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Abstract

Product lifecycle management (PLM) is a strategy of managing a company's products all the way across their lifecycles. Empowered by new capabilities, intelligent products enable seamless information flow and thus enable closed-loop PLM. Hence, one phenomenon of particular interest is the appreciation of beginning of life activities through middle of life information. Grounded on empirical data from a multiple-case study in three distinct manufacturing industries, we explore this emergent role of product usage data for product development. In detail, we address rationales, opportunities, conditions, and obstacles. Findings indicate that (1) heterogeneous motives drive the exploitation, (2) a positive impact on every product development stage is perceivable, (3) some products and industry ecosystems are more suitable than others, and (4) technical, economic, and social obstacles challenge the exploitation. With the limitation of an interpretive, qualitative research design, our work represents a first step to understand the role of closed-loop PLM.

Keywords: Closed-loop Product Lifecycle Management, Closed-loop PLM, Intelligent Product, Product Usage Data, Product Development, Case Study

1 Introduction

Product lifecycle management (PLM) is a strategy of managing a company's products all the way across their lifecycles (Stark, 2011). Within the context of manufacturing, an established conceptualization of the product lifecycle is the division into beginning of life (BOL), middle of life (MOL), and end of life (EOL). Thereby, BOL encompasses the actions *imagine/define/realize*, MOL encompasses the actions *support/maintain/use*, and EOL encompasses the actions *retire/depose* (Kiritsis, 2011; Stark, 2011).

The traditional understanding of PLM as design support system in BOL and as service support system in MOL does not satisfy future business needs anymore. In the light of changing value characteristics from product cost, quality, and time to market to holistic customer satisfaction through product-service-systems, a stronger focus on the entire product lifecycle becomes crucial (Terzi et al., 2010). Accordingly, the future role of PLM pursues a more comprehensive approach of lifecycle-oriented thinking – closed-loop PLM (Terzi et al., 2010; Kiritsis, 2011). Kiritsis (2011) describes the information flow in traditional PLM as forward-oriented and unidirectional. In contrast, the information flow in closed-loop PLM is characterized as seamless and multi-directional through all lifecycle phases (Kiritsis, 2011). These feedback loops are enabled by *intelligent products* (Terzi et al., 2010; Kiritsis, 2011), products characterized by sensing, memory, data processing, reasoning, and communication capabilities (Meyer et al., 2009; Kiritsis, 2011). These intelligent products are stated to be prospering areas: For example, the McKinsey Global Institute forecasts the number of connected devices from 25 billion to 50 billion in 2025. Thereby, an economic impact from 3.9 trillion to 11.1 trillion USD per year in 2025 is predicted (McKinsey & Company, 2015).

However, contingent upon its novelty, the idea of closed-loop PLM has been ideated at a comparatively conceptual level (Kiritsis et al., 2008). Comprehensive research in various fields is necessary for an advanced understanding (Kiritsis et al., 2003; Jun et al., 2007). As those new technologies make subsequent lifecycle stages more accessible for stakeholders in BOL, one phenomenon of particular interest is the appreciation of BOL activities through MOL information in order to improve subsequent product generations (Terzi et al., 2010). In other words, product information flows are not interrupted anymore as soon as a product is sold (Parlikad et al., 2003; Terzi et al., 2010; Lehmhus et al., 2015). Yet, literature is surprisingly sparse in investigating this emergent role of product usage data for product development (Shin et al., 2009; Shin et al., 2014). Above all, closed-loop PLM is considered as target state and long-term goal. Less evidence from the field is available what the current state in manufacturing enterprises is. Grounded on rich empirical data from a multiple-case study in three distinct manufacturing industries, the paper at hand addresses this research gap and explores the exploitation – i.e. the process from identification to analysis and application – of those backward-oriented data, information, and knowledge flows. In line with the exploratory nature of our research, we aim to investigate the manufacturers` points of view and examine potential positive and negative implications. Hence, we formulate the following research questions:

What is the role of product usage data for product development enabled by intelligent properties?
[RQ 1] Which rationales drive an exploitation?
[RQ 2] Which opportunities emerge from an exploitation?
[RQ 3] Which conditions support an exploitation?
[RQ 4] Which obstacles impede an exploitation?

For this purpose, the remainder of this paper is organized as follows: First, we provide relevant terms and related work. Second, we introduce the applied case study research methodology. Third, we present the study's findings in terms of rationales, opportunities, conditions, and obstacles. After a discussion, we conclude with our contribution, implications for scholars and practitioners, and research limitations.

