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Challenges and solutions in condition-based maintenance implementation - A multiple case study

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ABSTRACT

Previous literature has highlighted many opportunities for digital technologies, such as the Internet of Things (IoT) and data analytics, to enable circular strategies, i.e., strategies which support the transition to a circular economy (CE). As one of the key circular strategies for which the digital opportunities are apparent, maintenance is selected as the focus area for this study. In the field of maintenance, IoT and data analytics enable companies to implement condition-based maintenance (CBM), i.e., maintenance based on monitoring the actual condition of products in the field. CBM can lead to more timely and efficient maintenance, better performing products-in-use, reduced downtime in operations, and longer product lifetimes. Despite these benefits, CBM implementation in practice is still limited. The aim of this research is thus to understand the challenges related to CBM implementation in practice, and to extract solutions which companies have applied to address these challenges. Towards this aim, a multiple case study is conducted at three original equipment manufacturers (OEMs). A framework is derived which allows for a broad analysis of challenges and solutions in the cases. We identify 19 challenges and 16 solutions and translate these into a set of actionable recommendations. Our findings contribute to the field of CBM with a comprehensive view of challenges and solutions in practice, from the OEM's point of view. Moreover, we contribute to CE literature with a concrete case study about IoT-enabled circular strategy implementation.

1. Introduction

The circular economy (CE) has been defined as *"an economy that is restorative by design, and which aims to keep products, components and materials at their highest utility and value, at all times"* (Webster, 2015) [pp.16]. Design and business model strategies for the CE include product lifetime extension strategies (maintenance and repair) and looping strategies (reuse, remanufacturing, and recycling). While looping strategies are core to the actual circulation of products and materials, product lifetime extension strategies have a higher potential to reduce environmental impact (European Commission, 2008), as they keep products close to their original function and value (Potting et al., 2017). Based on this logic, maintenance and repair strategies are given higher priority than looping strategies in the EU waste directive (European Commission, 2008). Moreover, previous research has shown that increased maintainability and reparability of products in turn also benefits reusability and remanufacturability (Takata et al., 2004). As such, maintenance and repair are key strategies to explore for companies aiming to provide circular products and services. In this paper, we focus specifically on maintenance and its implementation in practice.

One of the most important trends in maintenance management is digitalization (Akkermans et al., 2016). Based on the Internet of Things (IoT) and data analytics, the condition of products in the field can be monitored continuously and remotely, enabling optimized condition-based maintenance (CBM). Condition monitoring also enables better insight into remaining product lifetime, degradation status, and environmental factors (Ren et al., 2019), which can be used to improve looping strategies (Bressanelli et al., 2018; Ellen MacArthur Foundation, 2016; Ellen MacArthur Foundation, McKinsey & Company, Google, 2019; Spring and Araujo, 2017;

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Ondemir and Gupta, 2014). However, actual implementation of condition-based looping strategies in practice remains low (Alcayaga et al., 2019; Ingemarsdotter et al., 2019).

As for all circular strategies, design is a key enabler of successful maintenance (Mulder et al., 2012). Original Equipment Manufacturers (OEMs) can intentionally design their products to facilitate CBM, for example by ensuring the integration of sensors needed to derive reliable insights about a product's condition. Previous literature has shown successful examples of OEMs monitoring their customers' products remotely and offering CBM as part of a service-based value proposition (Lightfoot et al., 2011; Rymaszewska et al., 2017). However, this is far from common practice and many OEMs, while seeing the business opportunity of offering CBM, still struggle with its implementation (Bouskedis et al., 2020; March and Scudder, 2017).

Previous literature highlights a gap between the current focus of academic research and the real-world challenges that companies face when implementing CBM. As such, there is a need for more practice-oriented research in this field (Fraser et al., 2015). Similarly, recent papers in the field of CE highlight a need for more case studies of IoT-enabled circular strategies (e.g., CBM), to better understand implementation challenges in practice (see, for example, Antikainen et al., 2018; Cattelan Nobre and Tavares, 2016; Pagoropoulos et al., 2017; Ingemarsdotter et al., 2020). Specifically, authors from both fields call for a wider understanding of implementation challenges beyond purely technological aspects (e.g., Kirchherr et al., 2017; Coleman 2017; Lee, 2020a).

