpretable (Wang & Strong, 1996). Accessibility refers to how easy the data is to access and how understandable it is (Strong, Lee, & Wang, 1997). Both the representational and accessibility aspects of the data emphasise the important role of IT systems, due to the fact that they provide the access control and data representation (e.g. Wang, 1998; Wang & Strong, 1996). Figure 5 illustrates the practical dimensions of data quality as modified by Loshin (2011).

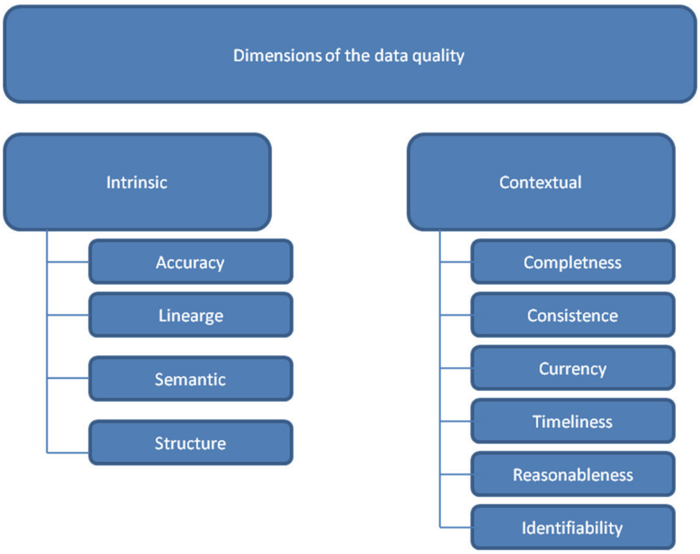

Fig. 5. Practical Dimensions of Data Quality.

The intrinsic dimensions include accuracy, lineage, semantic, and structure. Accuracy refers to the degree the data values match the source of the data. There can be several sources which make the matching difficult. Lineage refers to the dimension that measures the historical sources of data. It can be used to identify any new source or updated data. Lineage enables root cause analysis when documentation has been done properly. This type of analysis is used when assessing data quality. Semantic consistency represents a level of capability to obtain common agreement on business terms, and how widely this agreement is approved as a working practice across the enterprise. In practical terms, the agreement refers to the consistency of attribute definitions within data models that helps participants to understand the names, meanings, and characteristics of the different data elements. Structural consistency refers to the consistency of similar attribute values within the same data set across data models with related tables (e.g. Loshin, 2011; Schekkerman, 2003).

The contextual dimensions include completeness, consistency, currency, timeliness, reasonableness, and identifiability. Completeness refers to the expectation that certain attributes have assigned values in the data sets. Completeness describes the directive for data attributes, i.e. how different rules or constraints can be assigned to data sets to control completeness. Consistency describes the levels of data harmonisation across the IT system landscape in any enterprise. Currency explains how up-to-date the information is and whether it is correct in the changing environment. There can be rules and limitations assigned to check data currency at certain time intervals. Timeliness describes the means to measure time expectations to access information. It can be measured as the difference between the expected and the actual availability of information. Reasonableness describes general or rational expectation statements regarding the consistency or reasonability of values. Identifiability describes how the unique naming and representation of pivotal data objects can be utilised. In other words, identifiability refers to the ability to link entity data together based on certain attribute values (e.g. Loshin, 2011; Schekkerman, 2003; White & Genovese, 2006).

According to some researchers (Haug et al., 2011; Redman 1998), data quality problems can cause several issues and impact the entire enterprise result. Such an impact on an operational level can lead directly to customer dissatisfaction, increased costs, and even poor employee morale. Data issues can be very simple; for example, wrong or misspelled addresses can cause delivery problems that customers hate. Moreover, operational costs of the data quality work occur when time and resources are spent detecting and correcting data errors. Redman (1998) states that, based on some studies, the estimated total cost of poor data quality is in the range of 8–12% of a company's revenue. According to Olson (2003), the numbers can be even greater, and he states that experts estimate the costs of poor data quality to be 15–25% of operational profits. Furthermore, this number can grow due to the speed of IT systems development and the faster execution of the business processes. Therefore, a company's corrective reactions towards data issues needs to take place faster than in the past.

2.5.2 Data quality framework

According to Eppler and Wittig (2000), a data quality framework needs to achieve four goals. First, it should provide a set of criteria for the data evaluation. Second, it needs to deliver capabilities to analyse and solve data quality issues. Third, it needs to form and provide the basis for data quality measurement and proactive data quality management. Finally, it needs to present a conceptual map to structure the approaches to the DQ theories used behind the work and related data quality phenomena. There are different concepts that organisations need to understand to be able to align the data quality framework to meet the business targets of DQ activities (Eppler & Wittig 2000; Loshin, 2011). Data quality expectations need to be defined to:

- Develop measurements using data quality dimensions
- Define policies for measured observations of expectations
- Implement the data correction procedures to support those policies
- Align the management model with data governance practice
- Agree to the standards of the data
- Acquire the right technology to support the work
- Monitor performance of the framework

2.6 Theory synthesis

In summary of the literature review, there are four main elements that organisations need in order for their one master data management to be in place:

1. Business processes and how they are managed as well as their descriptions
2. Information Systems (IT) to provide data storing capabilities and the sharing of data with other systems in and outside the business processes to achieve the same understanding from the same data
3. Data definitions and the sharing and understanding of them
4. Data quality to be able to run the operations as required

When all these elements have been described, understood, and are being managed, one can say that a data quality framework exists.

Figure 6 illustrates the product data flow between the main enterprise applications and how the different main business processes interact with each other from a product data perspective. Table 4 summarises the main business concepts relevant to the dissertation.

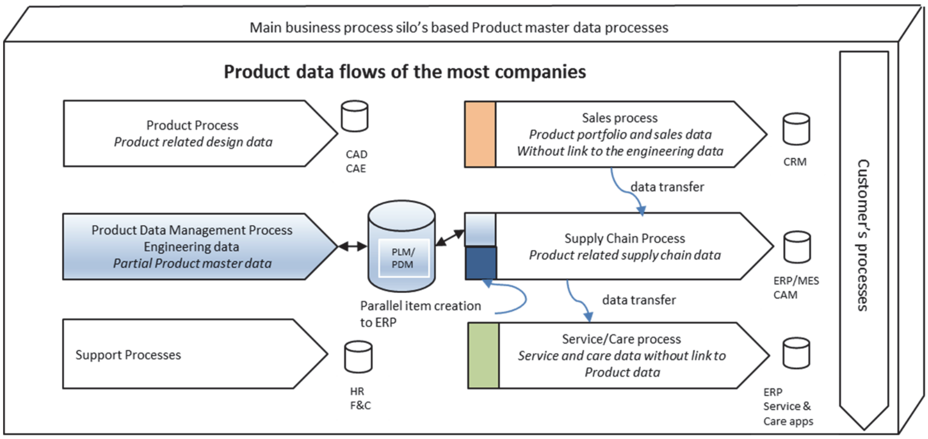

Fig. 6. Combined view of product data flows in companies between main business applications and processes.

Table 4. Main discussions relevant to this dissertation.

Topic	Key concept	Main references
1. Business process definition and how processes are linked to master data and IT systems?	How data definition is linked to the company strategy and business process management?	Stark (2005); Loshin (2009); White & Genovese (2006); Genaroro & Lourero (2015); Tian & Quan (2008)
2. What different IT systems companies have and how they are integrated?	List of IT systems and their roles in business processes. How systems are integrated?	Madu & Kuei (2005); Bradley et al. (2012); Loshin (2009)
3. What is master data?	Definition of the master data, to share the same understanding between stakeholders.	Loshin (2009); White & Genovese (2006), Loshin (2011); White & Radcliffe (2007)
4. Master data quality and framework.	How to classify the master data and what is the role of the data governance framework?	Wand & Wang (1996); Gustafsson et al. (2006); Eppler & Wittig (2000)

3 Research contribution

3.1 Challenges and preconditions for one master data

The first article (Silvola, Jaaskelainen, Kropsu-Vehkapera, & Haapasalo, 2011a) addresses RQ1 to understand the challenges and the preconditions that relate to one master data from a master data management capability perspective. The article includes a literature review to highlight the current state of the master data literature. Also, case companies were utilised to develop the empirical current state analysis to cover the daily practices.

