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What Got You Here Won't Get You There

A multi-case study on the challenges in the transition from traditional towards continuous data practices in the embedded systems domain

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Abstract: For decades, product data has been collected and used for quality assurance, for post-deployment defect detection and for informing the next generation of products. Across industry domains, and with the online domain leading the way, companies have adopted experimentation and data driven practices such as A/B testing to evaluate product performance, customer behaviors and for determining what adds value to customers. However, with the rapid changes that new digital technologies bring, companies are moving towards continuous value delivery and monetization models in which they offer their products as-a-service or offer services to complement and extend their existing products. In this transition, the traditional way of post-deployment data collection and use is no longer sufficient. While companies realize this, they experience difficulties in making the changes they need to transition towards continuous practices and new ways of working with data. As a result, companies risk wasting development efforts on functionality that have little or no customer value and they lose out on the competitive advantages that come with insights derived from continuous collection and use of data. In this paper, we explore the challenges companies experience in the transition from traditional towards continuous practices and the implications this shift has on their ways of working with data.

Keywords: Digitalization, digital transformation, data practices, continuous practices, continuous customer value delivery.

1 Introduction

Due to digitalization and technologies such as software, data, and artificial intelligence (AI), companies across domains are experiencing a fundamental shift in how to develop, deliver and monetize customer value. As recognized by e.g., [BO21], [PH14], [HE18], [OS22], digital technologies and digitization of products allow companies to expand and improve value creation in their existing products at the same time as they can provide customers with entirely new value in the form of e.g., data-driven service offerings and digital products. With the many opportunities to collect and leverage data generated by products in the field, companies are focusing their efforts on exploiting this data for

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competitive advantage [PF13]. By collecting, processing and actively using data generated by connected products, companies can advance not only their software engineering practices and their products, but also the understanding of their customers and what adds value to them. For companies in the embedded systems domain, software is rapidly becoming the central differentiator, whereas the traditional technologies such as mechanics and electronics are becoming commodities [Bo15], [BO21], [OB20]. With value creation being shifted from hardware to software, these companies experience a situation in which they can update and continuously improve their products after manufacturing and deployment at the customer. While this significantly extends the lifetime of a product and the experience of the customer, it also allows for new digital business models and recurring revenue streams [BO21], [Ge20], [LP15]. For decision-making, the increasing availability and access to data allows for entirely new ways-of-working characterized by data-driven approaches to e.g., feature prioritization, customer validation, and product and service innovation. As examples, companies that used to be heavy on waterfall approaches to development are adopting iterative and customer-centric methods such as design thinking and lean start-up to understand and empathize with customers [BO21], [CF18], [DP19]. Moreover, techniques such as A/B testing and feature experimentation are being explored to continuously evaluate and improve customer value [Fa17], [Fa17], [Is21], [Li21].

However, with the rapid transition towards continuous value delivery and monetization models, the traditional way of post-deployment data collection and use is no longer sufficient. Although companies realize this, they struggle in making the changes they need to transition towards continuous practices and new ways of working with data. In this paper, and to address this problem, we explore data practices in embedded systems companies. Based on multi-case study research, we explore the challenges companies experience in the transition from traditional towards continuous practices and the implications this shift has on their ways of working with data. The contribution of this paper is three-fold. First, we identify the key challenges that companies in the embedded systems domain experience in the transition towards continuous data practices. Second, we derive four organizational anti-patterns that we see reduce the benefits of data practices in large software-intensive embedded systems companies. Third, we provide a set of recommendations to help companies evolve beyond their current state.

The remainder of the paper is structured as follows. In section 2, we review literature and related work on digitalization and data practices. In section 3, we describe the research method that was adopted in the study. In section 4, we present our empirical findings, and we identify the key challenges the case companies experience. In section 5, we derive four organizational anti-patterns that we see reduce the benefits of data practices in software-intensive embedded systems companies and we provide a set of recommendations to help companies advance their current data practices. In section 6, we discuss threats to validity. Finally, in section 7, we conclude the paper, and we outline opportunities for future research.

