Digitalisation of a Company Decision-Making System: A Concept for Data-Driven and Fact-Based Product Portfolio Management

Abstract

The main objective of this study is to conceptualise data-driven and fact-based product portfolio management (PPM). This study examines how the PPM process has been internalised in eight international companies and suggests a concept that covers all PPM performance management areas (i.e. strategic fit, value maximization, and portfolio balance) to transform a profitability analysis from company-level to product-level. The study is founded on a literature review focusing on PPM process and other key business processes, data-driven decision making, company data assets, and business information technology (IT), which form a base for data collection and qualitative empirical analysis. The findings highlight how the strategic role of the PPM process and related targets and key performance indicators (KPI) must be internalised before adjusting business IT to utilise company data assets for data-driven, fact-based PPM. The data as a strategic asset provides whole new opportunities for PPM. The practical implications include providing a technology-independent concept for data-driven, product-level analysis of company products and product portfolio over the product's life cycle. The findings provide the means for a data-driven approach by the effective connection of the PPM process, company-widely governed data assets, and business IT systems to realise their full potential for fact-based decision-making. A new contribution is provided by introducing a concept for data-driven, fact-based PPM. The new contribution also elaborates on and extends the PPM discussion by conceptualising fact-based, product-level analysis, and decision-making by utilising company strategic data assets. This new contribution is also provided by combining business processes, information systems, and data assets for PPM, and by combining these to conduct analysis.

Keywords – Product portfolio management, Fact-based analysis, Data-driven decision-making, Data governance, Data assets, Business processes.

1 Introduction

Product portfolio selection and decision-making models in the 1960s and 1970s were highly mathematical and required high comprehension of linear, dynamic, and integer programming techniques, and the lack of reliable data was one of the major obstacles. The mathematical models were not able to identify interrelationships between multiple and interrelated criteria and were too tricky for managers to adopt in daily operations (Cooper et al., 1999). A widespread phenomenon beginning in the 1990s was using data to receive and process orders, thus producing internal transaction data related to business processes (Lang, 2012) that was left unused when transactions were completed (Fisher, 2009). Unlike during the 1960s and 1970s, data availability is no longer an obstacle. An increased amount of data and knowledge is gathered from customers, suppliers, partners, and competitors (Brynjolfsson et al., 2011). The size of the global digital data has reached the limit of zettabytes (Reinsel et al., 2017). The amount of data available is not the only change. A variety of new sources of data have become available inside and outside the companies. These include internal sources (e.g. weblogs, email servers, call centre systems, and document management systems) and external sources (e.g. websites and social media networks). These data sources enable understanding of customers' thoughts of a company's services and products and provide alternative ways to find new customers. (Lang, 2012). However, the extant literature is lacking insights on how company data assets can be combined and refined to produce added value.

A rapidly growing amount of structurally varying, structured, semi-structured, and unstructured data volumes have created needs for data storage and analytical processing to support decision-making based on the data. According to Walker and Moran (2017), the traditional way to integrate business applications and data warehouses (DW) to connect master data and other product data assets are inflexible and have proven costly. A new mindset is needed to adopt new technologies and employ skilled people to implement them (Anderson, 2015; Davenport and Patil, 2012). Based on Nelson (2003), both physical and social technologies must be adopted; physical technology is widely explained as information and communication technology (ICT), and social technology explains how the technology is adopted using best practices from business and social perspectives.

At the advent of rapidly evolving digitalisation, companies need to transform—from product information management to product information intelligence—to unlock the best possible business value by connecting product data assets to the original product master data to create high-quality customer-centric experiences (Walker and Moran, 2017). Today's smart products with rapidly expanding opportunities are crushing traditional product boundaries, forcing companies to holistically rethink their value chains from design, manufacturing, operations and service perspective, and especially to secure the benefits of necessary information technology (IT) infrastructure (Porter and Heppelman, 2014). The extant literature focuses much on technology without considering how data assets are utilised enterprise-wide for achieving business goals (e.g. Aiken, 2016; Wang and Krisch, 2019).

Data-driven organisations require a whole new cultural mindset to understand the value and importance of data in business decisions (Brynjolfsson et al., 2011; Carton et al., 2016) and to avoid emphasising emotions and varying opinions in decision-making (Maitlis and Ozcelik, 2004). The valid data must be recognised, and companies must understand how to realise its highest potential. The more the company is data-driven, the better its financial and operational success will be (Thusoo and Sharma, 2017; Brynjolfsson et al., 2011).

The product portfolio management (PPM) process is a strategic analysis and decision-making tool for companies to renew their product offerings (Tolonen et al., 2015a; Srinivasan et al., 2005; Weerd et al., 2006). Much literature is available on the early life-cycle stage of PPM (Cooper et al., 1999; Cooper et al., 2001; Cooper et al., 2002) and the overall concept for horizontal and vertical PPM throughout the entire product lifecycle (Tolonen et al., 2015a; Tolonen 2016). However, in the extant literature, there is a research gap on how to support data-driven and fact-based PPM based on data assets and company business IT. Recent previous studies show that data assets, product master data, and supply chain product data are not utilised for data-driven PPM and are poorly defined in companies (Hannila et al., 2019). Also, lack of a data-driven approach when implementing business IT systems has led to the siloed data in isolated business IT systems (Hannila et al., 2019; Aiken, 2016; Tao et al., 2018). This results in a lack of data-driven and fact-based support for common PPM challenges, including product portfolio explosion and cannibalisation of companies' product sales (Tolonen et al., 2014; Tolonen et al., 2015a; Srinivasan et al., 2005), which weaken the financial health and success of those companies.

This study aims to expand the current literature by providing a systematic concept to utilise the company data assets when analysing products and the product portfolio to enable practical business benefits in the context of data assets, business processes, and the IT applications. From a managerial perspective, this is a fundamental need since a relatively small number of companies' products are linked to the majority of sales volumes, and companies are unable to measure the product-level profitability without excessive manual work. Product-level profitability analysis is needed to maintain and renew the company's product portfolio strategically, commercially, and in a balanced way, as stated by Tolonen et al. (2015a). Product portfolios have been expanded based on customer requirements (Hayes et al., 2005), resulting in product portfolio explosions (Srinivasan et al., 2005) and weakening of sales profitability (Gunasekaran et al. 2014; Orfi et al., 2011). The current lack of product-level profitability analyses is resulting in negative managerial implications that prevent companies from knowing which products and customers are both strategic and profitable at the same time, and what share of the product and customer portfolio is represented by those products and customers.

In this study, we attempt to reorganise essential data assets and a variety of business IT systems and solutions capabilities, and we suggest a concept of organising different business IT solutions to communicate via a digital backbone to gather the necessary business-critical data for real-time PPM analysis and reporting. Our approach is to provide fact-based support for PPM from isolated business IT systems, where the necessary business-critical data is gathered and utilised from different business IT systems without sacrificing their original functional role. A generic conceptual model is proposed to interlink three elements: 1) PPM process and other critical business processes, 2) corporate-level data model, and 3) real-time reporting and analytics to enable vertical (i.e. commercial and technical product structure) and horizontal (i.e. through the product lifecycle) PPM throughout the entire ecosystem of a company. This model is condensed into three research questions (RQs) that are introduced in the sections where they are first operationalised.

From a PPM perspective, this study focuses on all PPM performance management areas: strategic fit, value maximisation, and portfolio balance. RQ 1 is approached by the literature review on PPM, data-driven decision-making, data virtualisation, and the evolution of IT systems and solutions. RQ 2 is approached via an empirical qualitative analysis supported by the literature to examine the status quo of PPM processes and current challenges in eight international companies related to the companies' products, product structures, PPM, enterprise data assets, and data governance with related IT systems and solutions. RQ 3 aims to develop a construct to support a data-driven and fact-based analysis of products and the entire product portfolio to enable real-time analysis and decision-making based on company data assets.