The literature has considerable content on master data. Master data has been looked at from several perspectives, and some good frameworks exist for implementing the practices in actual daily work. Such terms as "data governance model" and "master data rules definition" are used in the previous literature. The literature also presents master data challenges. The identified challenges are structured and presented in many ways, mainly covering the data itself, without adequate linkages to business processes and IT systems. The biggest deficiency identified in the literature involves the maturity of the business process definition, the IT system definition, and the master data, all of which are dependent on each other. It is the data that integrates the IT systems and the business processes.

The empirical study on the current state indicated that master data practices in companies are lacking or are poorly developed. Only one of the 10 analysed companies had some practices in place, while many of the companies did not have data governance models or data quality controls in place at all. Companies were familiar with data problems and had fixed them when the issues became unbearable. The non-systematic data practices meant that the direct costs of the bad data started to cause issues, such as not being able to ship products or receive orders. Fixing the data was done by people outside of their normal jobs. Having adequate data in place was not seen as an asset from the management perspective, or the issue had not been discussed at all.

MDM is a technology-enabled discipline in which businesses and IT systems work together to ensure the uniformity, accuracy, stewardship, semantic consistency, and accountability of the enterprise's officially shared master data assets. One master data can be defined as that between the IT systems, data, and processes where the content, places, and data owners form a tight governance network in which the big picture is a tightly managed entity. Figure 7 illustrates the one master data definition.

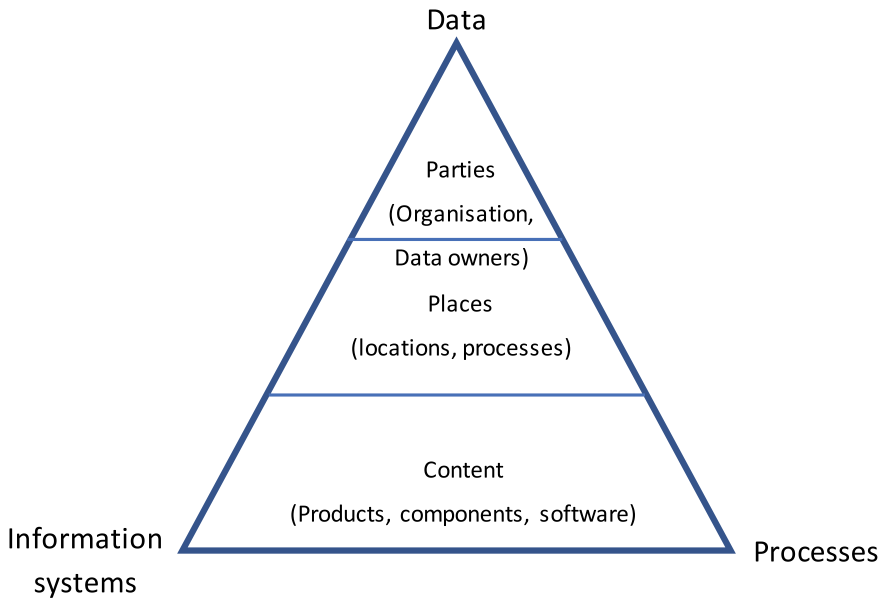

Fig. 7. One master data definition.

The study that formed the basis for article 1 revealed many master data-related challenges and preconditions, which were documented. Table 5 lists the challenges distilled from the current situation of the case companies. The first column includes the elements of one master data (process, data, and IT systems), the second column describes the challenges, and the third column describes the potential solutions, i.e. how to overcome the challenges.

Table 5. Challenges distilled from the current situation of case companies.

Element of one master data	Challenges	Responses
Data	Master data definitions are unclear Poor data quality	Identify the relevant business data Map the current state of the data Create a data model to support company's goals
Process	Data ownership is not clearly defined Incoherent data management practices No continuous data quality practices	Create a business case for gaining managerial support Start continuous data quality program Model the process for data life cycle
Information systems	Integrations between the applications cause data issues	Unify the data model Model the data flow across the systems Minimise the number of applications and integrations

The preconditions for one master data were collected from the companies participating in the empirical phase of the study and the literature used for the study. Table 6 presents the identified preconditions. The precondition criteria play a major role in making one master data a reality in companies. In sporting terms, one master data is not a 100-metre hurdle race, but more like a marathon. Also, the circumstances tend to change, so organisations need to pay attention to the operating environment continuously and adjust any plans and actions accordingly. This is very much the role of the management. Having the preconditions in place and in operative use can be understood as a success story of data management.

Table 6. Preconditions for one master data.

Preconditions for one master data	Description
Data model	Common definition on data model to be used across the organisation
Data ownership	Clear data ownership definitions
Data quality	Proactive data quality surveillance
Culture	Data-friendly company culture
Roles and responsibilities	Clear definitions for roles and responsibilities
Organisational structure	Organisation structure built to support data processes
Processes	Clear definitions for processes
Managerial support	Business case and support from the managerial level
Information systems	Unified data model

3.2 Product Data Ownership Network

The question of who owns the product data in the company is the focus of the second article. This article attempts to answer the RQ2 through understanding the elements of product data and how to set up a working data owner network for product data (Silvola, Kauhanen, Collin, Haapasalo, & Kropsu-Vehkapera, 2011b). The recommended practice in companies is to define the role of data owner, who is a key player in the management of the data. The data owner links the product strategy to the day-to-day product data management actions and, in most of the cases. the data owner is supported by several subject matter experts who know the IT systems and master data rules. Establishing the role of data owner between the R&D unit and other corporate functions is a challenge from the product and data life cycle perspective. In order to build the data owner role to cover the entire life cycle of the product, and across the main business processes, a framework for the sub-categories is needed. The framework elements include IT architecture and a governance model that can potentially involve an existing steering group to oversee the product life cycle, or a new data governance steering team may need to be implemented. The IT architecture's role is to guide the scoping of the data owner role by answering questions such as: In which systems are the products needed to do business process transactions? It is essential to include those requirements into the agenda and build a relationship between people and their roles in the PDON (Product Data Ownership Network). The PDO (Product Data Owner) acts as a support person towards other business processes to ensure an understanding of product data and to inform on updates and changes. Table 7 illustrates the key elements of the PDON.

Table 7. Key elements of PDON.

PDON Key element	Focus
Data governance	– Data governance is used to define, organise, and implement guidelines, policies, procedures, standards, roles, and responsibilities for building and maintaining the PDON.
Product data management	– Is based on policies and guidelines defined in data governance. – Forms the foundation for data maintenance, distribution, and storage. – Ensures that product data is in the right form, at the right place, at the right time. – Integrates business functions and their product data flows into a single network.

PDON Key element		Focus
Product data owner (PDO)	–	Primary responsibility is to ensure data quality, maintain product data, and make it available to other users.
	–	PDOs have to be in every business unit that creates product data and every part of product data needs to be owned.
Roles and responsibilities	–	There also has to be other roles and responsibilities aside from PDOs involved in the PDON.
	–	These are to support and enable the PDO's activities in order to have a functional PDON.
	–	These roles and responsibilities cannot be ambiguously defined, based on the literature.
Business functions	–	All the business functions are needed and must be involved in the PDON.
	–	Product data is created and/or used in every business function and therefore will affect them.
	–	There has to be a single version of truth of products and related data.
	–	Product data has to be made available for those needing it throughout the enterprise. Therefore, product data sharing and distribution have to be established according to product data management guidelines and policies, and this has to be implemented through the enterprise.

Table 8 illustrates some examples of who should have the responsibility to define data owner roles.

Table 8. Examples of who should have the responsibility to define data owner roles.

Responsibility	Examples of potential roles
Definition of roles and responsibilities of the PDON	Enterprise data committee/council Data steward
Implementation and monitoring of policies and guidelines	Enterprise data committee/council Product data manager
Data delivery actions	Product data manager Data delivery specialist Data owner
Overall responsibility of product/product data and product structure	Product manager Product data architecture Product technical owner Enterprise data modeler
Data quality	Data owner Data administrator Data quality team Data quality manager

Responsibility	Examples of potential roles
Product change management	Data owner
	Change manager
	Product change team
Support	All the roles

Implementing a product data ownership network requires an understanding of what the relevant data owner roles are. The simplified PDON definition process (Figure 8) supports the understanding of what is required from an enterprise to create and implement a PDON.

