



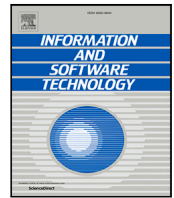
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Citation for the original published paper (version of record):

Olsson, H., Bosch, J. (2025). Strategic digital product management: Nine approaches. Information and Software Technology, 177. <http://dx.doi.org/10.1016/j.infsof.2024.107594>

N.B. When citing this work, cite the original published paper.



Strategic digital product management: Nine approaches

Helena Holmström Olsson ^{a,*}, Jan Bosch ^b

^a Malmö University, Department of Computer Science, Malmö, Sweden

^b Chalmers University of Technology, Department of Computer Science and Engineering, Gothenburg, Sweden

ARTICLE INFO

Keywords:

Strategic digital product management
DevOps
Data
Artificial intelligence
Digital ecosystems
Digitalization
Digital transformation

ABSTRACT

Context: The role of product management (PM) is key for building, implementing and managing software-intensive systems. Whereas engineering is concerned with how to build systems, PM is concerned with ‘what’ to build and ‘why’ we should build the product. The role of PM is recognized as critical for the success of any product. However, few studies explore how the role of PM is changing due to recent trends that come with digitalization and digital transformation.

Objectives: Although there is prominent research on PM, few studies explore how this role is changing due to the digital transformation of the software-intensive industry. In this paper, we study how trends such as DevOps and short feedback loops, data and artificial intelligence (AI), as well as the emergence of digital ecosystems, are changing current product management practices.

Methods: This study employs a qualitative approach using multi-case study research as the method. For our research, we selected five case companies in the software-intensive systems domain. Through workshop sessions, frequent meetings and interviews, we explore how DevOps and short feedback loops, data and artificial intelligence (AI), and digital ecosystems challenge current PM practices.

Results: Our study yielded an in-depth understanding of how digital transformation of the software-intensive systems industry is changing current PM practices. We present empirical results from workshops and from interviews in which case company representatives share their insights on how software, data and AI impact current PM practices. Based on these results, we present a framework organized along two dimensions, i.e. a certainty dimension and an approach dimension. The framework helps structure the approaches product managers can employ to select and prioritize development of new functionality.

Contributions: The contribution of this paper is a framework for ‘Strategic Digital Product Management’ (SDPM). The framework outlines nine approaches that product managers can employ to maximize the return on investment (RoI) of R&D using new digital technologies.

1. Introduction

Engineering is concerned with building solutions with the intent to solve a certain problem and to support and serve specific needs. In [1], the engineering method, and the role of an engineer, is described in terms of change, resources, finding the best solution to a problem and dealing with uncertainty. Although the reference dates back to the 80’s, the art and craft of engineering that is described applies well to the engineering of products and systems that we see today. In a software engineering context, and in development of software-intensive systems, this involves e.g., identifying and carefully considering customer requirements, designing an appropriate architecture, developing a detailed design, implementing and testing this before releasing to customers. However, whereas engineering is traditionally concerned with how to build products and systems, there is another activity

concerned with ‘what to build in the first place. And, perhaps even more importantly, ‘why’ we should build the feature, product or system. This activity is typically referred to as product management.

In research, the role of product management has been carefully studied and recognized as critical for the success of any product. In [2], product management is defined as “the discipline and business process which governs a product from its inception to the market or customer delivery and service in order to generate biggest possible value to the business”. Although the definition refers to “product management”, the authors detail this by explaining that this also includes “solution management” which is rapidly gaining importance in the software industry as well as in any industry with systems involving software parts and components. According to the authors and this definition, product management as a business process provides leadership to activities such

* Corresponding author.

E-mail address: helena.holmstrom.olsson@mau.se (H.H. Olsson).

<https://doi.org/10.1016/j.infsof.2024.107594>

Received 16 January 2024; Received in revised form 23 September 2024; Accepted 30 September 2024

Available online 5 October 2024

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as portfolio management, strategy definition, product marketing and product development. In the paper, the authors provide a detailed discussion on how a product manager looks to the overall market success and evolution of a product together with its subsequent releases and related services, and how this role involves and relates to management of software parts and components.

In software engineering research, there is rigorous research on software product management and the specific tasks and responsibilities that this role involves. The term software product management was coined already in 1997 [3]. With this, the idea of letting an individual manager championing and taking responsibility for a product, i.e., the product management role as described above, was applied to a software organization. According to [4] the software product manager extends configuration management of code and software artifacts with delivery data, customer data, and change requests. Today software product management is a discipline that is viewed as the bridge between software engineering and business. There is rigorous research to illustrate this. In [5] the authors describe how the success of a product depends on all the activities from strategy and marketing to product launch and customer support, as well as on the development activities. The authors suggest that by improving their overall product management practices, including software product management, companies can significantly reduce development and release cycle time. In [6], the authors recognize how the product manager is the key responsible for product requirements, release definition, product release, and for creating and supporting development teams as well as for preparing and implementing the different business cases. Another study describes software product management as a discipline involved in creating, delivering, and maintaining software products and systems [7]. As pointed out in [6], the product manager owns the business case and assures that a product release delivers the expected value to customers as well as to the business.

In our research, we focus on software-intensive systems. A software-intensive system is a system in which software influences the design, construction, deployment, and evolution of the system as a whole to encompass individual applications, subsystems, systems-of-systems, product lines, product families, whole enterprises and other aggregations of interest [8]. As recognized in [9], this can be products like e.g., phones, cars and airplanes. When looking at state-of-practice in development and delivery of software-intensive systems, there are numerous frameworks that support product managers in their daily activities as well as for strategic and visionary work. Based on our own experience from long-term collaboration with companies in the embedded systems domain, SAFe is one of the most common frameworks for product strategy, planning and road mapping.¹ In the companies we studied, SAFe is the primary framework for scaling agile practices and for supporting rapid and continuous development and delivery of system components ranging from mechanics and electronics to digital components such as software. For a product manager, as well as for a software product manager, agility is key. This function needs to decide how to realize agility in the system design, how to exploit its capabilities as well as focusing efforts on features that customers care about and that can be monetized.

During recent years, different versions of SAFe have become widely adopted by companies that wish to scale their agile practices, accelerate value delivery and shorten feedback loops to customers. However, there are several other frameworks for supporting and improving product management practices in general, and software product management in particular. As a few examples, the ISPM framework provides a holistic view on the activities of software product management,² the SPM reference framework identifies key process areas as well as the stakeholders and their relations [10], the SPM competence model

outlines key capabilities a software organization should implement to improve its maturity [11]. Similarly, other frameworks provide support for process improvement and process assurance [12] as well as for re-engineering product development management practices [13]. Also, numerous studies outline key success factors for product management [2] and best practices, e.g., [14–16] that are considered useful across industry domains.

However, although there is prominent research on product management and the importance of this discipline in relation to e.g., software and software development, there are few studies that explore how this role is changing due to recent, and profound, trends that come with digitalization and digital transformation. As concluded in our previous research [17], digital technologies fundamentally change development organizations and how these operate. When referring to digital technologies, we mean software, data and artificial intelligence (AI) and in our view, these have significant implications on product management and the practices that the product manager typically employs. Whereas earlier, product management was often pictured as primarily concerned with predicting the outcomes of development efforts and prioritizing requirements based on these predictions [16], digital technologies require a shift towards novel ways-of-working involving experimentation and continuous testing of hypotheses [18,19]. In particular, data and AI bring new opportunities in relation to e.g., obtaining customer feedback, generating documentation, providing insights to customers, conducting market and trend analysis, planning and prioritizing features and improving decision-making processes. At the same time, challenges are introduced as managing systems with data and AI components is different from managing a system with traditional hardware and software components. In our view, the rapid and continuous cycles, the dynamic nature, and the constant evolution that digital technologies bring to any system life cycle will have an impact on how product management practices are conducted.