2 Background and related work

2.1 Digitalization and digital transformation

At the core of digitalization and digital transformation is the opportunity for continuous value delivery to customers. Technologies such as software, data and AI transform the ways in which business entities operate, how they create value and how value is delivered and monetized with customers. According to [MHB15], digital transformation brings the opportunity for increases in sales and productivity, innovations in value creation, as well as novel forms of interaction with customers. In previous research, data is recognized as a key component to innovations and opportunities for new value creation and monetization [BO21], [BZN15], [IV19], [Kr22], [MHB15]. In [BZN15], data is referred to as the "new oil" and capitalizing on data is described as increasingly important for a business to remain competitive. As recognized in this research, businesses are developing new business models specifically designed to create additional business value by extracting, refining, and capitalizing on data. Similarly, in [KB19], the authors refer to data-driven business models as service-oriented business models which use data as key for new value propositions to customers. In our own previous work [BO21], we study how companies are transforming towards digital companies and how data is critical in this evolution. Also, we outline how data is becoming an asset as the basis for data driven and digital services allowing for recurrent revenue streams [OB22]. As examples of such services, data is used to provide insights, recommendations, and actions to customers. As a next step, data from customers can be aggregated and used to provide comparative analysis and insights. However, in the transition towards continuous practices, the traditional and often ad-hoc way of data collection is no longer sufficient [OB13]. In the following sections, we describe data practices and how these practices are shifting in character. As recognized in previous research, this shift brings numerous opportunities, but also challenges as companies need to adopt new ways in which they work with data.

2.2 Data practices

The collection and use of data in embedded systems companies is not a new phenomenon. Previous research has described the many benefits with using data as the basis for e.g., feature prioritization, for understanding feature usage, for innovation purposes, and for decision-making in organizations [BE12], [OB14], [Ro20]. If looking at the online domain, data practices such as A/B testing and feature experimentation are used on a continuous basis to learn how the introduction of new features affect user experience, satisfaction, and system performance [Fa22], [Fa17], [KT17]. In [Au21], the authors describe how decisions regarding what features to build are difficult for software development organizations and that the effect of an idea and its return-on-investment might not be clear before its launch. Moreover, the evaluation of an idea might be expensive. In most organizations, this leads to a situation in which decisions are taken

based on opinions and experience and on assumptions on what adds value to customers. With A/B testing, organizations can evaluate different versions of a software feature and collect data on which version performs the best [De17], [KTX20]. Based on this, data driven decisions can be taken regarding future development, improvement, and optimization of features. In [RBR22], A/B testing is described as an experiment-driven software engineering approach where assumptions about product features and requirements are continuously tested with users with the intent to reduce the risk of wasting development resources on requirements of little or no value to users. Similarly, [Da21], [Fa17], [Is21], and [OB14], recognize how use of data for experimentation purposes helps companies in the embedded systems domain minimize the risk of developing software that does not deliver value to customers. However, despite well-known benefits, the adoption of data driven practices is relatively slow. While the opportunities are many, the transition towards fully automated data practices requires not only new techniques and tools but also architectures and infrastructures as well as new competences and skills [Li21].

2.3 Towards continuous data practices

To realize the opportunities that come with continuous value delivery, companies are increasingly adopting continuous practices. For years, companies have been adopting DevOps practices. In [Mu20], DevOps is defined as a set of practices that helps to build a collaboration between software development and operations which reduces the software development lifecycle and helps in continuous and fast delivery of high-quality software. With DevOps, customer value is created in short cycles and deployed on a frequent, or even continuous, basis [Lw16]. Similarly, DataOps is a practice which aims at bridging the gap between data and operations teams and is viewed as an application of DevOps but for data analytics [Mu20]. DataOps practices are viewed as effective means to help companies make meaningful use of data and for keeping track of data and the purpose for which it was collected [BZ12], [Fi21]. In a report from Gartner, DataOps is described as a collaborative data management practice with the goal of delivering value faster by creating predictable delivery and change management of data, data models and related artifacts [DO23]. For companies in the embedded systems domain, DataOps is one of several continuous practices that support continuous value delivery to customers but that requires a fundamental shift in how these companies work with data. In what follows, we present a study in which we explore the challenges embedded systems companies experience in the transition from traditional towards continuous practices and the implications this shift has on their ways of working with data.