2 Literature review

The literature review aims to answer the first research question:
RQ 1: *What are the elements of data-driven decision-making, and how these can be connected for PPM?*

The question is attempted to answer by literature-based clarification of the elements of data-driven decision-making and by discussing how these elements can be connected for product portfolio management. This necessitates understanding the characteristics of a data-driven organisation, exploring the evolution and role of business IT systems and infrastructure from the PPM perspective, acknowledging the importance of data in PPM decision-making, and learning the role of data virtualisation. Each of these necessary viewpoints are discussed as follows and the answer synthetised in section 2.5.

2.1 Characteristics of a data-driven organisation

A data-driven decision-making culture and the accordingly adjusted organisational structure are the most critical enablers when aiming to establish a data-driven organisation (Anderson, 2015; LaValle et al., 2011; Thusoo and Sharma, 2017; Brynjolfsson et al., 2011), and it also requires systematic data asset management at a level beyond the (IT) technology (Aiken, 2016; Aiken and Billings, 2013; Pugna et al., 2019). Technologies are enablers but not responsible for decision-making itself (Wang and Krisch, 2019). The order of importance is that a data-driven decision-making culture must be assimilated at first; the data itself is secondary, and technology is the third element (Aiken, 2016; Thusoo and Sharma, 2017). Companies adopting data-driven decision-making can increase their productivity 5-6% (Brynjolfsson et al., 2011), and the best-performing companies see analytics as a competitive differentiator and use data analytics five times more than lower performers (LaValle et al., 2011). However, companies are struggling with siloed and fragmented data in business IT systems and processes (Hannila et al., 2019; Lans, 2012; Aiken, 2016; Fisher, 2009). Creating a 360-degree view of data is challenging due to inconsistencies, conflicts, and inaccuracies in data (Lans, 2012), but the most significant barriers are managerial and cultural, rather than related to data availability and technology, and involve lack of understanding of how to utilise analytics beneficially (LaValle et al., 2011; Pugna et al., 2019).

The importance of data in decision-making is understood in a data-driven organisation. Facts, numbers, and quantitative analyses are critical drivers in decision-making (LaValle et al., 2011; Anderson, 2015; Thusoo and Sharma, 2017); emotions and intuitions are not (Maitlis and Ozcelik, 2004). It is also essential to remove data silos (Lans, 2012; Jetson and Nelis 2008; Das and Mishra, 2011), consolidate all data from different sources, and make it accessible for those who need it (Thusoo and Sharma, 2017; Anderson, 2015; LaValle et al., 2011; Fisher, 2009). New business opportunities will be missed without an expanded effort to connect datasets to master data to realise the 360-degree view (Walker and Moran, 2017). Data consolidation from business and product applications, customer interactions, monitoring systems, and third-party data providers is one of the critical enablers for the data-driven organisations (Anderson, 2015; Lans, 2012; Lenz, 2018; Thusoo and Sharma, 2017), which highlights the importance of systematic data governance (Alhassan et al., 2019; Aiken, 2016; Brous et al., 2016; Fisher, 2009; Waddington, 2008). Data governance assists business lines by standardising how business data and metrics are defined, propagated, owned, and enforced, thus improving and maintaining the quality of data in business processes throughout the organisation (Waddington, 2008; Fisher, 2009).

In addition to a data-driven culture and data, technology is an essential enabler. However, technology is meaningless without the ability to integrate it into an organisation's data model (Aiken, 2016; Fisher, 2009). Also, companies need to have several technical skills, such as file system processing frameworks, cloud computing, and data visualisation technologies. (Anderson, 2015; Bonnet, 2010; Davenport and Patil, 2012). Executives need up-to-date trends and statistics about the status quo of the business—information that requires advanced data analytics capabilities (Thusoo and Sharma, 2017; LeValle et al., 2011).

Data management has a pivotal role in data-driven organisations. A robust, functional, and centralised data team ensures connectivity between departments of an organisation (Aiken, 2016; Thusoo and Sharma, 2017; Fisher, 2009), whereas multiple data teams embedded inside the organisation would quickly create functional data silos (Thusoo and Sharma, 2017; Fisher, 2009; Aiken, 2016). The data collected must be correct, relevant, timely, accurate, clean, and unbiased, and it must be accessible, joinable, and shareable throughout the organisation. A high number of reports or dashboards alone does not mean a company is data-driven (Anderson, 2015). The old-school view relies on *descriptive analyses*, the 'rear-view mirror', to describe what happened in the past (Thusoo and Sharma, 2017; Lans, 2012), while new practices, such as machine learning (Thusoo and Sharma, 2017) and data mining (Sarkar et al., 2019) provide capabilities for *predictive analyses* (i.e. what will happen) and *prescriptive analyses* to find necessary actions to make something happen (Thusoo and Sharma, 2017).

The summarised characteristics of a data-driven organisation start with a data-driven decision-making culture that embraces data and considers technology as a support. Organisational arrangements need to support the data-driven approach, which also entails going beyond the conventional operational needs. One of the pivotal aims is consistency in data, necessitating consistent data practices, emphasising data quality, and creating systematic data governance. Approaching new opportunities may also require ways to tackle the challenges of siloed data and those caused by lack of overall understanding of a data-driven approach. A basis upon which to embrace the potential of data is needed, alongside possibilities for approaching data originating from a variety of sources and applying the potential of new technologies.

2.2 The evolution and role of business IT systems and infrastructure from the PPM perspective

Business IT systems have been evolving during the past decades in parallel with evolving business needs. In the 1980s, several enterprise solutions were introduced, such as product data management (PDM) systems, enterprise resource planning (ERP), customer relationship management (CRM), and supply chain management (SCM), which were all dependent on products' master data and related product information but which focused on different products' lifecycle processes (Ameri and Dutta, 2005); this caused data silos (Jetson and Nelis 2008; Das and Mishra, 2011; Hannila et al., 2019; Aiken, 2016) and made information sharing complicated and demanding (Madenas et al. 2014). The product lifecycle management (PLM) paradigm, introduced in the early 1990s (Stark, 2016; Ameri and Dutta, 2005), was identified as one of the key concepts aimed to improve product quality, time-to-market, and costs within manufacturing industries (Stark, 2016; Marchetta et al., 2011; Saaksvuori and Immonen, 2008). The 1990s was also the decade when data warehouses (DWs) and related best practices emerged

(Thusoo and Sharma, 2017; Mousa and Shiratuddin, 2015), and the original purpose of DWs was to help organisations in accounting by processing financial data. DWs and product data sharing between business applications have later proven inflexible and costly (Walker and Moran, 2017); the access to the original raw data disappears because of an extract-transfer-load (ETL) process, and deep learning applications or analytics are not feasible because the data processing requires structured data, making unstructured data processing slow and costly (Thusoo and Sharma, 2017). Also, any changes or enhancements to static views of data must be made by IT professionals (Muntean and Surcel, 2013), which is remarkable since 80% of the data in organisations are unstructured (Muntean and Surcel, 2013). *Data lakes* as a data storage repository were introduced in 2010 to solve DW shortcomings by providing storage also for semi-structured and unstructured data. The data schema in a data lake is decided when the data is read, loaded, or written, which make it flexible related to any raw data, and the data need not be curated before processing it (Thusoo and Sharma, 2017). Thus, data lakes also provide a platform for experimental data collected in various databases by several departments of the company during the product lifecycle, which has previously caused several issues (Borgia et al., 2015) such as interoperability, redundant information exchanges, and interconnecting systems in all lifecycle stages (Marchetta et al., 2011; Hannila et al., 2019).