In this paper, we explore how trends such as DevOps and short feedback loops, data and artificial intelligence (AI) as well as the emergence of digital ecosystems challenge and change current product management practices. Our research builds on multi-case study research in companies in the software-intensive systems domain that experience rapid changes in the business environments in which they operate and as a consequence, need guidelines for how to approach and reason about their product management practices going forward. The research question we explore is the following: *“What are the novel approaches that product managers in software-intensive systems companies can employ to maximize the return on investment of R&D when having access to DevOps and short feedback loops, data and artificial intelligence (AI) and digital ecosystems?”*

This paper is an extension of the paper titled *“Strategic Digital Product Management in the Age of AI”* [19] presented at the 14th International Conference on Software Business, 2023. In the conference paper, and based on workshop sessions in four case companies, we identified the key challenges that companies in the software-intensive systems domain experience with regards to their current PM practices. In addition, we presented an empirically derived framework in which we outline six approaches for PM in the age of artificial intelligence (AI). In this extended paper, we present new empirical data that complements our previous findings and provides the foundation for an evolution and extension of the original framework. The new empirical data involves an interview study with 12 representatives from three case companies and brings new insights on how digital technologies are changing current PM practices. Based on our previous workshop study, and the complementary interview study, we present an extended framework that provides a more fine grained categorization with nine approaches that product managers can employ to maximize the return on investment (RoI) of R&D using new digital technologies.

The remainder of this paper is structured as follows. In Section 2, we review literature on product management and we present frameworks that are currently used to support and guide this role. Also, we detail

¹ <https://scaledagileframework.com/>

² ispm.org

three digitalization trends that we see challenge and change current practices. In Section 3, we present the research method we used and the case companies involved in our study. In Section 4, we present our empirical findings from workshop sessions and interviews in the case companies. In Section 5, we present a framework for ‘Strategic Digital Product Management’ in which we detail nine approaches that product managers can use to maximize the return on investment (RoI) of R&D using new digital technologies. In Section 6, we discuss threats to validity. In Section 7, we conclude the paper and outline future research directions.

2. Background

2.1. Product management practices

Engineering is concerned with solving problems and finding the optimal solution to the problem at hand [1]. In the engineering of software-intensive systems, i.e., systems in which software influences the design, construction, deployment, and evolution of the system [8], this typically implies activities such as e.g., requirements engineering, designing an architecture, developing software, implementation of software, testing and validation of the system and finally, release to customers. However, whereas engineering is concerned with ‘how’ to build systems, there is another activity concerned with ‘what’ to build and even more important, ‘why’ we should build the system in the first place. This activity is typically referred to as product management and over the years, numerous studies have explored the activities involved in product management and the role of the product manager. In [2], the authors conclude that the role is critical and that with a consistent and empowered product management role, the success rate of projects in terms of schedule, predictability, quality and project duration improves significantly. In [11], a product manager is referred to as the “*mini-CEO of an organization*” as they are positioned at the center of the organization where they keep in contact with all stakeholders to ensure that they work towards the same goal. In [20], the author discusses how proper product management processes improve resource management efficiency, lead to increased business growth, better budget control, higher user satisfaction, increased release predictability and faster release cycles. As depicted in [21], product management is the role responsible for what the product is, how it works, whom it serves and how it affects the company and its customers. A product manager needs a deep understanding of the customer as they determine the value of every solution. As a comprehensive summary, [22] outline key product management practices in a framework involving management processes, support processes and software lifecycle processes.

Recently, increasing attention has been directed towards understanding the role of product management in agile organizations and in relation to e.g., product owners. In [23], the authors describe how the product owner represents the customer but how this role may not be sufficient. What is needed is a dedicated manager who systematically discovers features that maximize the product value and who can quickly experiment with the delivery of those features. In the paper, the authors outline how product management is a discipline that can achieve such a flow and the role of a product manager is defined as someone who continuously develops product portfolios and sustains the link to customer demands. The authors conclude that they found that the essence of the product manager role in agile is to make sure that the products are continuously linked with market demands. Similarly, [24], focuses on the product manager role in agile organizations and how methods such as SCRUM are used to support product managers in software organizations. The authors propose an agile method that helps to improve the ability to handle large amounts of complex requirements in an agile software development environment. As can be seen in the studies mentioned above, and if looking at the impressive body of knowledge in the field, the importance of this role is only increasing.

2.2. Product management frameworks

There are several frameworks and models that provide support for product management. With a focus on how to effectively scale agile practices, SAFe has become one of the most common and widely adopted frameworks in industry and it is used by companies across industry domains. In the most recent version, product management is described as the function responsible for defining desirable, viable, feasible, and sustainable solutions that meet customer needs and as the function supporting development across the product life cycle. In SAFe, the guidelines that are provided target product managers in all types of organizations e.g., hardware as well as software-oriented organizations, and the framework provides detailed advice on the activities involved in solution development and integration. In [25], the authors conclude that increased transparency, alignment, quality, time to market, predictability and productivity are the perceived benefits of SAFe, while the challenges are associated with resistance to change and controversies with the framework.

In addition to SAFe, there are prominent frameworks directed to software product management e.g., the ISPM framework. This framework provides a holistic view of key activities and tasks with the intent to establish and improve these practices in software organizations. In [26], the authors build on the ISPM framework when providing best practices for product strategy, product planning, strategic management and orchestration of the functional units of the company. In a similar fashion, the SPM reference framework identifies key process areas as well as the stakeholders and their relations [10] based on an extensive literature study as well as industrial case studies. Closely related to this framework, the SPM competence model outlines key capabilities that organizations should implement to improve product management maturity and impact [11]. The model provides an overview of portfolio management, product planning, release planning and requirements management, and the focus areas for each of these functions. In addition, the model highlights the many interactions that take place between different stakeholders and how information flows between different organizational roles and functions.

In addition to the above mentioned frameworks, there are several models that, in different ways, provide guidance for how to improve processes and ensure value delivery and time-to-market. In [12], the authors present an assessment framework that targets the unique challenges that product development organizations operating in market-driven environments face and where product managers have a critical role in addressing and solving these. Other models combine business management and product development with the intent to provide organizations with a common understanding for how to organize software product development, and in particular, activities that fall under the responsibility of the product manager.

2.3. Digitalization trends

There are numerous studies that emphasize the impact of digital technologies and new ways-of-working. As only a few examples, in [27], the authors study how continuous deployment of software improves customer support and how the use of DevOps practices help in integrating development and operations of systems. In [28], the authors show how data from products in the field changes decision-making processes as well as insights provided to customers. In [29], the authors illustrate how experimentation practices can be introduced in large organizations as a primary mechanism for transitioning towards data-driven ways-of-working. Also, there are multiple studies that highlight the power of AI and how technologies such as e.g., ChatGPT are already changing current practices and ways-of-working [30,31]. In addition to our own previous research as well as research by others, our experiences from working closely with companies in the software-intensive systems domain for more than a decade helped us identify three digitalization trends that these companies recognize as having

a major impact on existing ways-of-working and that challenge their current product management practices. Below, we detail these trends and the effect they have on the product manager role as experienced by practitioners in the field. Hence, the trends we identify are based on our experiences from working closely with companies in a domain where product management practices are critical for the success of the system. We have selected the trends that we, over time, learnt about from industry as the major ones affecting their current practices.

2.3.1. DevOps and short feedback loops

The emergence of agile practices and the model with short sprints fundamentally changed the ways in which software was developed and delivered. Over the last two decades, these practices have been adopted across industry domains and companies report on increase in value delivery and decrease in cycle time. With the emergence of DevOps, the feedback cycle with customers is further shortened when bringing development and operations together [32]. DevOps is a set of practices intended to reduce the time between committing a change to a system and the change being placed into normal production, while ensuring high quality [33]. Often, DevOps is referred to as a mindset that encourages cross-functional collaboration between teams to accelerate delivery of changes using automated builds and continuous deployment. For DevOps to be effectively adopted, technical transformations include, e.g., automated deployments using build and continuous integration tools, treating infrastructure as code, and continuous monitoring of infrastructure and system behavior in production. On the organizational side, it is crucial to build and strengthen a collaborative culture to successfully establish a straightforward communication and shared responsibilities [34].