In this paper, we aim to understand the challenges that OEMs face when implementing CBM as part of the value proposition to their customers. More specifically, we study the challenges that they face when developing an IoT artefact for CBM and the solutions that they have applied to address these challenges. Towards this aim, we develop a framework, which takes a wide perspective on CBM implementation by integrating technological, organizational, and user-related aspects. The framework is used to analyse the cases. This way, we aim to contribute to CBM literature with empirically grounded insights from the OEM's perspective, beyond a purely technological focus. Moreover, we see CBM as one of the most commonly implemented IoT-enabled circular strategies, for which we were able to gain access to real-world company cases. As CBM shares key characteristcs with other IoT-enabled circular strategies, in particular condition-based reuse and remanufacturing, our aim is that the findings extracted from this paper will also be valuable for CE literature beyond maintenance.

The remainder of the paper is structured as follows. Section 2 first introduces the concept of CBM, including key steps and technologies (Section 2.1). Thereafter, we present previous literature on challenges and solutions in CBM implementation and argue for the need for an integrated perspective, considering technological, organizational, and user-related aspects (Section 2.2). Section 3 describes the research methods, while Section 4 explains how the integrated framework was developed based on previous literature. Section 5 presents the cases, and Section 6 presents the identified challenges and solutions. In Section 7, we discuss the results in relation to previous literature, and translate our findings into a set of recommendations for practitioners. Finally, Section 8 states the main conclusions of the paper and presents suggestions for future research.

2. Background

2.1. Introduction to condition-based maintenance

CBM has been defined as "*preventive maintenance which include assessment of physical conditions, analysis and the possible ensuing maintenance actions*" (British Standards Institution, 2017). If implemented successfully, CBM can reduce the number of unnecessary preventive maintenance activities as maintenance only takes place if the data shows signs of abnormalities (Jardine et al., 2006). Moreover, CBM has environmental advantages resulting from, for example, extended operational product lives, more intensive use of products, and reduced transportation of maintenance personnel and spare parts (Johansson et al., 2019).

Jardine et al. (2006) distinguish between three key steps in CBM: data acquisition, data processing, and maintenance decision making. Data acquisition includes collection and sorting of data about products in the field, both condition monitoring data (e.g., vibration data, acoustic data, oil analysis data, temperature, pressure, or moisture data) and so called event data, i.e., what happened to the product in a particular situation, or which maintenance tasks were performed on the product. Event data often requires manual data entry. Condition monitoring data can be collected both automatically through sensors or other measurement techniques, or manually through for example daily oil quality checks (Ahmad and Kamaruddin, 2012). While the definition of CBM does not explicitly require automatic sensor-enabled data collection for condition monitoring, this is often implicitly assumed in the current technological context. The data processing step includes data cleaning, analysis and interpretation. In the decision-making step, maintenance policies are selected, and maintenance actions are carried out, based on the derived insights.

CBM can be categorised into four types, according to the level of data analytics performed: descriptive, diagnostic, predictive and prescriptive analytics (Baum et al., 2018). According to Baum et al. (2018), descriptive analytics aims to understand events based on historical data, whereas diagnostic analytics investigates why an event took place. In predictive and prescriptive analytics, mathematical models are used to predict future outcomes and to prescribe optimal interventions, respectively. The term 'predictive maintenance' has been gaining traction in literature, with many studies highlighting its business opportunities (e.g., Bouskedis et al., 2020; March and Scudder, 2017). In this paper, we use the term CBM to include maintenance activities based on data analytics at any of the four levels.

An extensive body of literature has been built up around mathematical models and data analytics methods for CBM. Two closely related research areas can be identified: research into the selection of optimal maintenance policies, and research into data analytics for failure diagnostics and prognostic. Maintenance policy optimization is usually based on cost, reliability, or availability and considers parameters such as the products' degradation patterns, the resources available for maintenance, and the consequences of a potential stand-still (Alaswad and Xiang 2017). Recently, attention has also been paid to understanding dependencies between different components in complex systems, and how that might influence the optimal choice of maintenance policy for the system as a whole (Olde Keizer et al., 2017).