Cloud computing is fighting against traditional system integrations and DW platforms since it was introduced in 2007 and is rapidly growing (Bidgoli, 2011). It attracts users with features like scalability, elasticity, lower entry cost, ease of access, flexible payment options (i.e. subscription and pay per use; Agarwal and Srivastava, 2017), and its capacity to efficiently manage massive amounts of data (Sarkar et al., 2019). One driving force from the business side is an increased demand for sharing information (Goel, 2015). *Cloud computing* is defined "as a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (servers, networks, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (Mell and Grance, 2011, p. 2). For smaller enterprises, cloud computing offers a cost-effective and safer environment (Bidgoli, 2011). Data mining, together with cloud computing, help businesses make effective, data-driven decisions about predicted future trends and behaviours based on data (Sarkar et al., 2019). Cloud computing has been widely adopted, and internet of things (IoT) is penetrating close behind. (Wang, 2019). Not only is the data itself siloed in companies but also enterprise solutions that are acquired for a specific purpose, based on 'fit-for-purpose mentality' (Hannila et al., 2019). More research is needed on how the data should be considered corporation-wide in relationship with all enterprise solutions utilising the same (master) data complemented by solution-specific business data.

To summarise, consideration of the role of business IT from the PPM perspective includes the following factors. Enterprise solutions in companies have often been introduced over time for specific purposes to meet operational needs without considering the needs of PPM and other potential uses of data and with deficient consideration of the overall logic. The applications are dependent on product master data and related product information and have a specific focus. The specific focus is one cause of siloed data. Also, solution integrations and data sharing have proven costly and inflexible. Simultaneously processing different types of data (e.g. structured, unstructured, semi-structured) is challenging. New technologies such as cloud computing and data mining have some potential, and new data sources such as IoT exist but are not yet applied to PPM. Wider use of data needs to be considered, including the use of data for effective PPM along the product life cycle.

2.3 The importance of the data in PPM decision-making

Overall, 20% of company products bring 80% of sales volume (Tolonen et al., 2015b). For this reason alone, it is crucial to recognise strategic and profitable products, customers, market segments, and technologies, especially when renewing product and technology offerings by adding new products to a product portfolio (Tolonen et al., 2015a). This recognition prevents cannibalisation among the company's own products (Lomax, 1996; Van Heerde et al., 2012) and product portfolio explosions (Tolonen et al., 2014). However, product portfolio decision-making tends to include fluctuating and compelling circumstances and too many conflicting goals by multiple stakeholders (Cooper et al., 2001) and, thus, PPM decisions tend to involve strong emotions, pet products, and the mentality of rewarding who shouts the loudest (Matilis and Ozcelik, 2004; Cooper et al., 1999; McAfee and Brynjolfsson, 2012), often with either missing or deficient facts to support the decisions. Reliable data is, hence, necessary for fact-based analysis and decision-making. One challenge is that majority of organisational data is either redundant, obsolete, or trivial (Aiken and Billings, 2013); concurrently, the amount of data is increasing rapidly (Reinsel et al. 2017).

PPM is comprised of today's strategic choices and decisions about allocating resources for product, market, and technology management, thereby determining how the business will look like in the coming several years. (Cooper et al., 1999). A failure in PPM can result in far-reaching and severe negative consequences for a business (Cooper et al., 2001). PPM is a generic challenge regardless of the size, business maturity, or history of the company. Profitability is typically measured at the company level, product portfolios are exploding in size, cannibalisation between products exists, and the PPM process is not well-defined, nor has its role been well-understood (Tolonen et al., 2014; Tolonen et al., 2015a, Srinivasan et al., 2005). Executives are not able to identify which products and customers are simultaneously strategic and profitable and their share of the product portfolio because of the lack of defined PPM process and targets and related key performance indicators (KPIs) (Tolonen et al., 2015a). PPM strategic targets and KPIs must be defined to support data-driven decision-making (Tolonen et al., 2015a; Tolonen et al., 2015b), the correct data must be recognised, and possibilities of predicting the data must be understood (Thusoo and Sharma, 2017). Insufficient PPM results in many costly operational and financial difficulties (Cooper et al. 2001).

According to Porter (1998), the company's strengths and weaknesses lie in assets and skills relative to competitors assets and skills; these include financial resources, technological posture, and brand identification. Several scholars indicate that data is a vital strategic asset for companies (Aiken and Billings, 2013; Aiken, 2016; Fisher, 2009; Otto et al., 2007; Cleven & Wortman 2010), which may be the only thing to differentiate the companies from competitors and, thus, gives data and information management a crucial role in operations. (Fisher, 2009; Chaki, 2015). The people consuming the data do not typically have statistical or machine-learning algorithm skills, so they often consume the data from key performance indicator (KPI) dashboards around metrics. Business intelligence (BI) and dashboarding tools make the data consumable, thus revealing insights from the business (Thusoo and Sharma, 2017).

According to Cooper et al. (1997; 2001), Tolonen et al. (2015b), and Weerd et al. (2006), PPM performance management focus areas can be specified as 1) strategic fit, 2) value maximization, and 3) portfolio balance. *Strategic fit* aligns the product portfolio with the company strategy concerning products, customers, market segments, and technologies. *Value maximisation* is related to financial affairs, such as sales turnover, cost, profitability (i.e. gross/net margin), and growth. *Portfolio balance* refers to the balance of high and low risk as well as short- and long-term products, customers, market segments, technologies, and resources, and the size of the product portfolio. All PPM performance management areas should be managed systematically and consistently, and the performance should be measured by accordingly adjusted PPM targets and KPIs (Tolonen et al. 2015b).

To summarise the importance of data for PPM decision-making, it is first necessary to understand that the effective use of data is needed to support PPM decision-making. Data linking to products enables recognition of profitable products, customers, and market segments, and addressing those that are unprofitable or plus or minus zero. Indications of products being strategic can be linked to products to highlight the ones that are strategic and, hence, important, but also enables examination of those that are not to support keeping if supportive and removing if non-strategic. Importantly, analysing products and product portfolios necessitates data that is systematically linked to products over their life. Reliable and consistent data is needed to decide on products now and in the future. Decisions justified by trustworthy data are better for long-term business success than those based on emotions and strong opinions. The traditionally narrow focus on PPM and deficient understanding can be challenges. Data are necessary to address relevant PPM targets and KPIs.

2.4 Data virtualisation

In the past, different parts of companies were mainly responsible for storing data and managing it locally (Reinsel et al., 2017). The transition from traditional business IT infrastructure (e.g. integrated systems, data warehouses) to cloud-based models is not smooth, but it is necessary if companies hope to provide consolidated real-time data regardless of the source system, data format, or enabling data. *Data virtualisation* (DV) is often regarded as a synonym or equated with other concepts, such as enterprise information integration (EII), data federation (Lans, 2012; Xu et al., 2015; Katasonow and Lattunen, 2014), encapsulation, and information hiding (Lans, 2012). Different definitions for all these concepts exist (Lans, 2012). In this study, comprehensive coverage of these concepts is not provided, but DV is discussed on a general level as a part of the concept proposed in this study. Lans (2012, p. XV) defines DV as:

> Making data available in an integrated fashion to applications regardless of whether all that data is distributed over multiple databases, stored in different formats, and accessible through different database languages. It presents all these different data stores to the applications as one logical database.