With DevOps, the role of the product manager changes in several ways. First, it becomes much more integrated with the engineering teams. For a DevOps team, the intention is to have competences that cover the end-to-end life cycle of a feature. In this process, the role of the product manager is key in identifying, prioritizing and having the feature developed according to customer needs. In addition, the product manager in continuously concerned with adjusting and adapting the feature to potentially changing customer needs. Second, agile organizations shift from being specification-centric to becoming more experiment-centric. With an experiment-centric approach, and in each DevOps sprint, product managers have the opportunity to use data to continuously measure the impact of development efforts and hence, adopt a more customer-centric approach to product development. With DevOps, systems are grown instead of built. This means that rather than having the product manager elicit the requirements in the early phase of development and asking the team to build a feature according to a specification, the focus shifts to having the product manager define the outcomes and to ask the team to iteratively develop and deploy functionality that support these.

2.3.2. Data and artificial intelligence

Across industry domains, companies experience rapid changes to their existing practices due to the many opportunities that digital technologies bring. As recognized in e.g., [17,18], data and AI allow for continuous monitoring, improvement and optimization of system functionality and hence, continuous value delivery to customers. In addition, data and AI provide the basis for entirely new data-driven and digital offerings and companies in the software-intensive systems domain, as well as in other domains, are currently experimenting with how to monetize these offerings through new digital business models. While traditional products were typically monetized using transactional models, digital technologies bring the opportunity to have recurring revenue streams and continuous value delivery [35]. Finally, data and AI enable companies to shift towards customer business models based on customers' key performance indicators (KPIs) and two-sided markets. In KPI-based business models, companies monetize based on

how well they fulfill specific customer KPIs e.g., the number of successful deliveries on time if looking at a fleet owner within the logistic business. In a two-sided market model, data from existing customers is collected to then be monetized with a new customer segment. This allows for subsidizing the original customers while, at the same time, generating revenue from an entirely new customer base [36,37].

With data and AI, the role of the product manager shifts from being concerned with predicting the outcome of development efforts and prioritizing requirements based on these predictions, towards experimental ways-of-working where hypotheses are defined and where practices such as A/B testing are used to test these by collecting data on customer behaviors and feature performance. Also, the product manager can use data from products in the field to continuously monitor, validate and improve customer value.

2.3.3. Digital ecosystems

As a recent trend, business environments are being recognized as digital ecosystems in which different stakeholders collaborate, interact and use information technologies as common resources [38]. In [39], digital ecosystems are described as open communities where there is no permanent need for centralized or distributed control or for single-role behavior. The concept of digital ecosystems is proposed as a new way to understand the increasingly complex and interdependent systems that are being created and that are characterized by self-organization, scalability and sustainability. Furthermore, digital ecosystems have business models in which the main revenue stream no longer consists of the production of a product that is sold to customers, but rather, provision of a combination of services and products to their customers [38,40].

From the perspective of product management practices in the case companies we studied, digital ecosystems and platforms are increasing the importance of their ecosystem strategies, including activities such as e.g., establishing new strategic relationships, maintaining existing relationships to ecosystem stakeholders and being able to re-position and change the power balance if/when needed to maintain competitive advantage. Also, their ecosystem engagements are critical for development of new services as these typically involve third parties, for innovation efforts as these are often in collaboration with others, for shifting resources if and when needed. Although no business is an island and although collaboration platforms are not new, the notion of digital ecosystems come with an increasing focus on digital innovation platforms and digital marketplaces where every company need to position itself to be an attractive partner at the same time as reap the benefits of the collaboration. Since product management is critical in the planning, strategy and vision of new products, the product manager needs to have an understanding for the dynamics of the ecosystem, an understanding for how new digital platforms impact/allow for relationships to stakeholders and not the least, how to monetize and how to create monetize new/existing products in the different ecosystems in which they operate. Moreover, software product development is rapidly shifting from focusing on internal scale, efficiency, quality and serving customers in a one-to-one relationship, towards contributing to an ecosystem of multiple players [41]. In this shift, the product manager has a critical role in defining and realizing a sustainable strategy and vision of what adds value to customers. Finally, the ecosystem aspect is critical as it allows for product managers to strategically reason about, and decide, whether development of certain functionality should be conducted in-house or by an ecosystem partner.

3. Research method

3.1. Case study research

The research question we explore in this paper is the following: "What are the novel approaches that product managers in software-intensive systems companies can employ to maximize the return on investment of R&D

when having access to DevOps and short feedback loops, data and artificial intelligence (AI) and digital ecosystems?”

Our research question is of an exploratory nature. To allow us to study this research question in practice, we chose the case study method as our research approach. Case study research has become a well-established and appreciated method in software engineering research as it allows for in-depth empirical investigations of contemporary, and complex, phenomena [42]. Hence, the empirical findings and the contributions reported in this paper build on case study research conducted in close collaboration with multiple companies in the software-intensive systems domain. In [43], case studies are defined as information gathering from a few selected entities with little or no experimental control. Similarly, [44] emphasizes how case studies are useful when studying organizational contexts with complex and intertwined conceptual structures. Typically, and if looking at the many papers based on this research approach, case studies are rewarding when exploring organizational contexts and how stakeholders within these contexts experience the adoption, implementation and impact of new technologies. Also, the case study method is widely adopted when studying change management initiatives and similar situation in which different organizational and cultural perspectives and perceptions play a critical role. In our study, we adopted a multi-case study approach to explore how key trends such as DevOps and short feedback loops, data and artificial intelligence (AI), and digital ecosystems challenge current product management practices. The findings we present are based on close collaboration with a selected set of companies in the software-intensive systems domain. All the case companies are members of a larger research collaboration in which industry and academia work closely together to help accelerate digitalization (www.software-center.se). For the purpose of this research, we engaged with companies within the research collaboration of which we are part, and that expressed an interest in understanding the impact of digital technologies and how these impact and change their current practices. As mentioned earlier in the paper, we have been working with these companies for more than a decade and we meet on a regular basis. This means that we have had the opportunity and the privilege to be part of, and study, many aspects of their digital transformation journey and the implications of this. Recently, we experienced an emerging interest in product management practices and how these are changing due to digital technologies. Therefore, the case companies were selected based on their interest and willingness to explore this topic. Although the case companies differ in characteristics and domain, they are all world-leading companies with mature products, large-scale organizations that work in agile ways and with DevOps practices implemented and key stakeholders in their ecosystems. In addition, they all experience a situation in which software, data and AI are becoming increasingly important for the products and systems they develop and deploy.

In the remainder of this paper, we report on our research consisting of two phases. The first phase involves workshop sessions and frequent check-in meetings in which we discussed current practices and on-going use cases at the case companies. This phase was conducted between January 2023 and September 2023. The second phase involves an interview study conducted between October 2023–December 2023 in which we met with representatives from three case companies. In this phase, we extended the number of case companies when engaging also with case company E. This company operates in the physical security and video surveillance industry and was not part of the workshops in the first research phase. It should be noted that in addition to the empirical data collection for this paper, we also have had the privilege to work with all case companies as part of the larger research initiative for more than a decade. This gives us the opportunity to use insights and experiences from our previous work as complementary input also in this study.

3.2. Case companies

The following five case companies were involved in our study:

- **Case company A** is a networking and telecommunications company. For the purpose of this paper, we engaged with roles involved in product management, engineering management and data analytics.
- **Case company B** is a company manufacturing vehicles. For the purpose of this paper, we engaged with roles involved in product management, technology management and strategy lead.
- **Case company C** is a food packaging and processing company. For the purpose of this paper, we engaged with roles responsible for data management and connectivity and software and systems engineering.
- **Case company D** is a company manufacturing trucks. For the purpose of this paper, we engaged with roles responsible for product management, technology management and autonomous drive.
- **Case company E** is a networking and telecommunications company manufacturing network cameras, access control, and network audio devices for the physical security and video surveillance industries. For the purpose of this paper, we engaged with roles involved in data collection and data analytics.

In all case companies, we have key contacts with whom we collaborated closely with for more than a decade. When initiating the study, we reached out to these key contacts and asked them to provide us with key individuals and groups within the company for whom this research would be relevant. It should be noted that since the case companies were eager to explore this topic, they had already internal commitment from people who were interested in participating in the study. Since the companies are large multi-national companies, we interacted with a limited number of people but that represented key stakeholders with an interest in the topic.