Component-level diagnostic and prognostic approaches have been reviewed in multiple papers, e.g. by Atamuradov et al. (2017), Jardine et al. (2006), and Lei et al. (2018). Although different categorisations have been suggested in literature, three types of approaches are often put forward: model-based (or physics-based), data-driven, and hybrid approaches (Atamuradov et al., 2017; Kwon et al., 2016). Below, we briefly describe model-based and data-driven approaches. Hybrid approaches are defined as combinations of these two, with the aim to use the advantages of both.

Model-based approaches use mathematical models to describe degradation processes. Condition monitoring data is fed to the model, which calculates a predicted state. These kinds of models can be relatively accurate, also for long-term predictions, but requires in-depth knowledge about the physics of degradation for the specific product (Jardine et al., 2006; Shimomura et al., 1995). Moreover, the applicability of these degradation models in practice is sometimes limited by the complexity of the real-world system in which individual components operate. Examples of use cases where model-based approaches are common and effective include condition monitoring of bearings and of the structural health of materials (e.g., in bridges) (Atamuradov et al., 2017).

Data-driven approaches are instead based on analysing condition monitoring data to detect anomalies and translate such anomalies into insights about potential faults. This way, degradation models are built up from the data, often using machine learning techniques (Heng et al., 2009). Data-driven approaches require less expert knowledge about how the product or component fails, but instead requires more computational power than model-based approaches, as well as access to large amount of high quality data. The accuracy of the model depends directly on the amount and quality of the data that is used to build it (Atamuradov et al., 2017). In practice, challenges arise as the collected data is often heterogeneous and disperse. Research into new algorithms for prognostics evolves at a fast speed, see e.g., Stetco et al. (2019) or Kumar et al. (2020).

There is still a need to improve the available diagnostic and prognostics approaches to achieve high levels of accuracy in real world settings, especially in long-term predictions. Alaswad and Xiang (2017) highlight that most research has focused on single-component systems, and that more work is needed to understand the condition of complex products and systems with multiple different components. For example, they mention the need to model dependencies between degradation processes in different components, as well as possible human errors related to CBM.

2.2. Previous research on challenges and solutions in CBM implementation

Despite the abundance of technical literature, companies still struggle to effectively implement CBM in practice (van de Kerkhof et al., 2016; Tiddens, 2018). Based on a survey of 98 Swedish companies, Ylipää et al. (2017) found that maintenance personnel still mainly carry out reactive repairs, rather than proactive maintenance. Similar findings have been reported by Jin et al. (2016) and Chinese and Ghirardo (2010), based on data from the United States and Italy, respectively. Further, Veldman et al. (2011) and Tiddens (2018) noted that, among the companies who have set up CBM implementation projects, many do not follow systematic processes. As such, we note that there is a gap between the challenges faced by companies wanting to implement CBM and the advanced solutions presented in literature.

Other researchers have also highlighted such a gap and called for more empirically-based research which can actually help solving "*real problems in industry*" (Fraser et al., 2015). Olde Keizer et al. (2017) note that the fact that CBM implementation in practice is lagging behind could, at least partly, be explained by the complexity of real-life systems compared to the simplified systems often studied in academia. Other technical challenges related to implementing CBM in real-life settings include the lack of failure data from products in the field, making it challenging to develop robust diagnostics and prognostics (Jin et al., 2016; Goyal and Pabla, 2015). Selcuk (2017) and Rastegeri et al. (2013) both highlight technology selection as a critical factor for CBM implementation, including, for example, which components to monitor, which measurement techniques to use, and what types of data analytics models to apply. Stecki et al. (2014) conclude that challenges to widespread CBM implementation exist across all technical levels, from data collection, through data analysis to decision support. Related to this, Rastegari et al. (2013) highlight competence building around data collection and analysis as a critical challenge.