2 Background

2.1 Product development and product lifecycle management

Product development describes the process of bringing new products to market (Eigner & Roubanov, 2014). As core process of industrial enterprises, a wide range of conceptualizations and process models has been proposed (e.g., Andreasen & Hein, 1987; Ulrich & Eppinger, 2008). According to a recent conceptualization by Eigner and Roubanov (2014, p.7), product development encompasses "all activities and disciplines that describe the product and its production, operations, and disposal over the product lifecycle, engineering disciplines, and supply chain with the result of a comprehensive product definition". Although most authors emphasize the integrative function of product development (Andreasen & Hein, 1987; Ulrich & Eppinger, 2008; Eigner & Roubanov, 2014), industrial enterprises traditionally have very restricted information about the actual usage of their products as soon as they are sold to their customers (Parlikad et al., 2003; Terzi et al., 2010; Lehmhus et al., 2015).

From a historical viewpoint, PLM and antecedent forms are rooted in the early 1980s (Ameri & Dutta, 2005). With the appearance of computer-based support in product development such as computer-aided design (CAD), the need for a control instrument became a necessity. Simultaneously as product data management (PDM) systems were developed to support the design chain, enterprise resource planning (ERP) systems were designed to assist the supply chain (Ameri & Dutta, 2005). In the 1990s, the concept of PLM evolved by a horizontal and vertical extension of PDM (Eigner & Stelzer, 2008). Empowered by advancements in ICT at item-level, the concept of closed-loop PLM appeared in the 2000s as response to the wish of designers, manufacturers, maintenance, and recycling experts to benefit from seamless transparency on information and knowledge from other phases and players in the product lifecycle (Terzi et al., 2010; Kiritsis, 2011).

2.2   Intelligent products

Aside from advanced methodologies and processes (Terzi et al., 2010), intelligent products represent the main enabler for closed-loop PLM from a technological perspective (Terzi et al., 2010; Kiritsis, 2011). Describing products or systems with *intelligent* properties, various labels are used in literature. Table 1 provides an overview on established concepts from different scientific domains.

The term *intelligent product* was first discussed in 1988 and represents the predominant concept in research on closed-loop PLM (Meyer et al., 2009; Kiritsis, 2011). As we strive to contribute to this research stream as well, this paper employs the same nomenclature. *Cyber-physical system* is a notion which is rooted in the engineering and computer science domain and known from the German political initiative Industrie 4.0 (Lee, 2008; Acatech, 2011; Park et al., 2012). In contrast, the concept of *digital innovation* is native in the domain of information systems research (Yoo et al., 2010; Yoo et al., 2012). The term *smart, connected product* became famous within a seminal Harvard Business Review article (Porter & Heppelmann, 2014; Porter & Heppelmann, 2015). *Smart objects* have similar origins as intelligent products, but have been conceptualized slightly different (Kortuem et al., 2010; López et al., 2011). Although certain proximity exists, intelligent products have to be demarcated from the *Internet of Things* paradigm which rather focuses on identification and connectivity than on intelligence (Meyer et al., 2009).

Concept	Conceptualization
Intelligent products	"[…] contain sensing, memory, data processing, reasoning, and communication capabilities […]" (Kiritsis, 2011, p.480; Meyer et al., 2009)
Cyber-physical systems	"[…] are integrations of computation with physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa […]" (Lee, 2008, p.1; Acatech, 2011; Park et al., 2012)
Digitized products	"[…] digitization makes physical products programmable, addressable, sensible, communicable, memorable, traceable, and associable […]" (Yoo et al., 2010, p.725; Yoo et al., 2012)
Smart, connected products	"[…] consist of physical components, smart components (sensors, microprocessors, data storage, controls, software, operating system), and connectivity components (ports, antenna, protocols) […]" (Porter & Heppelmann, 2014, p.67; Porter & Heppelmann, 2015)
Smart objects	"[…] possess a unique identity, are capable of communicating effectively with its environment, can retain data about itself, deploy a language, and are capable of participating in or making decisions […]" (López et al., 2011, p.284; Kortuem et al., 2010)