3.3. Data collection and analysis

Our research was conducted following the typical guidelines for case study research as presented in e.g., [42]. Similarly to other guidelines and research protocols for case study research, these guidelines allow for careful research design, data collection and analysis. Our empirical data collection was conducted in two phases. In the first phase, we engaged in workshop sessions at case company A, B, C and D. The workshop sessions lasted for 1–3 h, involved 4–10 people and focused on current PM practices, challenges and opportunities that come with digital technologies, and best practices and strategies for how to address and mitigate the challenges. In addition to these workshops, we had bi-weekly and/or monthly check-in meetings (online) to review status of the initiatives and we continuously discussed solution development and next steps. In total, we met with the case companies in 12 workshops (7 workshops in company A, 3 workshops in company C and 2 workshops in company D). In general, we did not always have the same people in all workshops in the case companies. However, we made sure to have a good overlap so that there were always people attending who had experience from previous workshops. In a company context like the ones we study, it is difficult to have the same people participate in all activities due to their very busy schedule. Also, we view the variation of people as a positive thing as it helps disseminating the knowledge gained from the workshops in the company. With regards to the results, the different people brought their different expertise, and we were able to get input from several key roles and functions throughout our study.

With company B, we interacted primarily by using frequent check-in meetings (on-line) and e-mail conversations. As part of the collaboration with the case companies, we were able to follow several improvement initiatives as well as internal discussions on how to rethink and reinvent the product manager role. Also, the longitudinal nature of our research allows us to capture not only our most recent experiences in the companies, but also challenges and solutions that we have seen emerge over time and as a result of their long-term and ongoing digital transformation. It should be noted that we have worked with several of the case companies for more than a decade, and we have reported on specific teams, products and challenges in previous work. However, in this paper the focus is on product management whereas our earlier publications focused on the software engineering challenges that the case companies experience.

In the second phase, we conducted semi-structured interviews with company C, D and E between October 2023–December 2023. In this study, we met with 12 company representatives in 11 online interviews (the interview in case company E involved two people). It should be noted that case company E was added as an additional case company in this second phase of our research due to their interest in this topic and the many relevant challenges they experienced (that were similar to the challenges experienced in the companies that were already involved in the study). All interviewees were senior people with long and rich experience from their respective company and from working with software, data and AI in the context of software-intensive embedded systems. The interviewees were selected by key stakeholders with whom we have collaborated with for more than a decade and they are always very careful to only involve people with extensive knowledge and a good understanding for the company and the business. All interviews lasted for one hour and they were recorded and transcribed using the recording and transcription feature in Microsoft Teams. In addition to the transcription that was generated for each interview, one of the authors took complementary notes during the interviews. Our focus was on understanding the impact of digital technologies and how these change current practices and in accordance with this, our interviewees were senior people in roles related to digital innovation, digital transformation, product management, data analytics, marketing and sales and business development. The workshop discussions provided a valuable foundation for the interviews and the findings from the workshops were used as input, and basis for our understanding, when conducting the interviews. As only one example, the workshops revealed insights in how the product managers worked with data and this was a valuable starting point when discussing this aspect of digital technologies during the interviews. The interviews provided us with in-depth insights that helped us in our understanding of the use cases and the many ways in which digital technologies reshape and complement current PM practices.

As the basis for analysis, notes were taken during the workshop sessions, the check-in meetings and the interviews. In addition, all interviews were recorded and transcribed using Microsoft Teams. During data analysis, we adopted an interpretive approach [44,45] in which we used our documented impressions to carefully reflect on our learnings and what implications could be drawn from our empirical data. During analysis, the notes and the interview transcripts were read by both researchers to identify recurring elements and concepts. As an example, the workshops were centered around a few key themes around which our discussions focused. These themes lay the basis for our understanding of how the case companies work with customer value, how they use experimental practices and how they are increasingly using large data sets as the basis for development as well as for decision-making. When revisiting the workshop notes, we identified common patterns among the companies and these are what we report on in the results section. Similarly, the interviews were designed around a few key themes to help identify the impact of digital technologies and how these change current practices in the companies. Our analysis resulted in the nine approaches we present in the framework. The

approaches were derived from the workshop discussions and from the interviews with the intention to help structure the different approaches that product managers employ to select and prioritize development of new functionality. As suggested by [44], the generalizations we present are valuable for other organizations that experience similar challenges and contexts as the case companies involved in our study.

4. Empirical findings

The challenges experienced in the case companies are due to the rapid pace of digital transformation and the new ways-of-working that come with digitalization. From the perspective of PM, new digital technologies offer the opportunity to adopt novel approaches to key activities and tasks with the intent to significantly shorten time to market and enhance value delivery to customers. However, to achieve this, and to maximize the benefits of digital technologies, new guidelines are needed as existing frameworks often fail in effectively supporting e.g., short DevOps cycles involving continuous development and delivery of data and AI-intensive system components. This should not be interpreted as if existing PM frameworks do not provide valuable guidance and support. Instead, it should be interpreted as if existing frameworks need to be complemented with guidelines that help product managers reason about the different approaches that are available and how to best benefit from each of these. Especially, existing frameworks need to be revisited to allow product managers to expand their current tool box with new approaches that reap the benefits of e.g., data and AI. With toolbox we mean the different approaches that a product manager can employ to select and prioritize development of new functionality. If effectively exploiting these new technologies, product managers, as well as many other roles, can advance their practices and accelerate value delivery to customers.

Below, we present our empirical findings. First, we provide a summary description of the workshop sessions where we focused on the ways in which the case companies, and especially product managers, approach and manage their tasks. To illustrate the workshop discussions, we describe a few use cases that were discussed as part of the workshops. Second, we provide a summary of the interview study we conducted and in which we explored the impact of digital technologies and how these change current practices in the case companies. The workshop summary illustrates the challenges product managers face in their daily practices and the approaches they employ to manage their responsibility of realizing functionality that meet customer needs. The interview study summary provides additional details as well as an overall understanding of how different roles in the case companies experience digital transformation and the challenges and opportunities digital technologies bring.

4.1. Workshop summary

In the following sections, we share the key findings from the workshops that we conducted. We organize our findings along three main themes, i.e. customer needs, data and hypotheses and the use of artificial intelligence as these were themes that were used as overall starting points for the discussions. Based on our previous experience when working with the case companies, the challenge of how to identify and continuously ensure that customer needs are met, the challenges in adopting experimental ways-of-working and the novel challenge of using AI are key to advance and accelerate product development. Hence, these areas are critical for product management and a valuable starting-point for discussions.

4.1.1. Understanding, managing and validating customer needs

Key for all development activities in the case companies is an accurate understanding of customer needs and what brings value to the customers the systems they develop are intended to serve. Several of the case companies we studied develop safety-critical systems that are subject to strict regulations and high up-time demands e.g., telecommunications systems and networks, trucks, vehicles and manufacturing and production plants. This means that in addition to identifying and understanding requirements from customers, there is a large set of requirements that are defined by external forces. In the case companies, the primary approach to development has for a long time been a requirement driven approach where requirements are elicited and specified before any development activities are initiated. This is done through e.g., customer interviews, surveys, focus groups, and other qualitative techniques that help the development organization gather information from different stakeholders, such as e.g., customers, users, and partners, to understand what they consider valuable functionality.

From a product management perspective, requirements engineering is a critical task for understanding, managing and validating customer needs. In the workshop discussions, we learnt about several use cases where the product manager is responsible for collecting and specifying requirements as input for the development teams. Over the years, this input has been primarily qualitative in nature and based on direct customer feedback reflecting what customers believe they need and what they wish to see in the system. Based on our discussions with company representatives, we see that a requirement driven approach to development is well suited for situations in which features and functionality are well-understood, where there is a long-term agreement between the customer and the development organization and where there is less frequent change imposed on the system. The product managers we engaged with confirm that in such situations they rely mostly on qualitative customer feedback and that there is an underlying assumption that customers know what they want. However, when applied also in changing environments the requirement driven approach falls short. This was confirmed in all case companies and people report on use cases in which product managers “create an illusion of certainty” by taking a requirement driven approach also in situations characterized by uncertainty.