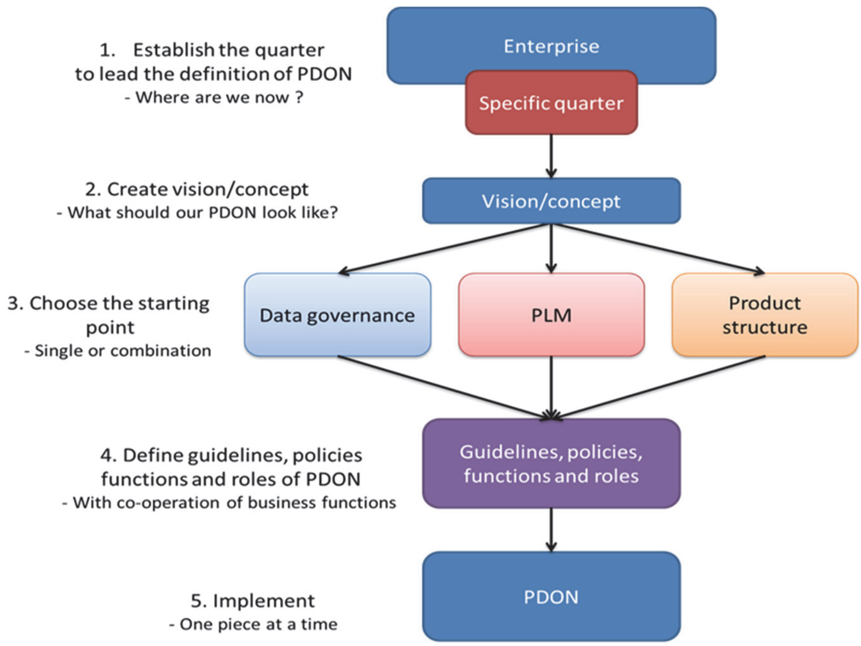

Fig. 8. A simplified PDON definition process.

The figure explains the five basic steps to build a solid data owner network. Each step details the data ownership from the organisation, business process, or data standpoint. Missing even one of the steps will cause later issues in the use phase.

3.3 Data quality

Knowing more about the data challenges can only happen through data quality analysis. RQ3 highlights this need from two points of view. First, understanding the specific data challenges of a data domain can only be achieved when there is an understanding about the requirements around the quality of the data. Data quality requirements drive the assessment further in IT technologies by setting a rule for the analytics side. Secondly, it is very important that data quality is monitored through its life cycle. Data needs to meet the quality requirements all the time (Silvola, Harkonen, Vilppola, Kropsu-Vehkapera, & Haapasalo, 2016).

Several frameworks have been published to support this work. However, the use of them varies as they might not be well known by companies. The frameworks mostly used are those developed by Wang and Strong (1996) and Eppler and Witting (2000). Both of these frameworks support the goals of describing the data quality requirements and of continuous monitoring of the data quality.

In the empirical phase, the use of a framework with so-called data domains was seen as useful for collecting and describing the essential findings from the interviews. These findings can be seen in Table 9 below.

Table 9. Data quality challenges and derived requirements.

Data Domain	Data Challenges	Data Quality Management Challenges	Derived Data Quality Requirements
Item data	Duplicates Missing data Irrelevant data	Validating Item data Managing irrelevant data Reaction times Business impact analysis Data governance Resources	Believability Security Value-Added Accessibility Accuracy
Company data	Duplicates Irrelevant data Missing reference data	Measuring data quality Reporting SLAs Data standards Reference master data Root cause analysis Data governance	Believability Relevance Reputation Consistent Representation Value-Added

Data Domain	Data Challenges	Data Quality Management Challenges	Derived Data Quality Requirements
People data	Incomplete data Outdated data	Root cause analysis Protocols for handling issues Understanding policies Data ownerships Technology Tracking issues	Accuracy Security Value-Added Timeliness Relevance
Service/Asset data	Missing data, Incomplete data Incorrect values Outdated data Duplicates	Requirements Metrics Measuring SLAs Policies Standards Root cause analysis Business impact analysis	Accessibility Value-added Completeness Timeliness Interpretability
Supply Chain Management	Design errors Duplicates Master data issues	Metrics Measuring Reporting SLAs Policies Protocols Root cause analysis Data governance Visibility	Accessibility Security Timeliness Accuracy Believability Value-Added Completeness

Data challenges are categories for typical data domain specific issues. There is some variation between the data domain challenges. Classifications according to selected data dimensions revealed that the five most valued data requirements across the data domains include believability, value-added, accessibility, accuracy, and security. However, the emphasis of the data requirements varies across the data domains.

To set up a continuous practice for data quality management, there is a need to describe the work clearly from a work practices point of view. It is also a learning process within companies. This means that, based on the frequency of the data quality follow up, the work needs to be repeated on a regular basis and continuous improvements need to be implemented.

The circle below shows the seven basic steps of data quality assessment and improvement (Figure 9). It illustrates the continuous learning process that follows in a clockwise direction. The proposed model consists of seven phases of data cluster steering group meeting: policy, data standards, dimensions, technology, protocols, and performance, and contains relevant processes, sub-processes, tools, and methods.

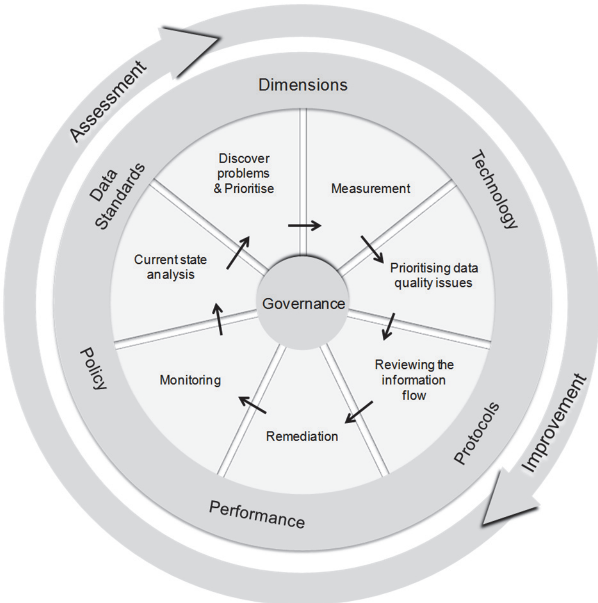

Fig. 9. Model for operationalising data quality assessment and improvement.

Data quality assessment and improvement can be challenging because several IT technologies are needed as well as sophisticated business understanding. Table 10 explains the sub-processes, tools, and methods that support the main process level. The tools and methods proposed are familiar in all companies; however, linking and using them efficiently for data quality assessment is generally lacking.

Table 10. Data quality assessment and improvement model – processes, sub-processes, and relevant tools and methods.

Process	Sub-process	Tool/ method	Purpose
Current state analysis	Information product (i.e. data) Information process (environment where data is located & influenced by processes)	IP-MAP (Visualization)	Assess the state of data quality Visualizing data and information environment

Process	Sub-process	Tool/ method	Purpose
Discover problems & Prioritise	Business impact/risk analysis	Business impact matrices Stakeholder interviews	Clarify the extent of data issues Prioritise issues impacting data quality
Measurement	Requirements Business rules Dimensions/ metrics	Interviews ETL-tools (Extract-Transform-Load) PSP/IQ (Product and Service Performance model for Information Quality)	Provide a reference point for data quality improvement
Prioritising data quality issues	Severity, impact, resolution feasibility	Prioritisation matrix	Ensure that the most relevant issues for business and operations are improved
Reviewing the information flow	Information product (i.e. data) Information process (environment where data is located & influenced by processes)	IP-MAP (Visualization)	Better understand the information flow Enable finding root causes
Remediation	Prevention, Auditing, Correction, and Usage	Activity/Data matrix ETL-tools (Extract-Transform-Load)	Address data issues Data correction/ cleansing
Monitoring	Issue tracking and service level agreements	ETL-tools (Extract-Transform-Load)	Enable ongoing improvement Aid in reporting on improvement

Data quality is best ensured when organisation-specific aspects are taken in to account in the operational model implementation. If companies sacrifice data quality and its fitness for use, and take product data management risks, the data itself loses its significance. The model for managing data quality proposed in this study can provide a starting point for operationalising data quality assessment and improvement. All the steps in the proposed model need to be in place or the shown model will not be worth implementing. Hence, to have a sound process in place, organisational learning needs to happen. The model may prove the most effective when the needs of data domains or processes are emphasised from the perspective of different data uses. Data use can change by adding new data or changing the importance of the data within the company. Continuous feedback and learning are important to ensure that company targets are covered with data quality assessment and improvement actions.