According to Earley (2016), DV—together with master data management (MDM)—ensures data consistency and accessibility from different sources, thus providing value for the business. Different frameworks for DV (Jankovic et al., 2018) have been provided to combine heterogeneous data sources, displaying it as one integrated data source (Mousa and Shiratuddin, 2015). An integrated data source is flexible and efficient when new data sources, data models, or new data storage technologies are combined. Also, Mousa et al. (2014) propose virtual data marts by using DV technology for real-time performance management monitoring via KPIs driven by business needs and organisational requirements.

DV with related new technologies (e.g. analytical database servers, mobile business intelligence tools, in-database analytics, highly parallelised HW platforms, and the cloud) can expand companies' reporting and analytics capabilities dramatically, thereby shortening data analysis from days, as with older technologies, to a few minutes (Lans, 2012). However, proper data management practices are required to process data and attain expected results, especially with unstructured data (Ikhlaq and Keswani, 2017). Much of ‘big data’ is unstructured or in multiple formats, and when it is necessary to combine it with structured data, the advanced business intelligence capabilities and architecture are needed; the answer might reside with DV (Lans, 2012).

To summarise the potential of data virtualisation, it is necessary to understand that a new type of approach to data might be needed in addition to addressing the operational needs with the existing business IT infrastructure. The goal is to gain new possibilities with data regardless of the data source and the format. Data virtualisation also offers one possibility for PPM decision-making. Data virtualisation may support consistency in data, combining data sources, data models, and new technologies, and it can support improving reporting and analytics capabilities to near real-time analytics.

2.5 Elements of data-driven decision-making and link to PPM

The previous literature provides several aspects for understanding the elements of data-driven decision-making and how they can be connected to PPM. First and foremost, addressing PPM necessitates understanding the nature of the products in the product portfolio. One effective way for consistent understanding of products appears to be approaching them via commercial and technical product structures. This means that products must be described in a consistent manner by using consistent logic. Data virtualisation can also support the consistency in data and opens new opportunities for reporting and analytics. Nevertheless, data-driven decision-making requires trust in data as the basis for decision-making, reliance on data analysis in decisions, predictions based on facts provided by data, and insights based on data. Data-driven decision-making links to the sources of data: the IT. The product-related data fragmented into business IT systems necessitates a holistic data governance—a layer beyond the IT technology—to avoid being drawn into the challenges of existing silos. Also, the strategic nature of the products must be understood since it can change during the product life cycle.

Finding 1: *Data driven decision-making necessitates truly trusting data and relying on data analysis and the gained insights. This necessitates holistic data governance beyond the IT technology, and avoiding the pitfalls of individual siloes. Data-driven decisions rely on understanding of products and creating consistency in product structures and logic. Data virtualisation and consistency in products support the necessary consistency in data.*

3 Research process

This research is based on three research questions (RQs), of which the first is based on reviewing the earlier literature. The literature review is based on keyword searches in article databases and covers related concepts of PPM, data-driven decision-making, data virtualisation, and the evolution of IT systems and solutions. The literature review is rather thorough within the selected focus but cannot be considered a systematic literature review as the focus was necessary basis and relevant understanding. The PPM is an underlying concept for this study, but the specific focus is on digitalising the company decision-making system in the context of data-driven, fact-based PPM. Hence, the paper largely builds on earlier PPM discussions (Cooper et al. 1999; 2001; 2002; Lahtinen et al. 2020; Tolonen et al. 2014; 2015a; 2015b) and scopes out important considerations such as PPM targets and KPIs (Tolonen et al. 2015b). The second research question is approached through an empirical qualitative analysis, supported by the literature, to examine how companies have assimilated the PPM process and to comprehend current challenges in eight international companies related to their products, product structures, PPM, enterprise data assets, and data governance with related IT systems and solutions. Based on the analysis, we found several factors hindering data-driven, fact-based PPM approach, and discussed these in section 4.2. As for a solution addressing research question 3, company processes, data assets, and business IT infrastructure are considered to support data-driven and fact-based decision-making. A practical concept for data-driven PPM is constructed in section 4.3.

Semi-structured, in-depth case company interviews (Merton et al., 1990) were performed to collect empirical data. To understand similarities and differences (Baxter and Jack, 2008) between company practices, multiple case companies were included (Table 1). The selected qualitative approach used an inductive logic for the empirical analysis. To gain an overall perception of the phenomenon, semi-structured, in-depth interviews (Merton et al., 1990) were used to understand the phenomenon as it was experienced by the case companies. The analysed companies were chosen based on their interests and intentions towards fact-based PPM. To discover the most authentic information and to avoid competing interests, companies represented non-competing business sectors. The turnover of the participating companies was between several million to billions of euros. The products that the companies design, manufacture, and sell are smart, modular, and configurable, including hardware (HW), software (SW), and services in half of the cases. Two case companies preconfigure their HW sales items for business-to-business (B2B) and business-to-customer (B2C) customers, and the SW item is a part of the product. One company produces HW products and services for an original equipment manufacturer (OEM) with a high degree of customisation. As observed in this study, typical PPM challenges in companies are balancing with the number of sales items, maximising high-selling sales items, and minimising low-selling sales items. The challenge for all companies is how to standardise the product offerings at all levels of the product structure in a strategically and financially balanced way.

Interviewees represented different roles and areas of responsibility in companies (Table 1) and provided their best knowledge of the research topics based on their roles and experiences in a company. The aim was to get informants involved comprehensively from different business domains. The interviewees were selected based on snowball sampling (Harrell and Bradley, 2009), allowing interviewees to propose knowledgeable participants, but simultaneously ensuring that key roles are included. Interviewees were introduced until no new insights were gained. The inclusion of several different roles enabled us to span a large range of perspectives for transverse coverage and reduced bias. The number of interviewees varied from two to thirteen; the variation was due to different numbers of employees in companies dedicated to the topic being studied. The company size also affected the number of interviewees. The interviews were supplemented by the company's internal materials to utilise varying sources of data for the empirical data collection.

Table 1. Characteristics of case company business, products, and interviewees.

Case	Market area	The nature of the business	The nature of products	Operational maturity	# of informants	Roles & responsibility areas of informants
A	Global	B2B	Hardware, software, service	Mature	5	Head of PLM, PLM professional (2), business development professional (2)
B	Global	B2B	Hardware, software, service	Mature	6	IT professional (2), digitalization professional, product professional, information professional, process development professional
C	Global	B2B, B2C, OEM	Hardware, software, service	Mature	8	Head of PLM, R&D professional (2) professional, Operations (SC) manager (2), product management professional, head of strategy, head of finance
D	Global	B2B, OEM	Hardware, software, service	Mature	5	Product development professional (2), PDM developer, PPM professional, Customer account manager
E	Europe	B2B, B2C	Hardware, software, service	Mature	2	Head of PLM, PDM professional
F	Global	B2B	Hardware, software, service	Mature	13	CEO, head of sales, head of marketing, production professional, PPM professional, PLM professional (2), R&D manager, R&D professional (2), product professional (2), sourcing professional
G	Global	OEM	Hardware, service	Mature	5	CEO, head of finance, head of sales, development professional, sourcing and operations professional
H	Europe	B2B	Hardware, software, service	Mature	3	Head of digitalization, business development professional, head of finance

The company representatives were interviewed by two to four researchers using a guideline. Notes were made, and recordings were utilised to support the analysis when allowed. Interviews were supplemented by the company's internal materials (e.g. guidelines, instructions, and process descriptions). Inductive thematic analysis (Braun & Clarke, 2006), was carried first researcher specifically, and classified, coded, and interpreted by each interviewer alone, after which the mutual understanding was confirmed. This enabled reduction of bias and took place first for each interview session separately and then for the whole. Company materials were utilised for triangulation. The interviews took place during the spring of 2019, and a separate seminar was arranged for participating companies to validate findings and conclusions.