While understanding customer needs is one critical task, it is as important to manage evolving and changing customer needs. As an example, case company A delivers systems to a large number of customers with very different needs. The role of product management is to inventory these needs, to combine, merge, and prioritize among these, and to present a road-map with a set of requirements for the next release of the system. However, the development of systems that serve a large customer group can easily lead to a tension between two conflicting interests. On one hand, the development organization seeks to achieve scale in terms of implementing as many new features to as many customers as possible. On the other hand, the development organization needs to show responsiveness to strategic customers. This requires the ability to balance exploration and exploitation which is a challenge in the use case we studied. From a product management perspective, the example in company A illustrates the challenge of balancing individual customer requests while at the same time serving a large customer base. During the workshops in company A, we learnt that the most rewarding approach is to have some of the organization's development teams dedicated to specific customers that are identified as the most strategic ones by the product manager. Based on the requests from these customers, teams explore new features, improvement of existing features and they release software updates in an iterative and incremental fashion. Once exploration of feature improvements is done with strategic customers, these are adapted to generic customer needs and included in the planned releases. The product managers participating in the workshops agreed that this approach allows for the ability to respond rapidly to strategic customers, while over time having the benefit of exploiting feature improvements and new software updates also with the larger customer base.

To continuously validate development of new functionality, and to ensure that the intended customer value is delivered, the case companies use different techniques to visualize a design of e.g., an app, a feature or a product. These activities are often done within the user experience teams but they also involve developers and product managers. In several of the companies, customers and users are invited to events and sessions where e.g., mock-ups are used to demonstrate new functionality with the intention to collect feedback on functionality that can be hard to envision by users before trying it out. The examples we studied range from graphical interfaces to the workflow and interaction patterns users employ when using new functionality. During the workshop sessions, we learnt that the feedback received from having users try early versions of what could become new functionality is especially useful in development situations characterized by low certainty and where customers do not know what they want. In such situations, only asking users is not enough as envisioning something that might be far out in the future, or something that is changing rapidly, is very difficult. Hence, visualization techniques are useful as it helps generate more tangible feedback.

4.1.2. Data-driven identification, exploration and testing of hypotheses

Although the case companies rely on traditional requirements engineering processes for large parts of their development efforts, the discussions in the workshop sessions reflect a shift in how requirements are generated. While traditional requirements engineering process focus on interaction with customers and on collecting qualitative feedback, the availability and access to large data sets allow for a shift towards the exploitation of historical as well as runtime data to understand customer needs and feature usage. In case company E, data is collected on the configuration of systems and how customers change these. This data has proven useful as a basis for new feature and product development and for understanding user patterns that might be relevant also for development of the next generation of the system. In company A, historical data collected from network nodes and base stations reflect user behaviors that help in identifying e.g., throughput and capacity needs for new systems. Also, it helps the company understand and predict potential peaks in the system. To use historical data as a complementary technique to generate requirements is a common approach in all the case companies and similarly to traditional requirements engineering approaches, people agree that this is a useful approach in situations where requirements tend to be stable and where the system context is well known.

In addition to identifying customer needs and behaviors, we learnt about situations in which data is used to help identify e.g., anomalies or any type of pattern that is considered unexpected and rare and where e.g., key performance indicators (KPIs) deviate from what is standard. This is especially true for evolving system environments in which data that reflects metrics that suddenly start to change can be used to trigger a change request to evolve a feature or a function in a system. For the product managers we talked to, techniques that help them identify the need to evolve system functionality is critical and data has become a key asset in this process. In several companies, there are examples of use cases where the analysis of data helped the development organization identify deviating user patterns that were used to trigger a change request before the user group was able to communicate this need verbally.

Situations with low certainty are challenging for all case companies. In our workshop discussions, we learnt about use cases where product management prioritized features that, in the end, were never used by customers or used so seldom that the development efforts could not be justified. To address this challenge, company B runs A/B experiments on test vehicles with the intention to e.g., evaluate different versions of an energy optimization feature with customers. The test fleet consists of a group of vehicles and the company uses an experiment design method to address the challenge of having a limited sample size and increase the experiment power with small samples. In [46,47], we

present the software engineering aspects of these experiments. Our recent interactions with product managers in the company confirm that experimentation practices such as A/B testing are well suited for situations where there is a need to test different hypotheses and where the solution to a problem is unclear. In addition to development of software features in existing vehicles, the company has started applying experimentation practices in innovation initiatives to explore and identify the potential value of new digital services and offerings. From a product management perspective, the example illustrates the fact that companies in the embedded systems domain, and product managers within these companies, are increasingly adopting and using data-driven development techniques involving data collection and analysis as key input for feature development and improvement. In doing this, the traditional, and often requirements-driven ways-of-working, are complemented with experimental ways-of-working in which requirements are viewed as hypotheses to be tested. This reflects an important shift in PM practices and approaches.

4.1.3. Creating, retraining and maximizing use of big data sets

A common pattern in all case companies, and a topic that was high priority in all workshops, is the increasing importance of data and AI. Regardless of company or company domain, the systems are becoming connected, they collect data and they involve AI technologies that allow for opportunities that were not present a few years back. Based on our workshop discussions, it is clear that all case companies have ongoing AI initiatives with hundreds of people working with these technologies. Despite the large range of topics and the questions each company seek to answer, typical areas include e.g., autonomous drive, fleet security, personalization of devices and/or offerings, driving assistance, predictive maintenance, connectivity security, supply chain optimization, and speech and/or image recognition. At the moment, the companies have their first deployments in operation, and they are exploring viable alternatives for how to further scale machine learning (ML) model deployment.

As an example of using ML to explore and optimize large data sets, company A uses ML models for improving a paging feature. The paging feature is an existing feature in the audio stream that detects when the connection is poor. Due to the increasing complexity associated with large telecommunication networks, and competing factors such as latency, resource consumption and number of paging requests, the intention was to explore to what extent the paging feature could be improved by using ML. Another example from company A is using an ML model for detecting noise in the networks. This model is based on the 3GPP standard and does not change as the behavior is fixed. From a product management perspective, the use of ML models in these contexts illustrates the opportunity to have AI technologies complement and even replace human efforts during software development. By reducing time and costs, and by increasing accuracy in decision-making, these technologies can reduce the overall effort spent by humans. For the case companies involved in this study, the use of ML and DL technologies have significantly reduced time and effort spent on e.g., shifting through data, performing certain analysis tasks, detect e.g., flaws and/or deviations in the production line etc. For the overall R&D organization, this has huge benefits as resources can be allocated elsewhere and to other tasks. Also, the return on investment (RoI) of R&D improve as less effort are spent but the similar, or even better, results can be achieved. Also, it shows how ML models can help realize system functionality and perform classification and prediction activities that would be challenging for humans to accomplish.

In company C, ML models are used to check the packages they manufacture in order to detect any flaws or deviations in the sealings, in the gluing, or in the way the package is put together. Temperature, anomalies, and edges are analyzed to ensure quality of the sealings. Here, the data set consists of packages with different patterns and types. The architecture of this use case was presented in [48] where we show how a global model in the cloud is trained with the knowledge gained

from local model training at each client site. The learnings from the cloud are fed back and shared to the client sites for inference using transfer learning. The data set consists of packages with different patterns, types and colors and with this approach the case company can optimize performance and minimize risks involved in the production line. From a product management perspective, this approach allows for an effective way to enhance quality assurance of products while at the same time reduce efforts and costs involved.

In company D, one of the development teams use reinforcement learning (RL) to explore the reward of introducing a new feature into existing autonomous trucks. The use case is concerned with monocular depth estimation and in a recent paper we present the software engineering aspects of this case by detailing the algorithm, the data sets and the simulations that were conducted [49]. The approach is of particular interest in contexts characterized by low uncertainty and where systems need to quickly respond to dynamic environments. From a product management perspective, the use case example illustrates how the reinforcement learning approach allows for effective exploration of an action space to determine if there is sufficient reward to be accomplished by introducing the monocular depth estimation feature to existing autonomous trucks. As a result of using the approach, product managers can increase efficiency of tasks where human effort would be too time-consuming, expensive and/or inaccurate.

4.2. Interview summary

Below, we present the findings from the interview study. Our focus was on understanding the impact of digital technologies and how these change current practices in the case companies. In what follows, we summarize the key insights from this study with the intent to provide an overall understanding of how the case companies experience digital transformation. We structure our findings using three areas that emerged from the interviews and that were mentioned by the majority of the interviewees as key areas where digital technologies have a major impact. The three areas are development lifecycles, new service development and business and ecosystem innovation.