3.4 One product data for business processes

The fourth article is in response to the question of what business processes need to be set for one product data. These requirements are essential as master data definitions are based on business processes. According to the definition of master data management (MDM), it focuses on business processes, data quality, and the standardisation and integration of information systems (e.g. Joshi, 2007). MDM is a process like any other business process. It supports the business processes by capturing the data needed by the business processes. IT technology defines how to define data from IT system set up perspective i.e. making the system work correctly and how to maintain the data. MDM has been defined as an application independent process that describes, owns, and manages core business data entities (e.g. Otto & Reichert, 2010; McKeen & Smith, 2007).

There have been many good practices developed and theories written about the corporate strategy processes and how to make them better. The same applies to master data as there are studies and best practices about how to manage the data itself and improve the quality and data maintenance practices. However, combining the strategy process with master data has gaps in understanding how to link top management requirements to actual detailed data management work. The gap in the definition process is that if the business drivers from the strategy process are not understood, it is very difficult to define the needs for the data itself (Silvola, Tolonen, Harkonen, Haapasalo, & Männistö, 2018).

In terms of the product data use of a PDM/PLM system, the product master data can be shared with other IT systems in a straightforward process. Sharing the most relevant data with operational systems, such as CRM, ERP, sales product and pricing configurator, and a service business system can be understood as a business enabling practice. The targets set in the corporate strategy are potentially the underlying motivations for such sharing.

Figure 10 explains how the one product data concept can be translated into practice. It is essential to have links between the product management strategy and different key stakeholders of the company such as those involved in marketing, sales, supply chains, R&D, and service businesses. By combining these linkages with product data content understanding, it is possible to have the one product master data concept in place.

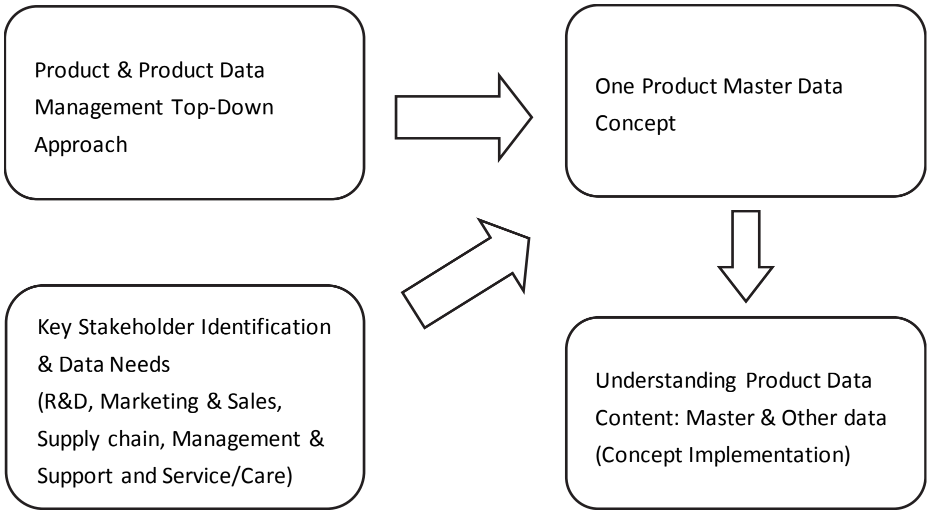

Fig. 10. Process to define one product data concept.

The value of the critical one product master data can be compared to human DNA. Each product has its own common data attributes and values which are also mapped in the product DNA, the product master data. Each product is a unique entity and has its own life cycle (Figure 11).

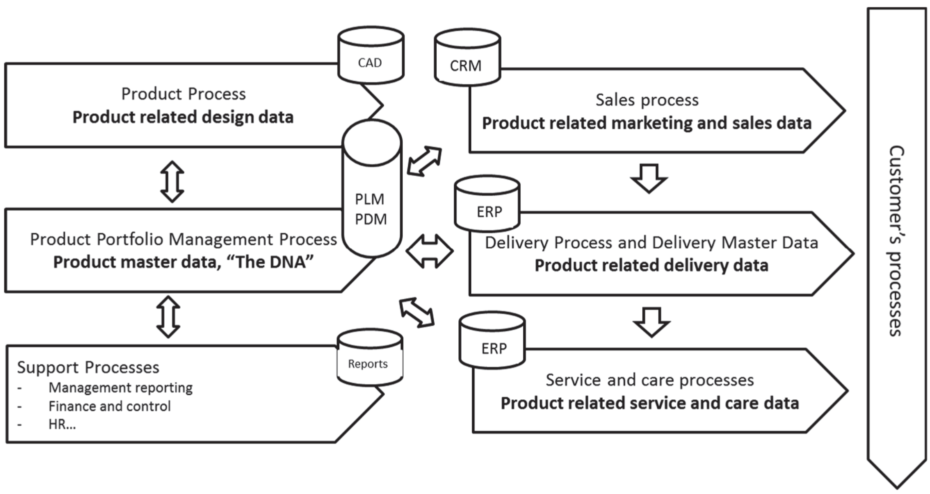

Fig. 11. One product master data ("DNA") and business process related data in integrated business processes and IT systems.

In terms of critical business drivers, i.e. the product DNA, a 100% data quality mindset is needed to ensure the completeness, relevancy, and timeliness of the critical data. This means that data will be created, updated, and removed within the product life cycle. In other words, data quality is monitored after the data has been released from the PDM/PLM system to the business processes of other IT systems. The product data monitoring should take place in almost real-time as deviations in the data quality would break the product DNA. It is important for all organisations to share the same understanding about the criticality of one product data due to frequent and continuous product data changes from the business side.

The high business value drivers and related one product data in business processes are targeted to reach a sufficient data quality level. While the quality of the product master data should be 100%, for business process related product data, the target quality has more variation based on the criticality of each driver from the perspective of strategy and business drivers.

From a literature perspective, it is interesting to notice that the discussions about strategy process, master data management, and product portfolio data management talk about the business drivers and master data as separate topics (e.g. Cooper, Edgett, & Kleinschmidt, 2001; Stark, 2005; Tolonen, Harkonen, Verkasalo, & Haapasalo, 2015). What has been missing in the literature is the link from the strategy process to one product data. This study provides a new contribution to the literature by describing the link from business drivers to one product data based on the product master data, business process related product data in integrated business processes, and the IT landscape.

Figure 12 lists the business drivers from one case company. What is notable is that there are three different categories of drivers listed: common, product category based, and low or no impact. The common business drivers represent the company's strategic point of view as to what requirements new product development (NPD) needs to fill. These requirements are linked to the product management approach (Figure 10) as well as to what key stakeholders need. The same applies to the product-specific categories which have been defined. There is also a low or no impact category for business drivers, which means that, in new product development, it is not possible or necessary to take those drivers into consideration. Some of the low or no impact category requirements will be fulfilled in other business processes, for example, the delivery process.