3 Research Method

The research presented in this paper is part of a long-term collaboration between 17 companies in the embedded systems domain and five Swedish universities (www.software-center.se). For more than a decade, we have had the privilege to engage with these companies in case study research [Ea08], [Ma12] within the field of software engineering. The companies represent different domains, and they share the similar experiences of digital transformation and the challenges and opportunities that come with new technologies such as software, data, and AI. Currently, all companies are exploring data practices and how to benefit from these. In this paper, we report on on-going research that was initiated in January 2022 in which we explore data practices in a selected set of the companies. In alignment with our research interests, we adopted a qualitative research approach with case studies as our method. Case study research is well-suited for research concerned with identifying patterns of action and for studying organizational contexts in which emphasis is put on stakeholder's perceptions and experiences [Ea08].

3.1 Case companies

As our empirical basis, we selected a set of primary and secondary case companies. As described in [Ge09] and [SG08], case study selection is critical as case study research is about something larger than the cases themselves. Typically, the chosen cases are asked to represent a population of cases that is larger than the cases themselves, and therefore, background cases play an important role for analysis. In accordance with this, the empirical findings we present build on research in three companies that were selected as primary cases. As secondary cases, we selected three companies that experience opportunities and challenges very similar to the primary case companies. The three *primary case companies* are briefly described below:

Case company A: A company providing product development, marketing, engineering, sales and support for crew planning and optimization. For this paper, we engaged with a team involved in development of new service offerings and roles representing software, architecture, and portfolio.

Case company B: A company manufacturing trucks, buses, and construction equipment as well as a supplier of marine systems. For this paper, we engaged with a team responsible for new service innovation and development.

Case company C: A company developing autonomous driving and advanced driver-assistance systems. For this paper, we engaged with product owners in areas such as fleet insight, data driven data management and data governance, as well as roles involved in business development and strategy.

In addition to the three primary case companies, we studied three *secondary case companies:*

Case company D: A company developing pump units, circulator pumps, submersible pumps, and centrifugal pumps. For this paper, we engaged with roles responsible for product management, sales, and architecture.

Case company E: A company manufacturing network cameras, access control, and network audio devices for the security and surveillance industries. For this paper, we engaged with roles responsible for software development, architecture, platform development, engineering, and management.

Company F: A company providing networking and telecommunications solutions and services. For this paper, we engaged with roles in management and software engineering.

3.2 Data collection and analysis

For data collection, we engaged in workshop sessions with both the primary case companies and the secondary case companies involved in our study. These workshops were organized either online or at the different company sites and gave us the opportunity to meet with key stakeholders in teams involved in, and responsible for, data collection, data analytics and data usage. Although our research collaboration with these companies covers more than a 10-year period, the study we report on in this paper was initiated in January 2022 and is on-going. During 2022, we organized on-site workshops at all primary case companies (company A, B and C) and at the three secondary case companies (company D, E and F). In addition, we met with all case companies in online workshops. The on-site workshop sessions lasted for 2 – 4 hours and involved 4 – 8 people. The online workshop sessions were typically shorter (30 minutes – 1-hour sessions) and a way to follow-up, share ideas and results and for monitoring progress in between the on-site meetings. In total, the research we report on in this paper is based on 12 on-site company workshops and 18 online workshops. In addition to these workshops, we met with both the primary and the secondary case companies at *two larger cross-company full-day events* that we organized to report our preliminary findings and get company feedback. As this research is on-going, we have company workshops with all case companies scheduled during spring 2023 and our intention is to scale the interactions with the secondary case companies. For data analysis, we adopted an interpretive approach [Ea08], [Ma12], [Wa95]. As suggested by [Wa95] the generalizations that are made based on case study research are valuable for other organizations that experience similar challenges in similar contexts to the case companies.

4 Empirical findings

For decades, the case companies involved in our study have harvested huge amounts of data from e.g., development and test fleets, from internal systems, and from products in the field. They have sophisticated infrastructures and systems in place for adding events,

enabling queries and questions, and for introducing and monitoring metrics. So far, the data has been used primarily for quality assurance of products, for post deployment defect detection, and for informing the next generation of products. However, due to digitalization and the many opportunities that come with new digital technologies, the companies are experiencing a rapid shift from traditional and product-oriented business models towards continuous and service-oriented business models. In this transition, the traditional, and often ad-hoc, way of post-deployment data collection and use is no longer sufficient. Instead, all the case companies seek to adopt new and more continuous ways of working with data. This implies a shift towards periodic and, in the end, continuous and automated collection, processing, and use of data.