4.2.1. Development lifecycles

As a common theme in our interviews, the interviewees recognized how new technologies in general, and the increasing amounts of data in particular, are changing the traditional development lifecycle. For almost every use case, there is now the opportunity to use data for exploration, development and optimization of that particular use case. While this brings a range of new opportunities, it also allows companies to revisit existing practices and improve these using data. As an example, all case companies use requirements-driven approaches where they identify customer needs and translate these into system requirements. Traditionally, this was done primarily by using qualitative approaches where customers were asked what functionality they need and what they wish to see in the system. While this is still a valid approach, the case companies are advancing their practices by using data to help them understand not only what customers say they do, but also to measure what they actually do in practice. Typically, there is historical data reflecting customer behaviors and feature usage and for the case companies, this data brings important insights that help in identifying, defining and realizing customer needs. This is particularly true for situations characterized by high certainty and where customer behaviors do not change that rapidly.

Besides historical data that reflect e.g., feature usage or customer behavior, all interviewees report on an increasing interest and ambition to use more real-time data. Especially, the automotive company representatives report on large amounts of high-frequency and real-time data with electric and autonomous vehicles. Similarly, the two interviewees in company E highlight how the number of connected devices is increasing and how this brings new opportunities in terms of larger data sets: “...the number of connected devices are growing and all the

technical capabilities are there. For us this means new opportunities both in terms of product improvements and in our understanding of our customers". It is clear from all interviews that the availability of data support the entire development lifecycle and that historical as well as real-time data serve different purposes. In addition, it allows for presence at customer site as recognized by one of the data scientists in company E: *"...you are able to be more 'present' at the customer site through a remote connection even if not there physically"*.

The five interviewees in company D all describe how development teams use data to explore the potential value of a particular use case, how they use data as the basis for development of new features as well as improvement of existing features, and for continuously optimizing functionality to even better serve customers. In one of the interviews, this is highlighted by the interviewee when saying: *"Nowadays we can use, process and access data in clever and effective ways to reach the outcomes we are looking for"*. Similarly, another interviewee from company D note that: *"Many of the use cases require pulling data from a variety of different sources. When successfully done, this allows for flexibility and for the ability to quickly respond and adjust to the needs of R&D which is critical during exploration and development of use cases"*.

In company C, one of the interviewees refers to the opportunity to use digital twins as a mechanism to explore, understand and validate potential use cases. According to this interviewee, the concept of a digital twin offers great benefits in contexts characterized by strict regulations and where simulations of real situations and their outcomes are critical for decision-making. While simulations are well-established as a practice, the increasing amounts of data help leverage the benefits, improve accuracy and increase the number of use cases that can be explored.

The product managers involved in our interviews refer to the increasing amounts of data as both a challenge and an opportunity. While the challenges are typically associated with how to effectively use the data and how to ensure the quality of the data, the opportunities relate to the potential to significantly improve prioritization and decision-making processes. As a common view, product managers appreciate the opportunity to base their decisions on quantitative feedback, i.e., by measuring customer behavior, as a complement to the qualitative feedback from customers in which they express what they did, do or will do. This opportunity has an impact in the early phases of development as well as during development, and it expands the tool box that product managers have available when identifying, prioritizing and realizing functionality.

4.2.2. New service development

In our interviews, we note a recurring theme of how digital technologies lay the basis for new and more advanced service offerings. The interviewees report on how the companies use data to provide customers with insights that help them monitor e.g., efficiency and productivity during the life cycle of their products. For example, company D collects data on the average load of trucks and offers fleet management solutions that provides fleet owners real-time insights into the location of vehicles, state of the drivers and other relevant information. Company A offers network status visualization tools that provide operators with real-time accurate and easy-to-use insights on the status of the networks allowing for identification of potential issues and accelerated troubleshooting. In one of the interviews in company C, the interviewee reflects on this when saying: *"We are continuously looking to generate data that allows customers to answer questions about their own performance, so that they can analyze their own performance"*.

As even more advanced services, the case companies use data to help customers compare their performance with others. For example, company D collects data that helps fleet owners compare their operational efficiency with other fleet owners. In addition, the company has a feature that allows trucks to download data from high-resolution commercial topography maps that are accessible online. This information is then used to help reduce fuel consumption when driving in e.g., rough

road conditions or up a hill. In this example, as well as in similar examples in other case companies, products in the field share data with the company that is aggregated and provided back to all products in the field. In this example, data is used to improve performance of all products of all customers. In company C, one of the interviewees who is responsible for automation and digital innovation refers to the ways in which data is fundamentally changing current businesses when saying: *"We no longer sell the filling machine and the material itself, we sell it as a service"*.

All interviewees highlight the increasing use of data, the increasing volumes of data, and the increasing challenge with data quality as new services build on this data. In particular, all interviewees agree on the importance of data quality. In all case companies, data lays the basis for new data-driven and digital services and it is also used as input to AI/ML models. Therefore, the quality of the data is critical and all interviewees report on significant efforts being spent on cleaning, processing and labeling data. One of the interviewees in company D emphasizes this when saying: *"Any data that is used for commercial data driven services needs to be in a 'data-as-a-product' state and this means high-quality and trustworthy"*. A dimension that was frequently mentioned by both data scientists and product managers involved in our interviews, is the importance of having high quality data as the basis for decision-making. For the product managers, data is the input for prioritization of features, monitoring of feature usage and whether or not feature perform as expected. Several interviewees emphasized the opportunities associated with data-driven decision-making but at the same time, they recognized the risks involved. As one example, one of the interviewees in company D shared how: *"It's also the cost of incorrect conclusions because of wrong analysis, or analytics on incorrect data, or simply misinterpreted data because of unclear semantics of the data"*. Everyone agreed on data as a key asset and that becoming data-driven is no longer an option. The ability to provide customers with data-driven and digital services is key to stay competitive and this will have an impact on all roles and all levels in the companies. From a ways-of-working perspective, data allows for more exploratory development in which data is used in short, iterative cycles to continuously test hypotheses and explore new innovative use cases.

4.2.3. Business and ecosystem innovation

The case companies operate in business ecosystems where they collaborate with, compete with, share with, and learn from other stakeholders. Several interviewees referred to digitalization as an opportunity to extend and improve existing product offerings and examples such as e.g., remote diagnostics, preventive maintenance, continuous deployment of software updates, automated troubleshooting, and automated release and configuration of systems were mentioned. However, a common opinion among the interviewees was that the main benefits with digitalization are not associated with adding digital capabilities to the existing physical products but rather exploiting data and AI for innovation of entirely new offerings. If successful, this allows for new and recurrent revenue streams, the opportunity to accelerate value creation, to replace transactional business models with continuous models, and rapid cycles for exploring, developing and validating customer and market needs. In the interviews, people mentioned subscription services, "pay-as-you-go" business models, recommendation and prediction services, and opportunities to have systems dynamically optimize parameters for self-monitoring purposes as examples of new innovations realized by digital technologies.

From the interviews, it was clear that digital technologies change the ways in which current business ecosystems operate and one of the interviewees refer to this when saying: *"We have these new technologies around AI which will basically shift the positioning of the ecosystem and remove certain players. Also, new players enter and in our business we see examples of companies forward integrating to e.g., get closer to customers and increase access to data"*. This interviewee continues by describing how digital technologies are changing the business landscape as well as

the pace of innovation. While this offers endless opportunities, there are challenges involved as well: *“The pace of innovation that you have around data, and the many new opportunities with AI, is difficult to grasp and many people have still not fully understood them”*. Similarly, other company representatives that we met with in our interviews emphasized the general need to step up and advance the digital capability in the companies. Also, everyone agreed on the challenge of follow and keep up with the speed of technology evolution in their respective industry domains.