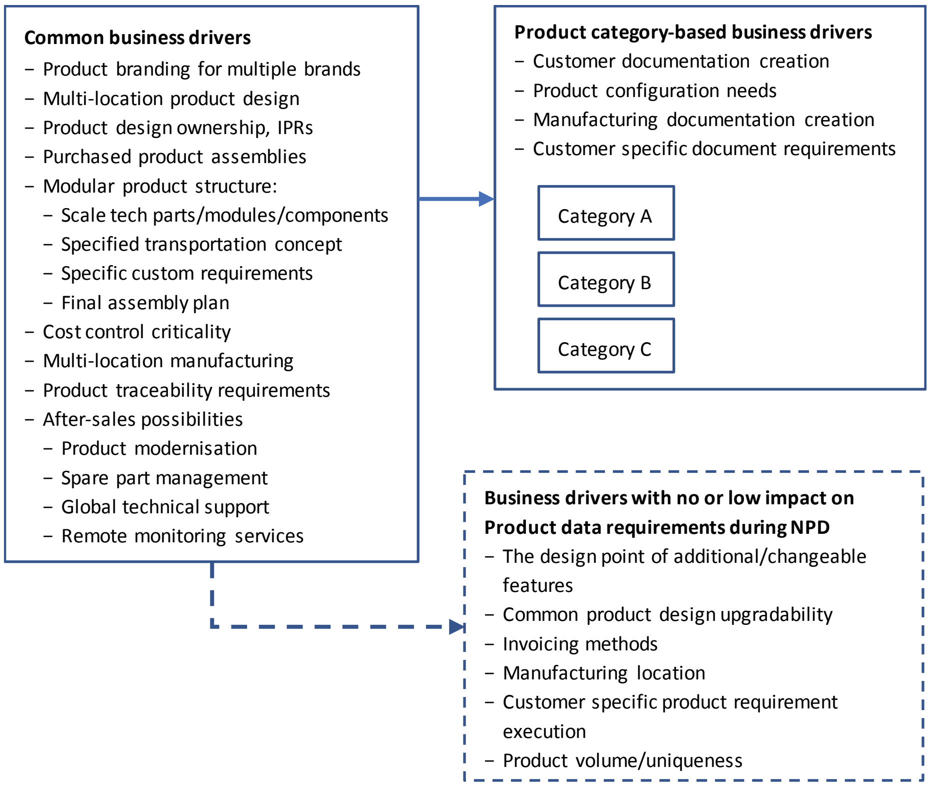

Fig. 12. Common business drivers, category-specific business drivers, and low impact drivers of a case company A.

3.5 Role of PDM in product launch

The fifth article (Silvola, Kemppainen, Haapasalo, Kropsu-Vehkapera, & Jaaskelainen, 2011c) looks at the service launch activities from a product data management perspective and answers the questions of how PDM supports the service launch and what key points need to be ensured for a smooth and successful launch.

The literature review suggests that proper data management practices can substantially benefit the performances of the service launch process and the launched services. The latest Product Development and Management Association (PDMA) study confirms that PDM systems are among the most utilised NPD tools. Several researchers (e.g. Barczak, Griffin, & Kahn, 2009; Stark, 2005; Philpotts,

1996) argue that PLM or PDM is a necessary enabler of concurrent engineering practices.

Service businesses possess some characteristic data attributes that need to be handled correctly in IT systems before launching the service publicly. These attributes are listed in Table 11. There is a clear link between the data challenge and the business process challenge. As the time to market is critical in some business cases, balancing the challenge of business opportunity vs. possible extra costs caused by the challenge is a typical decision-making driver.

Table 11. Detailed list of challenges in service launch process.

Business Organisation	Process challenges	Data challenges	Measurement challenges
New service development	Visibility of customer expectations Stakeholder involvement and communications Product documentation availability prior to launch	Product data availability Information for e.g. product structure and reporting	Documentation criteria and checklists Attractiveness
Sales & Marketing	Service maturity criteria to launch Billing and pricing support Training too late Offer type definition	Service maturity criteria to launch	Service maturity criteria to launch Checklist for front office training coverage
Delivery	R&D cooperation Extra work prior to launch to ensure delivery capability Insufficient automation levels	Several iterations to ensure 100% data cause additional costs	Time measures for delivery sub- processes and launch sub- phases Measures for service recovery (time to recovery. number of complaints and faults)
Support	R&D cooperation Help desk needs Preparation	NPV data availability and reliability	Help desk calls per number of sold services Multiple formats of reporting

Recalling a contract-based service once it has been delivered may pose difficulties. The provider may be stuck with providing low usage and low profit services for a long period (Voss, 1992). Further, Buchta, Eul and Schulte-Croonenberg (2010) and Tolonen, Harkonen, & Haapasalo (2014) suggest that the complexity of the services and product portfolio is the most significant external IT cost driver in telecom services. They argue that the complexity should be managed by fact-based and business case driven demand management, and life cycle management focusing on cleaning the product portfolio. The latter may be strongly dependent on the decisions made before the launch. Often high provision volumes in telecom services necessitate that the efficiency level of the service delivery system is considered closely. Generally, this means reducing the share of manual provision labour as the volumes grow. Internal productization and design for X, with X denoting, for example, implementation or end-of-life, are among the concepts that would assist these efforts.

Launching a new product or a service can be done to include check points to validate the master data definitions, data ownership, and how well the different processes are integrated. Table 12 shows the link between business organisation, business process, data management, and KPI quality measurement. The quality of the launch can be easily measured with KPIs coming from the data users after the launch. However, this is possible only if the master data is made available prior to the launch. If it is done after the service launch has taken place, there is a direct impact to the several organisations' daily work within the company. Setting up the master data afterwards may take considerable time, and it can last several months to complete to target state. Based on the interview and received comments, it can be said that companies do not recognise beforehand the risks they are taking because of the missing master data. These risks include losing customers due to services that do not meet the expected service levels or even do not work at all. The costs of the labour needed to support the service internally and externally can be high, and thus a negative financial impact will be generated.

Table 12. Surfaced long-term development targets for service launch process.

Business Organisation	Ideal Processes	Data Management	Measurement
New service development	Enterprise-level new service development process described with roles and responsibilities Early involvement of stakeholders	Product life cycle states defined Structured information for products and reporting created and in use	Milestone checklists and auditing
Sales & Marketing	Development cooperation responsibilities defined		Concurrent development of marketing and sales capabilities

Business Organisation	Ideal Processes	Data Management	Measurement
Delivery	Development cooperation responsibilities defined Automation level optimisation according to volume forecasts	Data quality ensured prior to launch Data ownership handover ensured prior to launch	
Support	Development cooperation responsibilities defined	Data quality ensured prior to launch	Business reporting capability ensured prior to launch

3.6 Results synthesis

The contribution of the work done in this doctoral dissertation relates to the context of defining the right building blocks to enable reusable one product data for business processes. Current state challenges were analysed within the context of product master data to enable an understanding of the relevant preconditions. The results indicated that product master data is still managed weakly, if managed at all, in the companies. Organisations too often work in a firefighting mode to fix issues as they arise. The valuing of data by businesses was mainly limited to their focus on serving the needs of the ERP system.

The companies' understanding of the significance of one product data for integrated business processes and how it influences the overall company success and efficiency was rather low. A list of preconditions was created to form the basis for validation points and for product master data work. The existing literature merely addresses the preconditions in silos and does not include the necessary managerial involvement in a number of elements. These silos include data quality under master data management, IT systems integration, main business processes individually, and the very scarcely dealt with end-to-end data ownership and its implementation. The PDON concept is needed as the reusable data requires a wide data ownership definition over the business organisations. Data quality monitoring and the right type of data quality targets for business process performance are also part of the preconditions. This is especially the case when combining product master data and product-related business data into one product data for business processes where IT systems give a framework for storing data and sharing the common data between different systems. Product-related business data means in practice product data where business process related additional data is needed to perform the process-specific transactions. These product-related business processes were divided into marketing and sales, supply chain, and service and care processes.

Figure 13 illustrates the framework of one product data for integrated business processes, created as the main contribution of this dissertation.