Below, we identify the *key challenges* the case companies experience in the shift from traditional towards continuous data practices. We structure our findings according to generic challenges that are prevalent both in traditional and continuous practices and challenges that we identify as unique for continuous data practices.

4.1 Generic challenges that are prevalent in both traditional and continuous data practices:

Combining qualitative and quantitative data: Both the primary and the secondary case companies involved in our study experience challenges with how to effectively combine different data sources. This involves how to generate insights that build on both qualitative data generated within the company, and quantitative data generated by products in the field. In traditional data practices, organizations rely heavily on individuals to collect, process, and analyze data based on requests from e.g., product management or from development teams. Often, such requests are ad-hoc requests concerning a specific feature and its behavior and requires manual efforts in identification and analysis of relevant data. In the shift towards continuous practices, companies need automated solutions that help convert qualitative data into quantitative data to enable frequent monitoring and control of the data analytics pipeline. As a common challenge in our case companies, people report on difficulties in e.g., combining feedback from customers with data from internal build systems (continuous integration and continuous deployment systems) and data generated by products in the field. While customer feedback typically reflects qualitative experiences of the overall system and individuals' perceptions on usability, build system and product data reflects quantitative measures of internal efficiency and performance.

Incorporating external data with internal data: Throughout our study, we learnt that the case companies experience difficulties when trying to incorporate external data produced by third parties, and other relevant data sources generated outside company boundaries, into their own data streams and as a complement to their own data sources. For example, while sources such as e.g., market trend data and social media data are viewed as sources that provide potentially valuable insights about customer behaviors, these are also perceived as more challenging to keep accurate to avoid invalid or inaccurate data. As companies are moving towards continuous data practices, one of the main

challenges is to ensure that the time and period of the internal data is aligned with the time and period of the external data.

Understanding the surrounding context of a metric: Although the case companies have a large set of metrics in place in their systems, they lack effective mechanisms that help them understand the surrounding context of a specific metric. For example, a metric can capture a certain action taken by a user but very often information such as when the activity took place, who initiated and performed the action, what the purpose or use case of the action was etc., is missing. As a result, the analysis of what a metric reflects becomes difficult as the context of the data that is collected is lacking. For example, one of the primary case companies describes a situation in which the same metrics are used to capture two user groups with very different behaviors. While one customer group interacts with the system on a very frequent basis for solving highly complex optimization tasks, the other customer group uses the system to perform basic tasks and with as little interaction as possible. Metrics are the same however, and during one of our workshops one of the product managers described the situation as *"...comparing apples and pears"* referring to the same metrics being used to capture two very different use cases and user scenarios.

4.2 Challenges unique for continuous data practices:

Limited scope of metrics: In the transition towards continuous data practices, the scope of metrics becomes increasingly important. While metrics in traditional data practices tend to focus primarily on performance and quality aspects of the system, metrics in continuous practices need to capture not only a certain aspect at a certain point in time, but also how aspects of the system change over time. In our study, the case companies report on challenges with regards to the scope of metrics and how to ensure that existing metrics capture accurate data on e.g., frequency, rate, duration, or interval of an event. Especially, the case companies experienced challenges with regards to how to continuously integrate changes in data while maintaining and ensuring high quality of data.

Metrics are "static" and viewed as "cast in stone": In the case companies we studied, metrics tend to show feature usage in terms of activation of the feature rather than providing insights that capture usage patterns, complexity of a user task, purpose of use or how feature usage changes over time etc. Most often, metrics represent the behavior of a feature or of a system as it was once specified in a requirement (static), rather than providing an understanding of what the feature or system should do and what could be expected from it in its evolution (dynamic). In addition, and as experienced in most of the case companies, people at different levels and in different functions often view metrics as "cast in stone", leading to a situation in which the introduction of new metrics, experimentation with metrics, and removal of existing metrics is regarded very difficult even if this is key for continuous data practices.