Table 1: Selected concepts related to intelligent products

2.3   Data, information and knowledge flows

Data, information, and knowledge flows in the product lifecycle were investigated from various perspectives. For the purpose of this paper, the terms *data* and *information* are used synonymously. From a holistic perspective, aspects of information flow in PLM were investigated by Jun and Kiritsis (2012). Beyond this comprehensive view, several publications address more specifically the information flow between individual lifecycle phases. Aligned with our research objective, we focus on product usage data. As necessary prerequisite, the definition of product usage data is a common research subject. For example, Wellsandt et al. (2015a) analyzed

content of product usage information from embedded sensors and web 2.0 sources. Furthermore, Wellsandt et al. (2015b) investigated sources and characteristics of information about product use derived from real products. As subsequent step, gathering of product usage data has been examined from multifaceted perspectives. For example, Carlson and Murphy (2003) selected product failure information as main source. In contrast, Vichare et al. (2007) applied a more comprehensive approach and collected environmental and usage loads. In terms of utilization of those defined and gathered product usage data, applications can be found in BOL, MOL, and EOL. Applications targeting the MOL phase usually pursue to improve maintenance procedures (e.g., Lee et al., 2006). In contrast, Cao et al. (2011) provide an example how to leverage product usage data for EOL decisions. Although some publications try to harness product usage data for BOL (e.g., Stone et al., 2005), existing research predominantly addresses the operations phase (Shin et al., 2009; Shin et al., 2014).

Finally, looking at the body of knowledge as a whole in order to aggregate the results: First, the utilization of product usage data has been rather investigated from maintenance points of view than from design points of view. Second, existing work is highly specific and contextual. Third, the empirical perspective has been comparatively neglected. In spite of much efforts it is still challenging to understand the new role of product usage data for product development. In the following we address this research gap.

3   Research methodology

Since up to the authors' knowledge, no research with congruent goals and conditions has been published, an exploratory research strategy was selected. Guided by the study purpose, an interpretative research design and a case study approach following Yin (2009) was chosen. A case study represents an "empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident" (Yin, 2009, p.13). More specifically, a multiple-case study was selected, as those are more compelling and robust (Yin, 2009). As qualitative research is often criticized for limited transparency and generalizability (Myers, 2013), we pursue a transparent and rigorous approach despite the limited space available.

We applied theoretical sampling (Lincoln & Guba, 1989) to iteratively approach our study objectives. The rationale for the case selection was put forth along three lines in order to meet the exploratory nature of our study: First, we structured our research along the continuum from batch production to bulk production. Second, we included companies which already exploit, plan to exploit, and currently do not exploit those possibilities. Third, we pursued internationality by selecting cases from different European countries. Case organization ALPA is a special engineering company producing special machinery for luxury goods. ALPHA is characterized by the development and manufacturing of individual and rather incrementally enhanced industrial equipment with long lifecycles for internal use. Case organization BETA is a materials handling original equipment manufacturer (OEM). In their competitive market, BETA aims to differentiate their products by high quality and durability from their competitors. Case

organization GAMMA is a first tier automotive supplier. Evolved from manufacturing solely mechanical components to the development of complex mechatronic systems, GAMMA supplies a large number of automotive OEMs. Table 2 provides an overview on the case organizations and interviewee profiles.

Organization	Industry	Revenue/employees	Interviewee profiles
ALPHA	Special engineering	< 1,000 MN €/ < 5,000	[A] Head of engineering design [B] Head of control engineering [C] Project lead control engineering [D] Head of manufacturing engineering [E] Head of technical IT
BETA	Materials handling (OEM)	> 2,001 MN €/ > 10,001	[F] Project lead strategic product platforms [G] Project lead advance development [H] Project lead advance development [I] Senior engineer advance development [J] Head of product lifecycle management [K] Head of master data management
GAMMA	Automotive (first tier supplier)	1,001–2,000 MN €/ 5,001–10,000	[L] Head of innovation and technology [M] Senior engineer product design [N] Senior engineer product simulation [O] Chief information officer

Table 2: Overview on case organizations and interviewee profiles

3.1 Data collection

For data collection, semi-structured interviews acted as main source of evidence (Eisenhardt, 1989; Yin, 2009). Thereby, the interviewee selection was guided by three criteria: First, we included professionals from relevant lifecycle phases, complemented by support functions such as IT management. Second, a mix of different seniorities was included to enclose those who drive decisions and those who are affected. Third, the sample comprised experts with a blend of operational reality and strategic vision. Interviews were conducted with a guiding questionnaire developed along recommendations by Schultze and Avital (2011). Thereby, the questionnaire encompassed sections related to the interviewee`s background and current trends and developments in product development. Subsequently, questions referring to actual strategies, processes, and information systems related to closed-loop PLM addressing rationales, opportunities, conditions, and obstacles were asked. Furthermore, additional sub-questions – wherever necessary – were posed for details. The interviews were completed from August 2015 to November 2015 on a face-to-face basis with a minimal interview length of 33 minutes and maximal interview length of 95 minutes, resulting in an average of 64 minutes. Interviews were recorded, anonymized, and transcribed with the result of 115 pages of single-spaced text. Furthermore, we included complementary sources of evidence such as artifacts and archival records (Yin, 2009). In detail, we had the opportunity to intensively explore ALPHA`s, BETA`s, and GAMMA`s product development-related (PLM) and industrial service-related (SLM) IT landscape. Furthermore, we included management presentations describing strategic initiatives: Machine connectivity at ALPHA (one document), smart, connected industrial equipment at BETA (two documents), and next generation PLM at GAMMA (four documents).