5. Strategic digital product management

Product management is concerned with determining what to build and why to build it. The goal of this decision process is to maximize the return on the investment of the R&D resources. To accomplish this, the product manager is required to predict what the impact of a function or features on the customer, market and other stakeholders will be. However, predicting the impact of new functionality is far from trivial and traditionally the product manager simply had to prioritize the content of a release based on their best understanding and assessment. Due to technology development however, we are gaining access to several new mechanisms that we can exploit to increase the accuracy of our predictions or, at least, decrease the amount of waste associated with building functionality that, in hindsight, turns out to be irrelevant. These technologies include DevOps, data-driven ways of working as well as artificial intelligence. Below, we discuss these technology trends and how they impact the role of product management.

5.1. Technology trends

With the emergence of DevOps, we gain access to a new mechanism: as the release frequency is significantly higher than with traditional approaches to software release, we can afford to experiment with new functionality before completing it. In this way, DevOps allows for building a slice of new functionality, get it out to some of the customers and use experiments to incrementally add and improve a feature. Experimentation is particularly important in cases where the certainty that a feature will add value is low. Research shows that potentially more than half of all features in a system are never used or used so seldom that the R&D investment was wasted [50]. Experimentation is a powerful approach to address this challenge as we can answer the question on whether functionality adds value with a much lower investment.

Although many may consider the era of Big Data to be concluded already, our experience shows that many companies still struggle with adopting data-driven ways of working. However, product management can increase its effectiveness as well as the effectiveness of R&D efforts significantly by using data as part of the prioritization and decision processes. Many companies use data primarily as a tool to confirm beliefs already held by key decision makers in the company [51], but the primary value that product managers can gain from using data is where it disproves commonly held beliefs in the organization.

The third technology that has a major impact on product management is, of course, artificial intelligence and specifically machine- and deep learning. Especially in cases where it is difficult to algorithmically develop a solution for a particular feature or requested functionality, the use of a data set to train a ML/DL model that embodies the desired functionality can be a powerful technique. Even in cases where we know how to build functionality in an algorithmic fashion, it may still be much more efficient to train a ML/DL model. These models can then perform classification, prediction as well as other forms of inference.

The technology trends we see build on each other and interplay with each other. In the companies we studied, DevOps and short feedback loops are required to use, and benefit from, data in an effective way. Using a DevOps approach, companies can continuously generate data and use this data in fast cycles. As recognized in the companies we

studied, this often results in an interest from partners in the ecosystem who wish to get access to, build on, and exploit the use cases this data represents in e.g., cross-industry collaborations and/or digital business platforms.

5.2. Uncertainty

As product managers predict the impact of new features or functionality, we can recognize that there are different levels of uncertainty to contend with. First, there are features and functions that the system simply needs to contain. This can be the case because of competitor parity, regulatory compliance or simply legacy features. Second, there is functionality as well as features that need to evolve over time. These changes can be in response to evolving customer preferences, for instance for recommendation engines in e-commerce sites, because of evolving contextual technologies, such as new release of operating systems such as Linux, or simply because other, related functionality in the system is changing. Finally, especially for more radical ideas and concepts, it is often quite unclear whether the new functionality or feature is even desirable and whether it delivers on the expectations that product managers and others in the company have. In this case, there is often a strong tendency to create artificial (or fake) certainty, as humans dislike uncertainty. In these cases, it is important to simply accept and communicate that the impact of new functionality is highly uncertain.

In our experience, digital technologies allow for more rapid response, as well as an increasing opportunity to learn from e.g., data, which improves the capability to respond to change and manage uncertainty. Also, we note how the contexts in which software-intensive products and systems are used are becoming increasingly complex and hence, dynamic. With new application areas, there is an increased uncertainty in what is the optimal solution for customers and this is something that PM's, as well as other functions in the companies, are trying dealing with. In the framework we present (Fig. 1), we offer techniques for low certainty situations. Although our focus is on management of existing products rather than innovation of entirely new products, the approaches we present might be helpful, also in this context. Our intention is that product managers can use these techniques to minimize investment in any type of innovation until it is shown that the idea indeed has traction.

The challenge of uncertainty and change over time also exists for ML/DL models. In some cases, the input data and the domain in which the system operates is rather static and it is sufficient to train a model once and deploy it. In many situations, however, the context in which the system operates evolves over time. In the context of ML/DL models, there are two basic approaches to accomplish evolution of models, i.e. retraining and reinforcement learning. We will discuss these in more detail below.

5.3. The SDPM framework

As a means to structure the different approaches that we see product managers employ to select and prioritize development of new functionality, we have developed a framework. This ‘Strategic Digital Product Management’ (SDPM) framework is inductively derived from our empirical findings and organized along two dimensions, i.e. a certainty dimension and an approach dimension. The framework reflects the insights we got from the case companies, and our generalizations we draw from the individual use cases. For example, our empirical data shows that all companies use a mix of traditional (e.g., requirements-driven), data-driven and AI techniques when continuously trying to identify, understand and improve customer value. Also, these different techniques are exploited in contexts ranging from very stable and high-certain to more uncertain contexts where customer needs change and where predictions are more difficult. These insights lay the basis for the two dimensions in the model and for each of these, we identify

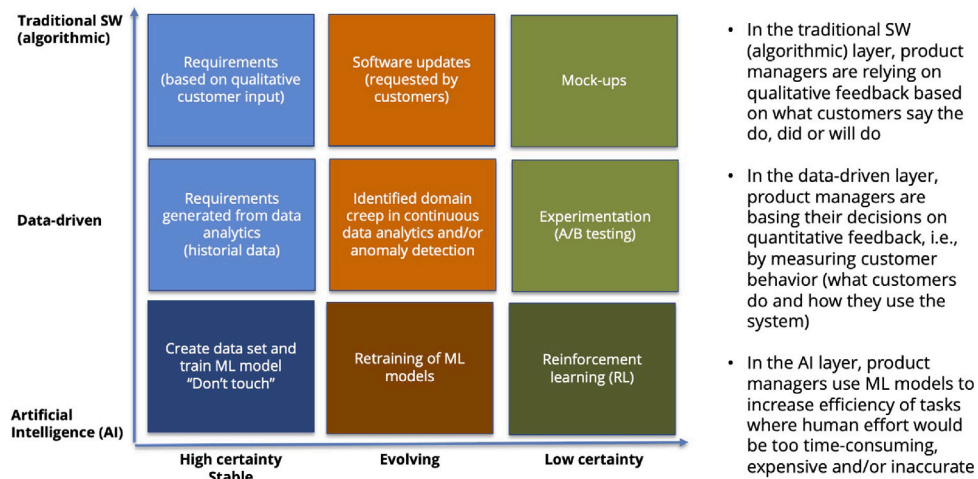


Fig. 1. Strategic Digital Product Management (SDPM) framework: nine approaches.

the available approaches to help structure the “toolbox”, i.e., the many available approaches, we see rewarding for PM. Our intention with the framework is to illustrate that there is an increasing need to adopt data and AI-driven approaches as these, in our experience, help product managers in maximizing the return on investment of the development efforts necessary to realize new functionality. The different use cases we describe and that were explored during the workshops and the interviews provide the basis for the nine approaches in the framework. While an individual use case are not directly represented, the framework reflects our overall understanding of the types of approaches that are rewarding in a particular situation. The approach dimension and the certainty dimension are a result of our understanding of the case companies and how they work. As illustrated in the empirical section, the case companies employ a range of different approaches, i.e. traditional, data-driven and AI. These approaches are more or less suited for different contexts (high certainty, evolving and low certainty). The dimensions are based on our interpretations and our analysis of the empirical data and the empirical examples we got from the companies. Our framework is intended to help structure the many available approaches that we see companies employ. Also, it helps identifying what approach is suitable for what type of context. In Fig. 1, the framework that we developed during our study is outlined.

As shown in the figure, we identify nine approaches that product managers can use and we discuss each of these in more detail below. It should be noted that the framework, and the nine approaches, are focused on the individual product manager in an organization and hence, can be viewed as a “toolbox” for this person/role.

- **Algorithmic & Stable:** This is the traditional product management case where product management collects qualitative input from customers, defines new functionality based on this input and then defines a requirement specification to reflect the customer input. This requirement specification is then provided to the development organization to execute upon.
- **Data-driven & Stable:** Once increasing amounts of data are collected from systems in the field or in the cloud, it becomes easier to use data instead of verbal customer input to identify new functionality. In this case, product management also develops a requirements specification but the content is based on quantitative data and often includes quantitative success metrics that need to be accomplished in order for the functionality to be considered successful.