Monitoring overall improvement: All case companies have DevOps practices in place and periodic deployment of software allow them to continuously measure and monitor

basic key performance indicators (KPIs). However, we noticed that despite this, the companies often lack mechanisms to determine if things are overall improving or not. In several workshops, teams reported how they continuously improve specific features and how they can monitor these improvements over time. Still, they are unable to understand to what extent, or if at all, the feature improvements they do contribute to an overall improvement of the system. In our experience, this is due to an unclear desired state meaning that teams and organizations don't know, or don't align, on what they are optimizing for. Also, slow customer activation of frequently deployed software functionality makes it difficult for continuous monitoring of overall system improvement. As one example, one case company experiences a situation in which the data coming back from their products is so complex that most developers have difficulties in understanding it. In one of our onsite workshops, one of the key stakeholders reflected on this and described it as "*You either have hardware people or you have software people but to combine these skills are hard. In addition, we have a problem with granularity as there are so many variables and factors that interact.*" For the company, this results in a situation where teams track a sub-set of metrics but where improvement of overall system performance is more difficult to monitor. This situation is valid also for the other case companies as they all report on difficulties in fully benefitting from the data they have available. Often, there is little agreement on what KPIs are the critical ones and hence, how team and feature level metrics correspond to high-level business metrics. Also, one problem is that initial data collection is often concerned with a specific use case while continuous improvements of this use case might make the case for analytics a different one and therefore, contextual data is required to fully benefit from data and analytics as mechanisms to monitor overall system improvement.

5 Discussion

5.1 Organizational anti-patterns

As reported in this paper, the use of data practices is challenging for companies with systems involving not only digital technologies but also mechanics and electronics. As a generalization of what we see happen in the case companies, we derive four anti-patterns that reduce the benefits of data driven practices in large-software-intensive embedded systems companies. An anti-pattern in software engineering, project management, and business processes is a common response to a recurring problem that is ineffective and that risks being highly counterproductive [Ga95]. In both the primary and the secondary case companies, we see the following anti-patterns (Table 1):

Anti-pattern:	Description:
The "worthwhile many versus the vital few" anti-pattern[1]	The lack of a shared understanding of the desired state makes prioritization and resource allocation difficult. This results in individuals and teams spending time and efforts on activities that don't directly contribute to business value and success.
The "homonym" anti-pattern	Companies fail to realize that they use the same metrics to capture two (or more) different customer groups with different preferences. This results in difficulties in analyzing and benefitting from any data that is collected, as well as an inadequate metrics system reflecting only a subset of what it potentially could.
The "what got you here won't get you there" anti-pattern	KPIs reflect requirements that was once accurate and that describe feature and system behavior but that have stopped being true. This results in an insufficient metrics system reflecting current state but that fail in capturing desired state, i.e., what the feature and system should do and what we expect from it over time.
The "Alice in Wonderland – if you don't know where you're going, any road will take you there" anti-pattern	The lack of a desired outcome and agreed upon key value factors make individuals and teams optimize for their own best but without a holistic understanding of the business. This results in conflicting KPIs, suboptimization of team efforts, and misalignment in business outcomes.

Tab. 1: Anti-patterns that reduce the benefits of data practices.

[1] The 'vital few' is a term is derived from the 80-20 rule (the Pareto principle) which asserts that about 80% of all outcomes are the direct result of only 20% of all inputs.

5.2 Recommendations

In this section, we provide a set of recommendations with the intention to help companies advance their data practices and evolve beyond their current state. The recommendations are inductively derived based on the insights we gained during this study, and during our long-term collaboration with the case companies. To further advance data practices in software-embedded systems companies, we recommend the following:

Experiment with proxy metrics that are indicative of customer value: Typically, the things companies wish to measure are difficult to measure. For example, most companies struggle with how to clearly describe what constitutes customer value and therefore, measuring customer value becomes a very difficult task. The consequence is that companies stop trying and fall back on traditional metrics focusing on internal efficiency, product performance and quality as indirect measures of value. Instead, we recommend that companies hypothesize proxy metrics that are indicators of customer value, measure these over multiple releases and do correlation analysis between confirmed customer value delivery and the proxy metric with the intent of identifying metrics that have a strong correlation with customer value.