4 Results and analysis

The empirical qualitative analysis aims to answer the second research question:

RQ 2: *What are the challenges of PPM in case companies related to the entire business IT landscape?*

This is to understand the challenges of PPM in case companies related to the entire business IT landscape. This objective is supported by a literature-based understanding. The considerations include PPM in the analysed companies, including products, and product structures, and enterprise data assets, and data governance with related IT systems and solutions. Based on the analysis, several factors hindering a data-driven, fact-based PPM approach were found, and these are discussed in section 4.2.

4.1 PPM in analysed companies

First, the lack of a consistent PPM process – a top management's strategic analysis and decision-making tool which products company should have in their offering – was a status quo in all case companies.

> *We do not have formal product portfolio management, but we do and think about similar activities in the background of our activities. These are things we handle before we start a new product development process. I would say it [PPM] happens on an unmanaged level*. (Interviewee in company F)

It was evident that supportive data is needed for PPM: "*Further, I would like to have data to make a decision based on the data instead of feelings*" (Interviewee in company F).

In company A, product managers were expected to take responsibility of PPM. However, they said PPM does not take place at the corporate level. The product-related decision-making [process] is not visible, either. '*This is considered case-by-case. Sometimes we do analyse business cases [related to products] retrospectively; e.g. after an unprofitable quarter* (Interviewee in company A).

The PPM process does not exist at company E, either.

> *We do not have a PPM process. We have a plan for three years, and it is reviewed yearly, and we create new [sales items] when necessary. . . . It is tough to kill existing [sales items]. In the past, we considered the whole product family. Currently, our target is to decrease the number of sales items to the optimum level. We do not have a formal process, but this is a kind of way to operate*. (Interviewees in company E)

In company D, interviewees were assumed to have "PPM process type" activities in one business area, but not systematically: '*We do this based on feelings and in short-term. We do not have a PPM process. Decisions are made by the head of the business unit and case-by-case*' (Interviewee in company D).

Several PPM process-related activities were found in company C, but these activities were not transparent through the organisation. The decisions related to products were made by top management and product management against the company strategy and with the comparison of the new products against the existing product portfolio.

Company B has recognised the need for a PPM process, but a clear deadline does not exist for it.

> *PPM decisions are done somehow, but much fragmentation exists. However, our high-volume products are managed very well. . . . As a part of the strategy process, we have some decision-making activities, but this is not formulated as a process. . . . much data is analysed as a part of it, and business intelligence analytics are used to support decision-making*. (Interviewee in company B)

In company H, some elements of the PPM process were recognised, but the formal process was missing. ‘*Some elements exist, but [PPM] is not systematically managed. All starts with customer needs and recognised opportunities. For analysis and decision-making, we have management process, which is based on recognised and understood customer needs’* (Interviewee in company H).

As a summary, companies have not internalised the strategic role of the PPM process, which is resulting in lack of PPM targets and KPIs. Some PPM-type activities are done reactively in some of the companies when required or in response to some event damaging the business. As a result, companies are not able to determine which products or customers are strategic and profitable concurrently, and the share of those products or customers in their portfolio.

4.2 Factors hindering a consistent data-driven approach

Based on interviews, several factors preventing companies from transitioning to a data-driven approach were recognised. The company size, organisational diversity, and the complexity of company products caused a divergence between companies, but the root cause remained the same. When companies were asked if they knew which of their products were strategic and profitable at the same time, they answered—without exception—that one should first know how the product is defined. It became clear that different parties within companies saw the products differently (e.g. ‘as designed’, ‘as manufactured’, or ‘as sold’). It was also unclear to some parties whether software should be included as an element of the product, and if the service provided to the customer is part of the product or more of a partnership issue.

The sales revenue of the products was tracked consistently in all the case companies, but the product-level cost control was mainly missing; sales figures were interlinked with related cost structures. The enterprise-level data governance model was found in none of the companies. The data ownership was an unknown issue in some of the companies, while others had defined the ownership on a business IT system level but without covering all IT systems.

The strategic nature of the products was typically discussed in the early phase of the product lifecycle, before starting a new product development project, e.g. comparing the new product against an existing product portfolio to figure out how the new product fits into the existing portfolio. However, none of the companies labelled or categorised products based on the strategic nature of the product in business IT systems.

Commonly for all companies, the product-related data was fragmented and siloed into several IT systems. All these IT systems had a functional role; for example, PDM/PLM was a design collaboration tool, ERP had various roles in the supply chain, and CRM maintained the customer-related information. Nevertheless, the company-level PPM analysis and reporting was missing.

The factors hindering a consistent data-driven approach can be consolidated as follows:

- Insufficient understanding of the nature of company products;
- Inadequate linkage of the technical and commercial sides of the product;
- Lack of a holistic data governance;
- Failure to understand the strategic nature of products;
- Inadequate IT support for a data-driven approach.

As a result of these factors, relevant, real-time, and reliable data is not exploitable for decision-making. These factors also prevent adequate business IT adjustments and result in a lack of relevant, real-time, and reliable information for PPM decisions. PPM is also not supported by business IT. A common understanding of the company products is prerequisite to constructing commercial and technical product structures, which together form the backbone for all product-related information and business-critical data for data-driven PPM analysis and decision-making, from both data and business IT perspectives.

Necessary steps towards a data-driven approach are distilled based on evidence and include the following stages. First, the strategic role of the PPM process and data-driven decision-making mindset must be assimilated. Three critical areas of the PPM process—strategic fit, value maximisation, and portfolio balance—define the foundation for PPM strategic targets and corresponding KPIs. Second, the company data assets need to be adjusted to support targets and KPIs of the PPM process. To make this possible, the company needs to have a clear understanding of their products both commercially and technically, then create a commercial and technical product structure which forms the corporate-level data structure in the related business IT landscape for PPM. Finally, the business IT technology must be organised to support data-driven decision-making by virtualising all the necessary business-critical information.

Finding 2: *The PPM related challenges in companies range from deficient overall PPM focus, lack of related process, and overall understanding over the strategic importance of PPM. As a result understanding over strategic and profitable products is lacking together with related performance management. These also relate to data and the entire business IT landscape. The product level approach beyond individual IT systems and their operational role is still deficient from the perspective of effective digitalised decision-making.*

4.3 A concept for data-driven, fact-based PPM

The third research question is addressed by constructing a practical concept for data-driven PPM:
RQ 3: *How should the company processes, data assets, and business IT infrastructure be organised to support data-driven and fact-based decision-making?*

The concept builds on company business processes through the entire product lifecycle (i.e. defining how the products are developed, sold, supplied, manufactured, ordered, delivered, invoiced, installed, maintained, and repaired). The data asset considerations and IT infrastructure are linked to the business processes.

Figure 1 presents the construction for data-driven, fact-based PPM created in this study. The construction is distilled based on the factors hindering the consistent data-driven approach in companies. The construct builds on company business processes that define how the products are developed, sold, supplied, manufactured, ordered, delivered, invoiced, installed, maintained, and repaired, and how data is enabling those processes. The construct provides realistic and practical means for data-driven, fact-based analysis by combining several sources of data, which together provide fact-based guidelines for PPM. These data sources consist of product/customer/supplier master data, transaction data, and IoT data, which are typically stored in different enterprise IT solutions (e.g. PDM/PLM, ERP, and CRM) as well as systems maintaining IoT data. To combine all significant data (e.g. the product sales and related cost information and sales volumes) requires a clear understanding of the company's products and correspondingly created commercial and technical product structures that form the backbone of the company business. The data is governed corporation-wide, at a level above the business IT solutions.