It is important to distinguish these two approaches. In the former, we are basing our decisions on what customers say they want whereas in the latter, we base ourselves on what customer actually do in practice. This is an important distinction as there is

ample research that shows that there are significant discrepancies between what people say they do and what they actually do.

- **AI & Stable:** The third approach in the stable context of development is where we, instead of using an algorithmic approach, resort to a machine learning (ML) and/or a deep learning (DL) model. In this case, the training data is largely timeless in that it is not expected to change much over time. This means we can train a model, deploy it and can refrain from updating it later on. An example of such a situation is e.g., an ML model based on a standard such as e.g., the 3GPP standard as is common in case company A. In such situations, the model does not change as the behavior is fixed.
 - **Algorithmic & Evolving:** When we do not have quantitative data coming back from the field, we need to rely on customer feedback. In this case, the customer provides input on the need for certain features or functionality to evolve. Based on that input and confirmation of it with other customers, the product manager defines a change request that the development organization uses to evolve the functionality.
 - **Data-driven & Evolving:** Once quantitative data from our systems is available, we can track in real-time whether functionality and features are performing as expected. When we see that the KPIs are starting to deviate and deteriorate, we can use that as a trigger to formulate a change request to evolve the feature or functionality. The challenge is that even if it is obvious that the system needs to respond to changes, it may not be obvious how it should do so. To address this, we propose exploratory development where teams try alternative solutions to figure out the most rewarding path forward.
 - **AI & Evolving:** Many ML models experience creep in the data that is used as input for the model. As a consequence, the performance of the model often starts to deteriorate over time. In this case, it is important to engage in periodic or trigger based retraining of the model. During the retraining, the most recent data is used in order to make the model as aligned with current reality as possible. Although the trigger for retraining may be automated, in most cases there is a human who decides whether a new model goes live or not.
- There are challenges around when to retrain, define trigger points and how to ensure that appropriate monitoring is in place. Still, the opportunity to use ML models for managing system evolution is critical for PM practices going forward as it comes with benefits that are hard to accomplish in traditional software development.
- **Algorithmic & Low Certainty:** In cases where new features or functionality is proposed, either by customers or from within the

company, but the certainty of this input having the expected impact is very low, we need to adopt an approach that limits the R&D investment between customer proof points. As we cannot measure the usage of partially developed functionality, the most suitable approach is to create mock-ups that can be used to collect qualitative customer feedback.

- **Data-driven & Low Certainty:** In cases where data can be collected from deployed systems, we can employ more experimental approaches such as A/B testing. In this case, we extend the system with a slice of newly developed functionality and provide it to some users but not to all. This allows us to measure the impact of new functionality. Of course, if we are confident that we need to build the feature or functionality, but are not certain how to realize it, we can experiment with multiple alternative implementations.

As we shared earlier in the paper, many features in contemporary systems are never or hardly ever used. The goal of experimentation is to determine whether a new features should be part of the system at all. If the product manager decides that a new feature or function should be realized through algorithmic code developed by a team, the suitable approach is to ask the team to conduct A/B experiments. The goal of the A/B experiments is to determine if there is sufficient value for customers or the company providing the system to its customers.

- **AI & Low Certainty:** In the case of AI, it is prudent to use reinforcement learning in cases of high uncertainty. In this case, the algorithm is given a state space and an action space. Based on the action the reinforcement learning algorithm takes it receives a reward. Based on this, the algorithm learns, over time, what action is preferred in each situation. In an evolving system, the algorithm continuously spends a small amount of its time exploring. Consequently, when an alternative action is becomes more suitable over time, meaning the reward goes up, the algorithm will learn this and adjust its behavior.

To summarize this section, the role of product manager is to decide what functionality to build in high degrees of uncertainty and a continuously evolving contexts. The SDPM framework we present identifies nine approaches of how to realize functionality that meets the specific constraints for each of the identified situations. In the end, the product manager needs to decide between these approaches based on his or her best understanding of the situation. In general our guidance is to select ML/DL models over algorithm-based development when feasible and to treat new functionality with more uncertainty than what one might initially believe. Both these guidelines allow for data-driven decision making and reduced development efforts.

While the individual product manager, as well as most roles within an organization, is subject to the influences of the surrounding business ecosystem, the approaches we present are intended to advance the ways in which the product manager can work to select and prioritize development of new functionality in collaboration with the R&D organization. The ecosystem perspective is primarily used as a context in which the product manager operates and in which e.g., requirements are formulated, experiments are conducted, hypotheses are tested, and prioritization of functionality is conducted. Hence, the nine approaches we present are applicable also to the ecosystem context as e.g., the hypotheses a product manager wants to explore, and test, will most often influence the surrounding ecosystem. In addition, input for hypotheses will often originate from the ecosystem and consequently, the product manager is in continuous interaction with the business ecosystem. As part of our research, and the results we present, we are looking for ways in which we can support product managers in a more systematic and strategic engagements with the ecosystem.

6. Threats to validity

The validity of a study implies the trustworthiness of the results, which is divided into construct, internal, external, and reliability [42]. In our first research phase, we collected empirical data from workshop sessions and frequent check-in meetings with key stakeholders within each case company. To address construct validity [45], we made sure to define key concepts and terminology in the introduction of each workshop as well as in the different meetings. This included a definition and a discussion with the company representatives on concepts such as DevOps, data, AI, and digital ecosystems as these were key concepts in our research. Although there were situations in which people had different understandings on the specifics of these concepts, they all agreed on the general characteristics and the broader definitions that we used as the basis for our discussions. In this way, we mitigated potential misunderstandings and situations in which the researchers and the workshop participants interpreted the discussions in different ways. To address external validity, we used our empirical cases to inductively derive our findings with the intention to provide value for companies that have common characteristics as the companies we studied. As such, we view our research contributions as related to the “drawing of specific implications” and as a contribution of “rich insights” [44]. We have no evidence that our findings would generalize and be applicable beyond the case company domains we studied. However, with the opportunity to study companies operating in several different industry domains we believe that the findings we present have the potential to provide relevance also in other companies with similar characteristics as the case companies in this study.

7. Conclusion

The role of product management is key for building, implementing and managing software products. In previous research [11], the role is even referred to as the “mini-CEO of an organization” and product managers are typically positioned at the center of the organization to ensure that stakeholders work towards the same goals and that the intended value is delivered to customers.

However, despite prominent research in this field, there are few studies that explore how the product manager role is changing due to digitalization and digital transformation. To address this, we explore how trends such as DevOps and short feedback loops, data and artificial intelligence (AI), and the emergence of digital ecosystems challenge and change contemporary product management practices. Our research builds on multi-case study research in companies in the software-intensive systems domain that experience rapid changes in the business environments in which they operate and as a consequence, need guidelines for how to approach and reason about their product management practices going forward. The research question we explore is the following: “What are the novel approaches that product managers in software-intensive systems companies can employ to maximize the return on investment of R&D when having access to DevOps and short feedback loops, data and artificial intelligence (AI) and digital ecosystems?”

The contribution of our paper is a framework for ‘Strategic Digital Product Management’ (SDPM) in which we present nine approaches that product managers can employ to maximize the return on investment (RoI) of R&D using new digital technologies. The approaches range from traditional software development approaches to data-driven and AI-driven development approaches. For each approach, we identify for which type of development context it is ideally suited for, i.e., high certainty and stable contexts, evolving contexts and low certainty contexts. We conclude that the product manager needs to decide between these approaches based on his or her best understanding of the situation. Our general guidance is to select ML/DL models over algorithm-based development when feasible and to treat new functionality with more uncertainty than what one might initially believe. Both

these guidelines allow for data-driven decision making and reduced development efforts.

In future research, we aim to validate the SDPM framework and study the application of this in additional case companies. Also, we aim to extend it with new techniques that can be used by companies to effectively increase the RoI of R&D investments.

CRedit authorship contribution statement

Helena Holmström Olsson: Writing – original draft, Conceptualization. **Jan Bosch:** Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgements

We would like to thank all industry representatives and member companies in Software Center for their support and contribution to this research.

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