Seek to continuously shorten feedback cycles with customers: The ability to continuously evaluate improvements relies on accurate and frequent feedback from customers. In addition to being critical for validation of improvements, customer feedback is important as companies seek to minimize development efforts and investments in between proof points. The shorter feedback cycle, the faster teams learn, and the smaller the investment is if a feature turns out to not prove valuable. One of the key enablers to this is DevOps practices. We recommend companies to adopt DevOps capabilities for at least parts of their systems as it allows for the opportunity to start running A/B experiments to measure the impact and value of new features on a frequent basis.

Develop an experimentation infrastructure: The ability to run experiments provides companies with the foundation to learn about feature and system usage and about what adds value to customers. A/B testing is a powerful mechanism for identifying and evaluating value and it forms the basis for a hierarchical value model in which metrics at different levels contribute to an overall understanding of customer and business value. We recommend companies to develop an experimentation infrastructure and capabilities involving e.g., randomization algorithms, assignment methods, and the data processing mechanisms. To scale these practices, we recommend companies to have dedicated groups that build, manage, and improve the experimentation infrastructure so that it can be effectively employed by many teams.

Develop a hierarchical value model: Establishing a quantitative understanding of the use of the system is critical. Companies can either use historical data to understand usage of a certain feature or instrument the software to start collecting data revealing feature usage. To evaluate feature improvements, and to understand if the overall system is improving as desired, companies need a hierarchical value model. In such a model, there

needs to be a single, or at least very few, high-level metrics that translates into lower-level metrics and to which the lower-level metrics contribute. A hierarchical value model details the relationships between metrics and incorporates the tradeoff among lower-level metrics. With a hierarchical value model in place, companies can continuously monitor and evaluate value to ensure that development efforts and investments are allocated to functionality with proven customer value.

Continuously validate the hierarchical value model and evolve it over time: To avoid misalignment between teams and sub-optimization of efforts, the value model needs to be maintained over time. This involves having teams responsible for parts of the system and its related metrics, it involves having teams responsible for the overall alignment of the value model as it evolves, and it involves continuous introduction and evaluation of new metrics. Over time, evaluating and adjusting the high-level metric(s) and understanding causes and effects becomes easier. By running experiments and interpreting the results companies will not only learn what metrics work best for certain types of experiments but also learn how to develop and introduce new metrics into the value model.

6 Threats to validity

As the basis for our understanding of digital transformation and the role of data in the shift towards continuous practices, we reviewed contemporary literature on this topic. Based on this, we conducted multi-case study research in selected primary and secondary case companies in the embedded systems domain. To mitigate validity threats, and to address construct validity [Ma12], we started each workshop with sharing our view on digitalization and the impact digital transformation has on the ways in which companies work with data. By doing this, we established a common understanding, and we could focus the discussions using terminology that was familiar for everyone involved. With regards to external validity, our research contributions are related to what Walsham [Wa95] defines as "drawing of specific implications" and as a contribution of "rich insights".

7 Conclusions and future research

At the core of digitalization and digital transformation is the shift towards continuous value delivery to customers. For companies in the embedded systems domain, this shift implies that product sales and transactional business models are increasingly being complemented with service sales and recurring revenue streams. For companies in the embedded systems domain, this includes traditional service approaches where the physical product is offered as a service or where other aspects, such as maintenance of the product, are provided as a service [BO21]. In this transition, data practices are critical as they lay the basis for new data driven and digital offerings. In this paper, we explore the challenges

companies experience in the transition from traditional towards continuous data practices and the implications this shift has on their ways of working with data. In the paper, we identify the key challenges that companies in the embedded systems domain experience in the transition towards continuous data practices. Second, we derive four organizational anti-patterns that we see reduce the benefits of data practices in large software-intensive embedded systems companies. Third, we provide a set of recommendations to help companies evolve beyond their current state.

In future research, we aim to study how to better combine and make effective use of different data sources that companies have available. Our goal is to provide a holistic understanding of the opportunities that continuous data practices bring and how different organizational roles can benefit from these for decision-making purposes.

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