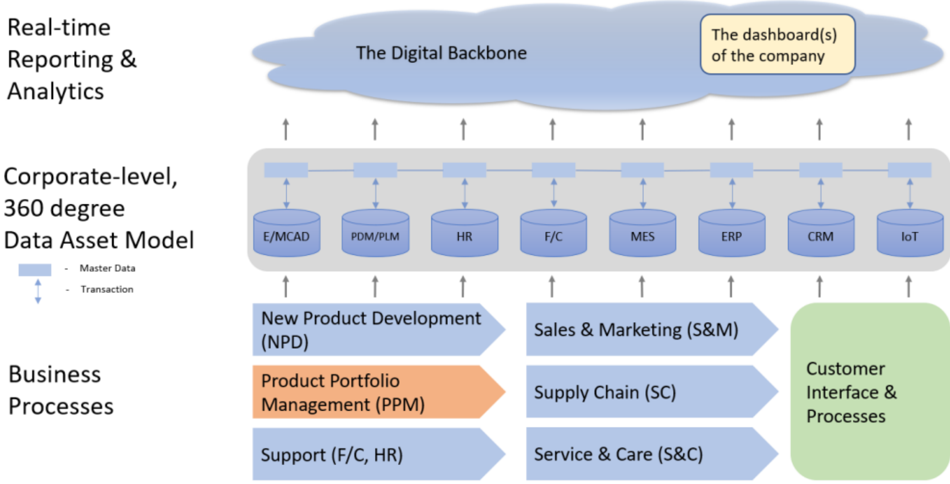

Figure 1. The developed construct to support data-driven and fact-based analysis of products and the entire product portfolio to enable real-time analysis and decisions, thus digitalising the entire corporate ecosystem.

Data governance and a holistic, *corporate-level data model has a central role in this concept to connect business processes via master data* and to ensure trustworthy data sources over business IT silos. A corporate-level data model pays attention to all *data assets, starting from master data, supplemented by transactional data and IoT data*. These assets together provide a 360-degree view of the company's data assets and simultaneous reporting and analytics capabilities through all enterprise solutions containing relevant data for fact-based PPM analysis according to company PPM performance management targets and KPIs.

The top level of *the concept provides a digital backbone*—a digitalisation platform to further digitalise the entire ecosystem of the company, not only for PPM purposes. Its role is to provide a digital platform where different enterprise solutions are connected but retain their original functional roles. For example, the PDM/PLM system retains its role as a design collaboration enterprise, and ERP remains as one of the vital tools in the supply chain. The real-time reporting and analytics are done through combined data assets from all necessary enterprise solutions by utilising all the relevant data they provide.

The overall aim is to accomplish data-driven and fact-based analysis capabilities over both products and the entire product portfolio to enable real-time analysis in which products, customers and market segments, their strategic nature, and profitability can be simultaneously assessed. Similarly, the share of products, assemblies, and components can be analysed along with the product portfolio through the lifecycle. For example, it would be possible to see which products are aligned with company strategy and, simultaneously, unprofitable. Also, it would be possible to see whether the entire product portfolio is balanced in terms of high- and low-risk products and numbers of sales items. Based on the nature of the business, *real-time* may have different meanings for different organisations, whether daily, weekly, or monthly. The data-driven analytics are necessary as company-level profitability measurement is not enough. Sustainable long-term business success and competitiveness necessitate the product-level analysis.

The concept aims to provide data-driven, fact-based support by analysing and visualising all PPM performance management focus areas: strategic fit, value maximisation, and portfolio balance. The necessary data is gathered from several business IT systems, combined, and analysed for reporting of PPM performance. Accordingly, adjusted dashboards can provide real-time information for decision-making by showing which products, customers, and market segments are strategic and profitable at the same time, and how sales turnover, costs, and profitability of products are developing and their status according to company strategic PPM targets and KPIs.

Finding 3: *Company business processes through the product lifecycle should form the basis for data-driven and fact-based decision-making to effectively involve and link to all the vital functions. This as data assets link inherently to products and business processes through the business IT infrastructure. Several data sources must be possible to combine, supported by sufficien understanding of products. Holistic data model is also necessary to link business processes via master data to gain trustworthy data . The digital backbone is a necessity to enable digitalisation to provide possibilities beyond the PPM purposes.*

5 Discussion

Conceptualising data-driven, fact-based PPM necessitates that the strategic role of the PPM process is internalised. The PPM key performance management focus areas of strategic fit, value maximisation, and portfolio balance must resonate with company strategy, which further frames PPM strategic targets and KPIs. It is also necessary to have a mutual understanding of the company products and, accordingly, established consistent commercial and technical product structures to provide the link to the related data. This data can, for example, include sales and cost information or strategic nature of products, but it is not limited here as the digitalisation of the corporate ecosystem provides a multitude of opportunities for analysis.

The presented concept for data-driven, fact-based PPM provides the initial logic for data-driven decisions in the PPM context to support the necessary consistency in data via both product structure and data virtualisation. The concept has the ability to combine data of different natures and a variety of data sources without being linked to individual systems. The independence from existing individual systems and silos has been required by companies for PPM analysis. In this way, the operational role of the existing systems remains as it is currently. The technology for applying the concept exists already.

5.1 Scientific implications

This study is in line with the extant PPM literature (Tolonen et al., 2015b, Tolonen et al., 2014; Tolonen et al., 2015a; Van Heerde et al., 2012; Cooper et al., 2001; Lomax, 1996) that emphasise the strategic role of the PPM process for the top management's decision-making based on strategic PPM targets and KPIs. Novel contribution is provided by introducing a realistic concept for data-driven PPM decision-making based on company data assets rather than on fluctuating and conflicting goals, emotions, and pet products (Matilis and Ozcelic, 2004; Cooper et al., 1999; McAfee and Brynjolfsson, 2012). This study also supports previous studies (Anderson, 2015; LaValle et al., 2011; Thusoo and Sharma, 2017; Brynjolfsson et al., 2011) by highlighting the role of data-driven decision-making culture as the most essential enabler when aiming to have a data-driven company, while the data itself is secondary, and the technology is the third element (Aiken, 2016; Thusoo and Sharma, 2017).

5.2 Managerial implications

To retain the business-driven approach, executives must understand the strategic nature of the PPM process and, accordingly, set targets and KPIs, which are the starting points to digitalise the company ecosystem for data-driven PPM. Equally crucial for executives is an understanding of the nature of the company product—whether it is HW, SW, service, or any combination—because it forms the commercial and technical product structure and related data assets (i.e. master data, transaction data, and IoT data) in business IT systems. The presented concept provides new opportunities for PPM-related analysis and decision-making by introducing a realistic setup for analysing data assets. Product-related data assets are further combined in the concept, analysed, and reported, which requires a consistent, corporate-level data model to provide necessary data for analysis and to realise the highest potential of data assets for the business. The necessary technologies exist, and the opportunities provided are not limited to PPM analysis and decision-making.

A new mindset for organisations is needed, however, to adopt new technologies and analytical skills, such as file processing frameworks, cloud computing, data visualisation technologies, and advanced analytics models, and skilled people are needed to implement them. A cultural transformation is also required for companies to embrace the role of data and its insights for fact-based decision-making.