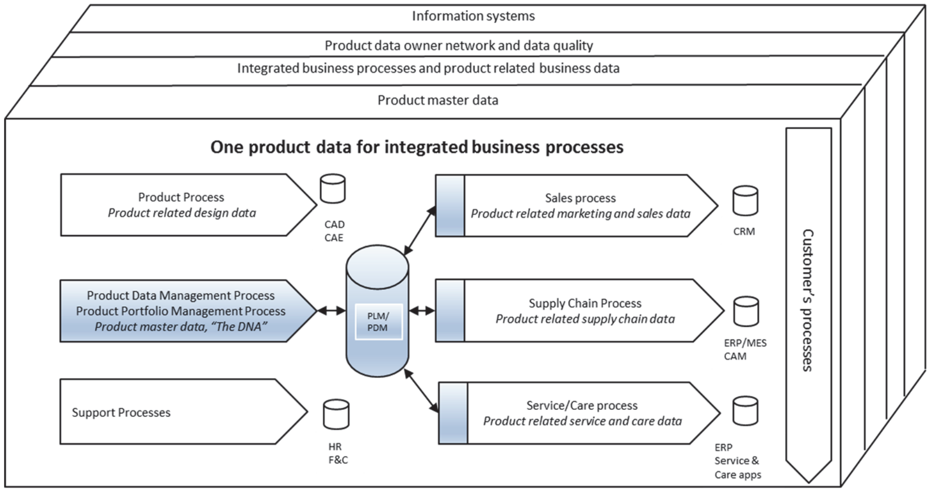

Fig. 13. One product data for integrated business processes.

One product master data is highlighted as blue in the figure, emphasising how the PDM process is a part of the product portfolio management (PPM) process that creates the one product master data, the product "DNA". One product data is the sum of the highlighted one product master data (blue areas in the figure) and the product-related business data in business processes (white areas in the figure). The PLM/PDM system acts as a central data repository for the product master data. This system controls the data entries and updates all the receiving systems simultaneously with the common product data. These updates are based on It architecture and business process setup decisions. The role of the receiving systems, which in Figure 13 are shown on the right side of the PDM/PLM system (CRM, ERP, and Service/Care ERP), is to use the one product master data and to add the business process specific data for the product. It is very important to note that within the receiving system the one product master data cannot be touched or changed. Business process specific product data that is added has a different life cycle and purpose than one product master data. Business process specific product data is business process specific master data and is very important. The product change process is easier (only within one system), and changes take place more often. The business processes contain product-related business data, signified by the white parts of the business processes. Business process specific product master data defines how the product is marketed sold, manufactured, and purchased. Product-related service and care data belong to this category also. Commonly, the blue shaded areas of business processes signify the one product master data, as without common and quality-wise correct one product data, transactions would not be possible. Common data also supports process integration. The created framework emphasises the product data elements necessary for one product data in business processes and the relevant preconditions.

Most of the companies have product data practices in place, including one product master data and product-related business data with opportunities to improve. However, most companies have deficiencies in their data practices. Data in some companies is managed rather well. This might be due to the particular business circumstances. The findings indicate that there needs to be some type of trigger or a new element to change the corporate culture, which might be required from outside the companies. These triggers might be new legislation or new products entering the portfolio caused by mergers and acquisitions. The main thing that needs to happen is that the company starts to value one product data in its daily operations. Business process definitions need to be done to the level where information flows are understood and IT system integrations are in place to support seamless data flows. It is important to remember also the management's role in supervising the end-to-end processes with KPI measurements that have been distilled from the strategy.

In an ideal situation, one product master data would be created once and would then be used efficiently in the later phases. This would:

1. allow control of the product life cycle across the business processes,
2. through data integration, promote natural cooperation between the different organisations such as R&D, Sales, Delivery, and Service,
3. minimise the data quality control points as the integration role of the IT system is to take care of the data sharing between the different IT systems, and
4. facilitate the data analytics and reporting processes as there would be a clear data model in use.

The framework of one product data for integrated business processes has been tested in a product launch study. The study indicated that one product data fits well the service business where some of the products can be used 24/7 online, that is, one product data supports a company's digitalisation strategy by making the launching of new services significantly easier. Table 13 summarises the research contribution.

Table 13. Summary of research contribution.

RQ#	Main results
I	
What are the challenges and preconditions for one product master data?	Preconditions: One product master data definition Common definition of the data model to be used across the organisation Data-friendly corporate culture Clear definition of the business processes Unified data model across the IT systems
II	
What are the elements and how is the product data ownership network implemented?	Management board to oversee the data governance. Product board/PDM steering Product structure is defined clearly across the corporation/organisations PDON policies and guidelines exist, stakeholders have been trained in them, and they are in use
III	
How can data quality be ensured for product data management?	Current state analysis and action plans have been done based on the findings. Prioritise actions and follow up on those that have been completed. Measure data quality to see the results. Set target levels for the data quality.
IV	
What are the business process requirements for one product data?	Business drivers need to be part of the company strategy. Strategy sub-elements need to have a link to business process KPIs defined to measure the change. Common data model across the business processes provides a framework to define the one product data.
V	
What is the role of PDM in product launching?	Data availability validation in different gates and checklists, especially before the launch. Smoothness of the handover from R&D to the sales, delivery, and service divisions. Meeting the customer expectations and product costs set before the development.
Overall contribution	Created the framework of one product data for integrated business processes.

4 Discussion

4.1 Theoretical implications

This study defines the foundations for one product data from several perspectives, including the challenges and preconditions for one product master data, implementing product master data ownership, and the importance of a governance model for master data.

The study provides a new contribution to the previous literature (e.g. Wailgum, 2007; McKeen & Smith, 2007) by highlighting the importance of shared one product master data across the main business processes and supporting IT applications. This DNA of the product master data requires that the company strategy process is integrated through business drivers to the master data management. The master data role is to ensure that strategic goals and business KPIs can be measured, and thus meeting them becomes one step closer. This also means that a data model is described across the business processes and that the data flows are integrated between the main business applications. One product data is the sum of one product master data and business process-related product data. One product master data is created by the product portfolio management (PPM) process and stored and controlled by a PLM/PDM system that updates the receiving systems with the one product master data. Product-related business data is created directly in each business process.

Table 14 summarises the theoretical implications of the five individual articles. The first article defines the exact checklist way of working as well as highlights the activity level for the master data operations. The study provides a new contribution to the previously more technical perspectives (e.g. Berson & Dubov, 2007) by showing how understanding the basic challenges and preconditions can support forming useful checklists, especially when considered alongside measurable business drivers. The study also forwards the importance of selecting the right master data activity level based on the company's strategy and mission, rather than looking at master data from an IT or enterprise architecture view only. This is a new aspect to the previous master data discussion (e.g. Freidman, 2006; White & Genovese, 2006; McKeen & Smith, 2007) that has not particularly emphasised the activity levels with a direct link to the corporate strategy process. Real-time prevention of data issues can be costly to implement from the master data perspective, but in some business cases, there is no other choice because of intensive business activity model requirements towards master data. This came up in the last article (V) where one of the companies had many online services. For such a business, it is essential to have 100% correct data; otherwise, the services stop or become unstable, which can cause losses to the company quickly. This had happened in the case company, and they were developing the handover processes from a new service design to use phase.

This study complements previous literature (e.g. Hameri & Nihtila, 1998; Bradley et al., 2012; Kettinger & Grover, 1995), highlighting how business processes, data, and IT systems must be in balance in order to have "one product data" capability in place.

Introducing the importance of the 'triangle' of business processes, data, and IT systems is in line with the previous literature (e.g. Hameri & Nihtila, 1998; Bradley et al., 2012; Kettinger & Grover, 1995) in that it emphasises that master data is not a sole entity in companies. However, this integration can only take place if a company has a data-friendly culture in place. Data friendliness can be hard to measure, but overall it means that master data-related actions are as important as IT investments or continuous business process development. Master data work is part of daily work and business process KPIs, and there need to be resources dedicated to this work.

Table 14. Summary of theoretical contribution article by article.