3.2 Data analysis

For data analysis, grounded theory analysis techniques (Strauss & Corbin, 1997) were employed. Following an inductive approach, open, axial, and selective coding procedures were applied which is an established methodology in qualitative research (Strauss & Corbin, 1997). With the objective of rigorous and efficient data analysis, computer-assisted qualitative data analysis software (CAQDAS) NVIVO 10 was utilized (Alam, 2005; Sinkovics et al., 2005). Upon the novelty of the subject and the exploratory nature of our study, codes were aggregated inductively without applying existing concepts or theories from the body of knowledge. In the open coding stage, we generated codes and categories of recurring salient concepts that guided us during the compilation of the interview questionnaire, but strived to remain as open and unbiased as possible. In the axial and selective coding stages, we identified relationships in-between and condensed our categories. In sum, 268 codes were identified as empirical evidence. As our research is interpretive in nature, the concepts of reliability and validity need to be substituted with credibility, corroboration, and generalizability (Lincoln & Guba, 1985; Klein & Myers, 1999; Myers, 2013): First, we planned, conducted, and documented the research process rigorously to our best knowledge. Second, we applied data and investigator triangulation (Yin, 2009) by applying multiple data sources and involving two independent researchers. Third, we are aware of contrary interpretations and strived to take alternative perspectives. Finally, we evaluated our findings within focus group workshops at the case organizations (Yin, 2009).

4 Results

In the case studies, rationales, opportunities, conditions, and obstacles for exploiting product usage data for product development enabled by intelligent properties were identified. Table 3 provides an overview. Following the Pareto principle, we seek to present the most impactful aspects with subsequent in-depth discussion, rather than outlining all identified factors. Accordingly, we list the first four factors in a compact form. Although differences in the cases were carved out in a cross-case analysis (Yin, 2009), this paper refers to their commonalities.

Perspective	Identified factors
RQ1: Rationales	R1.1 - Importance of customer- and user-centric innovations R1.2 - Resource-intensive back-loaded physical testing and feedback from field R1.3 - Demand for data- and information-driven decision making R1.4 - Ubiquitous available data from secondary sources
RQ2: Opportunities	R2.1 - Specification of requirements R2.2 - Customer- and user-centric product portfolio planning R2.3 - Design and process planning for usage R2.4 - Shortening and replacing of physical prototyping and field testing
RQ3: Conditions	R3.1 - Products with long and individual operations determining lifecycle costs R3.2 - Products with self-contained systems featuring high transferability R3.3 - Products with notably high share of intelligent components R3.4 - Products in homogeneous and standardized ecosystems
RQ4: Obstacles	R4.1 - Individual and complex character of products and development projects R4.2 - Identification, collection, storage, analysis, and application of data R4.3 - Quantification of costs and benefits for an investment decision R4.4 - Preservation of the ecosystem stakeholders` interests

Table 3: Overview on identified factors

4.1 Rationales

Addressing research question 1, we identified rationales that drive the exploitation of product usage data from intelligent products for product development. First, leveraging product usage data is reasoned in the increasing importance of customers and users as source of product innovations (R1.1). Second, the resource-intensive back-loaded physical testing and feedback from the field drives the exploitation of product usage data (R1.2). Third, another motive for leveraging product usage data is the demand for data- and information-driven decision making (R1.3). Finally, in addition to those three pull factors, also a push factor was identified: Products get augmented with intelligent properties upon other reasons, for example to monitor their status or to ensure machine operator safety. Hence, ubiquitous data from secondary sources make their way into the product development departments (R1.4).

4.2 Opportunities

Addressing research question 2, we identified opportunities that emerge from the exploitation of product usage data from intelligent products for product development. Drawing on the established framework by Eigner and Stelzer (2008) who provide a more detailed product lifecycle model, four opportunities were carved out: First, product usage data enable the specification of requirements (R2.1). Second, product usage data support the creation of a customer- and user-centric product portfolio (R2.2). Furthermore, by the aid of product usage data, products can be designed and planned for usage overcoming assumption- and experience-based development processes (R2.3). Finally, product usage data have the potential to shorten and replace physical prototyping and field testing (R2.4).