5.3 Limitations and future studies.

This study involved only eight companies that are in a mature business stage, which might raise a limitation of a somewhat narrow research scope. This was a conscious choice and provided necessary insights to conceptualise data-driven, fact-based PPM. However, it would be interesting to study further how PPM is understood in very early-stage start-ups, emerging companies, or those in growth or expansion phases, or further differences and similarities between companies. Also, a company with a well-established PPM process, targets, and KPIs would have offered useful perspectives for this study. The actual in-depth analysis or size of the product portfolios was excluded as out of the scope of this study, which provides an opportunity for entirely new research in which the concept constructed in this study can be evaluated. The concept provided in this study offers a potential tool for more in-depth analysis of product-level profitability and its relationship to the financial health of the company. Especially interesting would be an analysis of early-stage start-up or emerging companies when the number of products begins to grow from one product to multiple products. One important area for future studies is examination of the real nature and role of the data and how to refine it in the best possible way to realise its full potential. Based on the literature and our empirical observations, data seems to be one of the most misunderstood and underutilised assets in companies. Finally, the opportunities provided by the digitalisation of the corporate ecosystem would yield exciting topics related to the presented concept to study further.

References

Agarwal, M. and Srivastava, G.M.S. (2017), "Cloud Computing: A Paradigm Shift in the Way of Computing", *International Journal of Modern Education and Computer Science.* Vol.12, pp.38-48.

Aiken, P. (2016), "Experience: Succeeding at data management-BigCo attempts to leverage data", *Journal of Data and Information Quality*, Vol.7 No.1-2, pp.1-35.

Aiken, P., Billings, J., 2013. Monetizing data management. Unlocking the value in your organization's most important asset. *Technics Publications, LLC U.S.A.* 2013.

Alhassan, I., Sammon, D. and Daly, M. (2019). "Critical success factors for data governance: a telecommunications case study", *Journal of Decision Systems*, Vol.28 No. 1, pp.41-61.

Ameri, F. and Dutta, D. (2005), "Product Lifecycle Management: Closing the Knowledge Loops", *Computer-Aided Design & Applications*. Vol.2 No.5, pp.577-590.

Anderson, C. (2015), Creating a Data-Driven Organization: Practical Advice from the Trenches, O'Reilly Media Inc., Sebastopol, CA.

Baxter, P. and Jack, S. (2008), "Qualitative Case Study Methodology: Study Design and Implementation for Novice Researchers", *The Qualitative Report*, Vol.13 No.4, pp.544-559.

Bidgoli, H. (2011), "Successful Introduction of Cloud Computing into your Organization: A Six-Step Conceptual Model", *Journal of International Technology and Information Management.* Vol.20 No.1-2, pp.20-38.

Bonnet, P. (2010), Enterprise Data Governance: Reference and Master Data Management Semantic, John Wiley & Sons, Hoboken, NJ.

Borgia, E. (2014). The Internet of Things vision: Key features, applications and open issues. *Computer Communications*. Vol.54, pp.1-31.

Borgia, O., Fanciullacci, N., Franchi, S. and Tucci, M. (2015), "The use of product information along its entire lifecycle: A practical framework for continuous development", *Issue Industrial Systems Engineering*, 2015, pp.177-182.

Brous, P., Janssen, M. and Vilminko-Heikkinen, R. (2016), "Coordinating Decision-Making in Data Management Activities: A Systematic Review of Data Governance Principles", 5th International Conference on Electronic Government and the Information Systems Perspective (EGOV), Sep 2016, Porto, Portugal. *in Lecture Notes in Computer Science*, Vol.9820, *Springer International Publishing,* pp.115-125.

Braun, V. and Clarke, V. (2006), "Using thematic analysis in psychology", *Qualitative Research in Psychology*, Vol.3, No. 2, pp.77-101

Brynjolfsson, E., Hitt, L.M. and Kim, H.H. (2011), "How does data-driven decision-making affect firm performance", Available at SSRN: http://dx.doi.org/10.2139/ssrn.1819486. Retrieved May 2019.

Carton, F., Hynes, T. and Adam, F. (2016), "A business value oriented approach to decision support systems", *Journal of Decision Systems*, Vol.25, No sup1, pp.85-95.

Chaki, S. (2015), *The expert's voice in information management. Enterprise Information Management in Practice*, Springer, New York.

Cleven, A. and Wortmann, F. (2010), "Uncovering four strategies to approach master data management", in *Proceedings of the 43rd IEEE Hawaii International Conference on System Sciences,* IEEE, Honolulu, HI, USA, pp.1-10.

Cooper, R.G., Edgett, S.J. and Kleinschmidt, E.J. (1999), "New product Portfolio Management: Practises and Performance", *Journal of Product Innovation Management,* Vol.16 No.4, pp.333-351.

Cooper, R.G., Edgett, S.J. and Kleinschmidt, E.J. (2001), “Portfolio management for new product development: results of an industry practices study”, *R&D management,* Vol.31 No.4, pp.361-380.

Cooper, R.G., Edgett, S.J. and Kleinschmidt, E.J. (2002), *Portfolio management: fundamental to new product success*. New York, Wiley.

Davenport, T.H., Patil, D.J. 2012. Data Scientist: The Sexiest Job of the 21st Century. Harvard Business Review Vol.90 No.10, pp.70–76.

Earley, S. (2016), “Data Virtualization and Digital Agility”, *IT Professional*, Vol.18 No.5, pp.70-72.

Fisher, T. (2009). The Data Asset: How Smart Companies Govern Their Data for Business Success. John Wiley & Sons, Inc., Hoboken, New Jersey.

Goel, R. (2015). Trusted Supply Chains: Surveying Competitive Value of The Cloud. *International Journal of Management & Information Systems*. Vol.19 No.1, pp.43-50.

Gunasekaran, A., Patel, C., McGaughey, R.E. (2004). “A Framework for Supply Chain Performance Measurement”, *International Journal of Production Economics*, Vol. 87, pp.333-347.

Hannila, H., Tolonen, A., Harkonen, J. and Haapasalo, H. (2019), “Product and supply chain related data, processes and information systems for product portfolio management”, *International Journal of Product Lifecycle Management.* In press.

Harrell, M.C. and Bradley, M.A. (2009). Data Collection Methods: Semi-Structured Interviews and Focus Groups. RAND Corporation, 1-140.

Hayes, R.H., Pisano, G.P., Upton, D.M., Wheelwright, S.C. (2005). *Operations, Strategy, and Technology: Pursuing the Competitive Edge*, John Wiley & Sons, Inc.

Ikhlaq, S. and Keswani, B. (2017), “Computation and management of bigdata using cloud map table framework”, *International Journal of Applied Engineering Research*, Vol.12 No.15, pp.5181-5186.

Jankovic, S., Mladenovic, S., Mladenovic, D., Veskovic, S. and Glavic, D. (2018), “Schema on read modeling approach as a basis of big data analytics integration in EIS”, *Enterprise Information Systems*, Vol.12 No.8-9, pp.1180-1201.

Jetson, J., Nelis, J., (2008), Business process management: practical guidelines to successful implementations. Amsterdam: Elsevier.

Katasonov, A. and Lattunen, A. (2014), A semantic approach to enterprise information integration, 2014 IEEE International Conference on Semantic Computing, ICSC 2014, pp.219-226.

Kumar Das, T. and Mishra, M.R. (2011), “A Study on Challenges and Opportunities in Master Data Management”, *International Journal of Database Management Systems*, Vol.3 No2, pp.129-139.

Lahtinen, N., Mustonen, E., Harkonen, J. (2020) "Commercial and technical productization for fact-based product portfolio management over life-cycle", *IEEE Transactions on Engineering Management*, 10.1109/TEM.2019.2932974.