Article/Title	Theoretical contribution
I	
What are the challenges and preconditions for one product master data?	Documenting the one product master data specification One product master data definition Common definition of the data model to be used across the organization Data-friendly corporate culture Clear definition of the business processes Unified data model across the IT systems
II	
What are the elements and how to implement product data ownership network?	Management board to oversee the data governance. Product board/PDM steering Product structure is defined clearly across the corporation/organisations PDON policies and guidelines exist, stakeholders have been trained in them, and they are in use PDON implementation has clear steps, and best practices can be used as a guide line

Article/Title	Theoretical contribution
III	
How to ensure data quality for product data management?	Current state analysis and action plans can be done based on the findings. Prioritisation is needed to get results faster. Follow-up and feedback loop is needed to ensure that actions have been completed. Measure data quality to see the results as those quality measures have business value. Set target level for the data quality to ensure business organisation targets for business processes.
IV	
What are the business process requirements for one product data?	Business drivers need to be part of the company strategy process outcome. Strategy sub-elements need to have links to business process KPIs defined to measure the change. Common data model across the business processes provides a framework to define the one product data.
V	
What is the role of PDM in product launching?	Data availability validation in different gates and checklists, especially before the launch. Smoothness of the handover from R&D to the sales, delivery, and service divisions. Meeting the customer expectations, and product costs set before the development.
Overall contribution	A framework was created for one product data for integrated business processes, which has practical business value and smooths the execution of the end-to-end processes.

Combining master data management theory with business change management and process leadership theory provides the basis for a successful data ownership definition. Expanding the data ownership implementation to practical examples in the second article explains the implementation steps in terms of real-life situations and hence contributes to the work in this area (Stark, 2005; Hameri & Nihtila; 1998). The main issue is to understand the IT system and data model landscape, the enterprise structure of the company, and the data itself to be able to properly implement roles and responsibilities. The study also contributes by highlighting that business process integrity needs to be supported by data quality measurement as a feedback loop, thus ensuring that governance is in place for the whole process to work properly.

The contribution of the third article is in line with other studies (Wang & Strong, 1996; Eppler & Witting, 2000) in emphasising that defining and ensuring data quality requires a learning process before it can be adequately implemented in a company. The study highlights the basic steps of defining data quality measurement criteria. The study also provides a contribution to the previous literature (e.g. Wang & Strong, 1996; Eppler & Witting, 2000) by indicating that selecting what to measure and understanding why requires in-depth business process understanding in order to prioritise correctly and thus gain business value. The study also raises the need for continuously improving the process. Regarding continuous improvement and the value it provides to the company, a framework is introduced to support the necessary practical work.

The fourth article, which covers one product data for a product, gives new thoughts to the previous literature (e.g. Otto & Reichert, 2010; McKeen & Smith, 2007) by indicating that there should be common data across the business processes, data that is created once during the product process and used without any data changes in sales, delivery, and service/care processes. This is only possible, however, when the business processes are fully integrated. Some researchers (Otto & Reichert, 2010; McKeen & Smith, 2007) talk about the theoretical model from an IT viewpoint. However, the practical understanding from a business perspective, and what one product data means from a business process management and development perspective, is a challenge. It is the data-friendly culture of an organisation that enables the understanding which many companies lack in their daily work practices. To increase understanding, the comparison provided in this study of one master data to human DNA can help managers in talking about the benefits of one product master data to their companies. The findings highlight how it is necessary to understand the master data logic to truly lay the foundation for one product data on a practical level. This understanding provides a new contribution to the previous literature (e.g. Otto & Reichert, 2010; Stark 2005 & Smith et al., 2008). Additionally, one product data for the product provides a new contribution to product portfolio management studies (e.g Tolonen, Haapasalo, Harkonen, & Verrollot, 2017) by potentially facilitating new product and service introductions, and overall providing good analytics in the product portfolio management.

The fifth article, clarifying the role of PDM in the product/service launch, brings insights to the previous literature (e.g. Barczak et al., 2009; Stark, 2005; Philpotts 1996) by providing practical ways to improve the handover from service design to execution phase. As one of the case companies provided online services, it was noticed that common data across the main business processes plays a key role in smooth service execution. Moreover, this study confirms that the DNA data logic supports the handover from the R&D department to the sales, delivery, and care/service processes. To make the DNA logic a success, data quality needs to be validated as specified by those receiving business processes before the launch. Also, a set of handover meetings may be necessary to ensure organisation between the different divisions and specialists.

In summary, the fundamental scientific contribution of this study lies in outlining a one product data checklist tool for defining master data, organising the data ownership, and linking the master data to the strategy process through the business drivers. This work highlights a one product data framework for business processes and IT systems from a management perspective.

4.2 Practical implications

Managers can benefit from the practical checklists for one product data introduced in this study, and from the explanation of the one product master data (DNA) and business process-related product data. Understanding that one product master data is product-related master data that forms the unique DNA of the product is important from the strategy perspective to reach the goals set for the company. Companies and managers responsible for data can benefit from the understanding that any strategy can be only partially implemented if the business drivers for the one product data are not described, understood, and implemented as measurable targets within the company. This dissertation provides support for this necessary understanding.

Once the one product data is in place, different organisations in a company's enterprise structure can benefit from the one product data in their operations and contribute to the company's success by delivering such data through IT systems for other organisational structures of the business. People working with the corporate support functions that are responsible for data maintenance can benefit from this study by enriching their understanding about the integration of one product. Questions such as who uses the data, and who is responsible for the data in later life cycle stages, can be answered easier. The product data owner network responsibilities presented in this study are often considered in siloes, or they do not exist at all. Should such a network with roles exist, it is often without support towards those data owner roles. This understanding can support the data maintenance practitioners' work, as it is vital to realise that any role or competence needs to be supported and maintained, especially in change situations. This further links back to the strategy.

During the completion of this thesis, process themes such as IoT (Internet of Things) and digitalisation became standard in business life. In the light of such themes, this study can support practitioners by emphasising the importance of one product data as a foundation for digitalisation. The results of this study highlight the support that the one product data theme can provide for analytical purposes. Business persons and IT leaders who drive new business opportunities can benefit from the results when they understand the importance of the level of data integrity and quality of the data. In addition, the introduced data owner network concept provides linkages to the data processes and practices.

Top management is responsible for the strategy implementation in companies. Questions as to how well the company implements the strategy are supported in this dissertation through the understanding that data support can close the gap between the business drivers derived from the strategy and the business processes. The management might also question the value of making vision statements that do not correlate with the reality in the company. In order to implement a fully working strategy in today's modern IT landscape, a balance is required between business process management, IT management, and data management. Companies and practitioners can benefit from the findings of this dissertation in that respect by building the data, processes, and IT systems for one product data. It is to be noted, however, that not every company needs real-time digitalised data management, but those that do should have the basics in place.

4.3 Reliability and validity

This study pertains to the data, processes, and IT systems needed to organise one product data properly from the research perspective. The origins of the themes discussed date back to the 1960s. This study aimed to summarise the requirements and steps in a form of checklist content to ensure that data management actions go in the right direction. The new information or ideas presented in this study are part of the simplification of the message of one product data, for example, the DNA context and the PDON. According to Brymand and Bell (2003), qualitative research can be viewed from four observational perspectives that give understanding about the validity and reliability of the research:

1. Trustworthiness of the achieved results
2. Validity of the results in different environments
3. Repeatability of the observations
4. Impact of the researcher's experience and overall value of the results

When looking at the trustworthiness of the study results, it can be said that the results correlate with the real world. The multiple case studies used in this research, and the research methods, contribute to the theoretical and practical results in the category of the trustworthiness. The results have been impacted by the earlier literature on MDM, data governance, BPM, IT, and many other categories which were studied based on the key words such as master data, data quality, business processes, IT systems, governance models, performance management, strategy process, and integration. Hence, the results of earlier studies correlate with the real world through each researcher's work. The interviews for this study involved several companies for each article, and several people from each company were interviewed. The interviews were organised in a semi-structured manner, thus allowing the freedom to collect additional viewpoints during the interactions between the researcher and interviewees. Those viewpoints often explained the content better and opened up several perspectives on one product data. One product data can be viewed in many ways, but when used best, it integrates the organisations within a company and therefore has a multidimensional role. As a method to ensure trustworthiness, a memo was written from each interview session and shared with the interviewees to ensure correctness. Also, the participants from the case companies were invited to a sharing meeting where the complete results were explained and feedback from them was collected.

The validity of the results in different environments is intentionally based on a study by Brymand and Bell (2003). In this study, the one product data concept was validated by involving large companies from different business segments. The selection of these companies was intentional so that the results could be validated. From the basic product master data perspective, the physical (HW), software (SW), and Service areas were covered by the case companies. As a basic result for one product data, it was observed to fit well across different business models. The main difference noted was in the interviewees' interest in the context per the company perspective. For example, while on the telecom service provider side, there was good interest in the product data and governance model as a new learning topic, this was a known topic in other industries (e.g. manufacturing and food industry).