4.3 Conditions

Addressing research question 3, we identified conditions that support the exploitation of product usage data from intelligent products for product development. First, products which exhibit long and individual operations that determine lifecycle costs seem particularly valuable (R3.1). Second, products with self-contained systems such as product platforms and product families featuring high transferability are qualified (R3.2). Third, products with a notably high share of intelligent components tend to be suitable as those offer additional information consuming solely minimal additional resources (R3.3). Finally, another suitable context factor are homogeneous and standardized ecosystems as such a setting facilitates data and information exchange (R3.4).

4.4 Obstacles

Addressing research question 4, we identified obstacles that impede the exploitation of product usage data from intelligent products for product development. First, from a technical perspective, products and accordingly their development projects are often characterized as highly individual and complex without the security of transferability of insights (R4.1). Second, another technical issue refers to uncertainties along the chain of identification, collection,

storage, analysis, and application of product usage data (R4.2). Third, from an economic perspective, the insecure quantification of costs and benefits for an investment decision in product (retro-) fit, IT infrastructure, and human resources was considered as a hindering factor (R4.3). Finally, the preservation of the ecosystem stakeholders` interests such as know-how protection (external view) or inordinate transparency (internal view) became apparent as critical factor for a seamless and multi-directional information flow (R4.4).

5 Discussion

The manufacturers` motive to leverage product usage data from intelligent products for product development to support customer- and user-centric innovation goes in line with existing approaches in literature of democratizing the innovation process from producer to customer and user (von Hippel, 2005; Chesbrough et al., 2009). Furthermore, the rationale to overcome back-loaded physical testing and feedback from field can be interpreted as a continuation of other measures applied to frontload engineering activities, such as modelling and simulation (Eigner & Roubanov, 2014). The goal to archive data- and information-driven decision making is familiar from related efforts summarized as *business intelligence and analytics* (Chen et al., 2012). Lastly, the rationale of ubiquitous available data can be discussed in the light of the *generativity* concept (Zittrain, 2009). Intelligent properties are added for a special primary purpose, but enable unanticipated, secondary purposes through contributions from broad and varied audience (Zittrain, 2009). Findings indicate that product usage data can be harnessed for all sub-stages of the product development process in a value-adding manner. Hence, this result contradicts the fact that current research on product usage data predominantly addresses the operations phase (Shin et al., 2009; Shin et al., 2014). As one study participant (BETA, interviewee [I]) stated: "It is smarter to leverage product usage data to design a product without failure than to employ product usage data to predict it`s failure." Whereas emerging opportunities to support product development in early stages (e.g., specification of requirements) can be advocated, the benefits of shortening and replacing physical prototyping and field testing have to discussed critically in view of the customer`s safety. Furthermore, existing literature (Kiritsis et al., 2008; Kiritsis, 2011) suggests that closed-loop PLM is valuable for various kinds of products. This study is conform, however, our research proposes that the expected benefits are dependent of variables such as product type and industry ecosystem. In this context, two phenomena need to be debated: On the one hand, the identified suitability for products with long lifecycles contradicts the opportunity of short-cyclical iterative product improvements. On the other hand, the eligibility for usage data-driven product improvement may decrease within the general trend of shortening lifecycles. The identified obstacles refer to challenges at a technical, economic, and social level. Accordingly, obstacles at various dimensions need to be overcome to successfully exploit the whole potential of intelligent products.

6 Conclusion

The paper at hand aims to explore the role of product usage data for product development enabled by intelligent properties. Our research is located in the field of closed-loop PLM. Grounded on empirical data from three distinct manufacturing branches, we identified rationales, opportunities, conditions, and obstacles. Our findings indicate that (1) heterogeneous motives drive the exploitation, (2) a positive impact on every product development stage is perceivable, (3) some products and industry ecosystems are more suitable than others, and (4) technical, economic, and social obstacles challenge the exploitation. We contribute to the body of knowledge as follows: As closed-loop PLM is a key enabler for a less resource intensive society and a more competitive industry (Terzi et al., 2010), our work presents a first step to understand the role of closed-loop PLM.

From a practitioners' perspective, we would like to encourage producers for a more comprehensive and overarching lifecycle thinking. Product designers and manufacturers should assess and leverage these new opportunities. However, our study should be regarded in the light of some limitations. Although we tried to cover the spectrum of manufacturing industries as a continuum, we had to focus on three discrete industries. This implies that our findings are on the one hand not representative and on the other hand bound to specific branches, companies, and products. Given the interpretative nature of our analysis, other teams of researchers might have identified other factors. Furthermore, due to the exploratory nature of our research, we cannot guarantee completeness. In the narrower sense, future work for scholars might encompass further empirical validation of the identified factors, for example on the basis of a quantitative survey. In a broader sense, remaining lifecycle information flows may represent a fertile field for further research.

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