Lans, R.F. (2012), *Data Virtualization for Business Intelligence Systems. Revolutionizing Data Integration for Data Warehouses*, Elsevier, Morgan Kaufmann Publishers in an Imprint of Elsevier, Waltham, MA, USA.

Lenz, J., Wuest, T., Westkämper, E. (2018). Holistic approach to machine tool data analytics. Journal of Manufacturing Systems 48(C), 180-191.

LeValle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. (2011), "Big Data, Analytics and the Path From Insights to Value", *MITSloan Management Review*, Vol.52 No.2, pp.21-31.

Lomax, W. (1996) "The measurement of cannibalization", *Marketing Intelligence & Planning*, Vol.14 No.7, pp.20-28.

Madenas, N., Tiwari, A., Turner, C.J. and Woodward, J. (2014), "Information flow in supply chain management: A review across the product lifecycle", *CIRP Journal of Manufacturing Science and Technology* Vol.7 No.4, pp.335-346.

Maitlis, S. and Ozcelik, H. (2004), "Toxic Decision Processes: A Study of Emotion and Organizational Decision Making", *Organization Science*, Vol.15 No.4, pp.375-393.

Marchetta, G., Mayer, F. and Forradellas, R. (2011), "A reference framework following a proactive approach for Product Lifecycle Management", *Computers in Industry*. Vol.62, pp.672-683.

McAfee, A. and Brynjolfsson, E. (2012), "Big Data: The Management Revolution", *Harvard Business Review,* October, pp.61-68.

Mell, P.M., Grance, T. (2011), The NIST definition of cloud computing. doi.org/10.6028/nist.sp.800-145

Merton, R., Fiske, M., Kendall, P., 1990, *The Focused Interview: A Manual of Problems and Procedures.* 2nd ed. New York: The Free Press.

Mousa, A.H., Shiratuddin, N. and Abu Bakar, M.S. (2014), "Virtual data mart for measuring organizational achievement using data virtualization technique (KPIVDM)", *Jurnal Teknologi (Sciences and Engineering)*, Vol.63 No.3, pp.67-70.

Mousa, A.H. and Shiratuddin, N. (2015), *Data warehouse and data virtualisation, International conference of Development of E-Systems Engineering*. In IEEE International Conference on Developments of E-Systems Engineering (DeSE), pp.369-372.

Muntean, M. and Surcel, T. (2013), "Agile BI – The Future of BI", *Informatica Economica*, Vol.17 No.3, pp.114-124.

Nelson, R. (2003), "Physical and social technologies, and their evolution", Working Paper Series, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies. Pisa, Italy.

Orfi, N., Terpenny, J., Asli, S.S. (2011). "Harnessing Product Complexity: Step 1-Establishing Product Complexity Dimensions and Indicators", *The Engineering Economist*, Vol. 56, pp.59-79.

Otto, B., Wende, K., Schmidt, A. and Osl, P. (2007), "Towards a Framework for Corporate Data Quality Management", in *ACIS 2007 Proceedings of 18th Australasian Conference on Information Systems.* Toowoomba, Australia, pp.916-926

Porter, M.E. (1998), *Competitive strategy. Techniques for analysing industries and competitors: with a new introduction.* Free Press, New York.

Porter, M.E., Heppelmann, J.E. (2014), "How smart, Connected Products Are Transforming Competition", Harvard Business Review, Vol.11, pp.64-88.

Pugna, I.B., Dutescu, A. and Stanila, O.G. (2019), "Corporate attitudes towards Big Data and its impact on performance management: A qualitative study", *Sustainability*, Vol.11 No.3, pp.1-26.

Reinsel, D., Gantz, J., Rydining, J. (2018), The Digitization of the World. From Edge to Core. *An IDC White Paper - #US44413318.* https://www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-dataage-whitepaper.pdf. Retrieved 18th Apr 2019.

Saaksvuori, A. and Immonen, A. (2008), *Product lifecycle management*, 3rd edition. Springer.

Sarkar A., Bhattacharya A., Dutta S. and Parikh K.K. (2019), Recent Trends of Data Mining in Cloud Computing. In: Abraham A., Dutta P., Mandal J., Bhattacharya A., Dutta S. (eds) Emerging Technologies in Data Mining and Information Security. Advances in Intelligent Systems and Computing, Vol.813. Springer, Singapore

Seifert, R.W., Tancrez, J-S., Bicer, I., (2016), "Dynamic product portfolio management with life cycle considerations", *International Journal of Production Economics*. Vol.171, pp.71-83.

Srinivasan, S.R., Ramakrishnan, S. and Grasman, S.E. (2005), "Identifying the effects of cannibalization on the product portfolio", *Marketing Intelligence & Planning*, Vol.23 No4, pp.359-371.

Stark, J. (2016), *Product Lifecycle Management. Vol.2, The Devil is in the Details*. Third Edition. Springer International Publishing Switzerland.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. (2018), "Digital Twin-driven product design, manufacturing and service with big data", *International Journal of Advanced Manufacturing Technology*, Vol.94 No.9-12, pp.3563-3576.

Thusoo, A., Sarma, J.S. (2017), Creating a Data-Driven Enterprise with DataOps. Insights from Facebook, Uber, LinkedIn, Twitter, and eBay. O'Reilly Media, Sebastopol, CA.

Tolonen, A., Harkonen, J., Verkasalo, M. and Haapasalo, H. (2015a), "Product portfolio management process over horizontal and vertical portfolios", *International Journal of Product Life Cycle Management,* Vol.8 No.3, pp.189-215.

Tolonen, A., Kropsu-Vehkapera, H. and Haapasalo, H. (2014), "Product Portfolio Management – Current challenges and preconditions", *International Journal of Performance Measurement*, Vol.4 No.2, pp.69-90.

Tolonen, A., Shahmarichatghieh, M., Harkonen, J. and Haapasalo, H. (2015b), "Product Portfolio Management – Targets and key performance indicators for product portfolio renewal over the life cycle", *International Journal of Production Economics*, Vol.170, pp.468-477.

Van Heerde, H.J., Srinivasan, S. and Dekimpe, M.G. (2012), "Sibling Rivalry: Estimating cannibalization rates for innovations", *Marketing Intelligence Review*, Vol.4 No.2, pp.32-41.

Waddington, D. (2008), "Adoption of Data Governance by Business", *DM review*, Vol.18 No.12, pp.1-5

Walker, S & Moran, M. (2017). Create Powerful Customer Experiences With a 360-Degree View of Your Products. Gartner report, ID:G00328027.

Wang, S. and Krisch, U. (2019), "A foundation for building a data-driven culture", *Applied Marketing Analytics*, Vol.4 No.3, pp.238-252.

Wang, Y. (2019), Understanding the impact of emerging technologies on the freight sector. Future of Mobility: Evidence Review. Government Office for Science. February 2019. Retrieved from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/777689/fom_emerging_technologies_freight.pdf

Weerd, I., Brinkkemper, S., Nieuwenhuis, R., Versendaal, J. and Bijlsma, L. (2006), "Towards a reference framework for software product management", *Requirement Engineering, 14th IEEE International Requirements Engineering Conference,* Minneapolis, pp.319-322.

Xu, X., Yang, J. and Tang, Z. (2015), "Data virtualization for coupling command and control (C2) and combat simulation systems", *Communications in Computer and Information Science*", Vol.525, pp.190-197.

Zhonglin, H. and Yuhua, H. (2011), Preliminary study on data management technologies of Internet of Things. *International Conference on Intelligence Science and Information Engineering (ISIE 2011)*, pp.137–140.