The repeatability of the study evaluates the likeliness of reaching the same results regardless of who conducts the interview (e.g. Yin, 2003). It is possible to impact the repeatability by having well-documented research materials and questioners. However, the persons and teams doing the research can influence the results because their individual competencies about the topic are different (e.g. Saunders & Pearlson, 2009). This was the case with one product data research to some extent. This was tackled by using overlapping teams to collect the data from the case companies. The issue was managed by having proper arrangements for the research data collection and storing the data systematically (e.g. Yin 2003), and then having the research team input to the data collection so that individual competencies were dealt with properly.

The researcher's interests, experience, and competencies may challenge the objectiveness of the qualitative research work (e.g. Yin 2003). This can happen more often when semi-structured interviews and workshops take place. In this study, when the researcher was part of the data collection, the interviewees were instructed to provide full, complete, in-depth answers to the research questions and not to leave anything out that might need to be added by the researcher. Thus, having as accurate a questionnaire as possible was the guiding principle. Moreover, the researcher did his best to stay as objective as possible during the analysis.

4.4 Recommendations for further research

As a terminology, master data is very old. Many studies had been conducted in this area already before this study began. However, rocket science was the flavour of the previous research, and thus there is still limited understanding of the topic. Yet, what if the understanding of the term "master data" was changed to include the idea of important business data?

Future studies are needed with regards to master data representing the most important business data through the digitalised processes. Things happen faster on the business process side, and often the readiness to manage lags behind. Sound practical tools for management are needed in the areas of leadership and understanding of data. Company managers need to learn more about data, business processes, and IT architecture. This also challenges IT organisations to change and adopt new approaches to their work. Data, thus IT, is part of the product, which means that the traditional organisation-specific data model as cooperation does not work anymore. During the study process, several discussions were held on the topic of where master data management belongs in the corporate structure. The first priority is to ensure that data management is established, and the second priority is to decide from where in the company it should be driven. In the end, the authority in a company sets the location question. Why data organisation does not have the necessary authority would require further studies from the data-driven organisational perspective. This issue is close to the psychological view to the topic of why leaders behave in certain ways. Studying this topic from a modern data-driven leadership perspective would give further insight into behavioural themes.

Business needs for data are approaching the change that took place with mobile phones. Data is expected to be online 24/7 and easy to use. With one product data, there is still a long way to go to ensure it is practically understood and easy to manage. IT application providers play a major role in the complex data silo models that exist today. Cloud technologies challenge the traditional IT architecture and business models and make integrated data easier to implement and gaining business value from the data. New IT technologies such as (AI) Artificial Intelligence and (RPA) Robotics Process Automation can offer great deal of help in data harmonization and value proposition from the data as a business driver. It is worth of mentioning that value of the data can get new meanings for example through social media. What is a product evolves with the new technology becoming available and challenges all of us on daily life. Therefore, further research on one product data should be continued as a basis for the developments in digitalisation of the company business.

5 Summary

The literature provides many best practices in the fields of master data management, enterprise architecture, running business IT systems, and business process management. However, the challenge many of the companies participating in this study face is how to build a bridge between these fundamental elements. Several simplifications on this topic were introduced in this study, and by understanding, implementing, and continuously managing the basic concepts, companies would have a very good foundation for their future challenges in competition within their business segment. Based on the articles discussed, those basics are:

1. Establishing a checklist for one master data and corrective actions
2. Building a data owner network to support data management best practices
3. Ensuring generic data quality based on business value and implementing a continuous process
4. Incorporating one product master data, i.e. DNA thinking. Integrating the corporate strategy process, business process management, and IT systems to ensure one product data over the business processes
5. Ensuring that data is at the core when doing handover between organisations

These five topics include pitfalls, as revealed in the assessments of current practices done in many of the case companies. However, it is also clear that best practices exist. Those practices have been listed in this study as preconditions which, based on the participating companies, showed positive impact compared to the old ways of working.

As the number of the participating companies was limited, and there was variation between the business segments represented by the companies, there are some practical limitations to this study.

During this study, several questions and “aha” statements were raised by the participants. These give guidance as to where more understanding could be reached by other researchers and by universities and companies working together. For example:

1. The DNA concept aptly explains the meaning of enterprise architecture.
2. Business drivers are essential as they translate business needs to master data.
3. Data ownership goes over the organisational boundaries in PLM.
4. Digitalisation can be enabled by one product data.
5. The data quality activity level is forgotten in practice. There are many aspects to take to the next level.

As was revealed in the literature review, master data as such is not anything new. What this study highlights is that the expectations around data management in companies have increased, and thus the efforts to ensure good quality data for integrated business processes are much higher. This study emphasises the importance of the preconditions for building a proper approach to one product data for business processes. The existing literature has considerable content on the topic but does not list clearly the basic elements. One of the most challenging basic elements is the data ownership. This is because ownership requires life cycle thinking from the owner, and data owners need to have a support network in place. The data ownership building blocks are the strategy, process, data model, and IT architecture. However, perhaps the most important element is having data owners in place who take the role seriously enough. There are several implementation steps in the data ownership model for products.

The basis of ensuring data quality is that there are continuous activities and processes in place in the company where the master data quality is measured and followed up on, and that this is tied to the management process. Also, the role of top management in setting the requirements for a data-friendly corporate culture is of utmost importance. One topic revealed in all the research papers is the importance of the data model, process, and IT architecture as a big picture. Practically, this is about the quality of cooperation between the business and IT. That is, to enable the establishment of a proper data governance model, IT needs to support business processes by supplying the details related to the data model in business understandable terms that reflect the big picture. Moreover, master data across different data domains needs to be understood to enable an understanding of business processes and their efficiency. For example, the marketing and sales process requires customer master data and product master data to be able to offer customers the products. If a company wants to improve its main business processes, one product data needs to be improved also. If one product data is not in the core list to improve, the results from the process improvements will not be met. The statement, “You get what you measure” is often used in business KPI reporting as a slogan. This is exactly the point. What companies want to measure and how well they want to perform their business processes needs to be defined so that it goes deep enough to the master data level.

The practical way of doing this properly would be to understand what the corporate strategy is in terms of the overall target state and then to combine this goal with the product strategy. A key topic is how to turn the strategy elements to business drivers that actually represent the business process requirements in order to define one product data. In practice, for each business driver, there needs to be measurement capability (KPI) which links to the actual master data quality, processes, and IT data technologies. The role of IT is to ensure that data gets created once but is used efficiently and enriched in the business processes. Without one product data, there is limited efficiency in the organisations, processes, IT systems, and digital systems.

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I Silvola, R., Jaaskelainen, O., Kropsu-Vehkapera, H. & Haapasalo, H. (2011). Managing one master data - Challenges and preconditions. *Industrial Management & Data Systems, Vol. 111*, No. 1, pp. 146–162.

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V Silvola, R., Kauhanen, J., Collin, J., Haapasalo, H. & Kropsu-Vehkapera, H. (2011). A framework for improving the launch concept of new services. *Proceedings of TIIM2011 Conference*, 28–30 June, 2011 Oulu, Finland, pp. 692–706.

The original publications are not included in the electronic version of the study.

670. Hartmann, Robert (2018) Flotation using cellulose-based chemicals
671. Porambage, Pawani (2018) Lightweight authentication and key management of wireless sensor networks for Internet of things
672. Bibikova, Olga (2018) Plasmon-resonant gold nanoparticles for bioimaging and sensing applications
673. Venkatraman, Ganesh (2018) Traffic aware resource allocation for multi-antenna OFDM systems
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681. Tolvanen, Jarkko (2018) Novel sensor and switch applications for flexible and stretchable electronic materials
682. Alatarvas, Tuomas (2018) Evolution of inclusion population in calcium treated ultra-high strength steels : Novel applications of sample data treatment
683. Tomperi, Jani (2018) Predicting the treated wastewater quality utilizing optical monitoring of the activated sludge process
684. Fazel Modares, Nasim (2018) The role of climate and land use change in Lake Urmia desiccation
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