Some research is available which aims to support companies in overcoming these technical implementation challenges. For example, Lee et al. (2014) and Tiddens (2018) presented methods for selecting critical components to monitor as well as algorithms to use when processing the data. Stecki et al. (2014) formulated recommendations for how to set up an effective CBM program, highlighting the need to understand the risks to which a system is exposed, as well as to analyse and define failure dependencies. Mourtzis et al. (2020) presented a framework which used Augmented Reality (AR) technology to support effective real-time communication and data exchange between service technicians in the field and expert engineers located remotely.

However, technical aspects only form one of several important dimensions in CBM implementation (Lee, 2020a). A recent Deloitte report emphasises the importance of looking beyond technology and focus more on processes and organizational changes needed for successful CBM implementation (Coleman, 2017). Similarly, Lee (2020b) argues that the biggest challenge of Industrial AI (including CBM) is not a lack of suitable technology, but rather how to create real value from a combination of technologies in a resource efficient and collaborative way. Selcuk (2016) highlights organizational challenges related to the fact that CBM implementation is a multidisciplinary undertaking with implications for, for example, hardware, software, personnel, and training requirements.

With this in mind, our research takes a wide perspective on CBM implementation, including technological, organizational and user-related aspects. A small set of previous papers take a similar direction. Veldman et al. (2011) identified challenges in CBM implementation related to a lack of strict procedures, and a lack of employee training to support correct execution. More recently, Jin et al. (2016) highlighted barriers related to costs, workforce and level of skills, organizational and technology readiness, and complexity of system design changes. They also saw a need for clear strategies to motivate and train personnel, create incentives, and ensure interdepartmental collaboration. Bokrantz et al. (2020) identified implementation challenges for CBM related to, for example, costs and cultural resistance. Rastegari et al. (2013) concluded that one of the main challenges when changing the company culture from reactive to proactive maintenance strategies is a lack of management support. Golightly et al. (2018) studied human and organizational factors in CBM implementation and derived high-level recommendations related to company culture, effective processes, resource deployment, and collaboration. In Section 7, we discuss how our findings relate to these previous papers.

3. Method

We conducted a multiple case study at three original equipment manufacturers (OEMs). Case study methodology is suitable when studying "*a contemporary phenomenon within its real-life context*" (Yin, 2014). This aligns with the aim of this research, i.e., to understand challenges and solutions related to CBM implementation in practice. In each of the studied cases, we were interested in challenges and solutions related to developing and implementing the technical artefact needed to realise CBM (the 'IoT artefact'). Below, we describe how the cases were selected, and how data was collected and analysed. Section 4 describes how we developed the integrated framework which was used to analyse the data.

3.1. Case selection

To be considered a relevant case for this study, three criteria had to be fulfilled. Firstly, the case should be embedded within the context of a manufacturer of high value, complex products. This ensured comparability between the cases, and is based on the notion that maintenance costs for such products are high in relation to production costs, compared to other types of products (Mulder et al., 2012). Secondly, the case should describe an, at least partly, implemented CBM solution. Thirdly, the CBM solution should be part of a maintenance service delivered to the end user of the product. The type of product that was studied for each of the selected cases is presented in Table 1. More detailed descriptions of the cases are given in Section 5.

3.2. Data collection

Semi-structured interviews were conducted with company representatives (Table 2) using an interview guide. The interview guide is presented in Table A.1 in Appendix A. The interviews, which were audio-recorded, took place between April and July 2019, each lasting between 40 and 75 min. The aim was to interview at least one person from the R&D department who had experience in IoT and/or data analytics, and one from the maintenance or aftermarket department. This way, we could capture the views of actors involved in developing the IoT artefact as well as actors using it. For Case B, no one from the maintenance or aftermarket department could be accessed. However, a user experience (UX) designer could provide insights into how the maintenance and customer support staff used the CBM solution.

3.3. Data analysis

The data analysis process is shown in Fig. 1. The audio recordings of the interviews were transcribed, and then coded using the software ATLAS.ti. The transcriptions were broken down into "quotes", and in a first step, each quote was coded based on the framework which is used to analyse the data (presented in Section 4). More specifically, each quote was coded as a challenge or solution in a specific 'alignment type' (explained in Table 4). For example, the following quote was coded as a 'challenge' in the 'Work system-Context' alignment type because it shows how the regulatory context surrounding the work system needs to be in alignment with the work system:

> *… first of all, what we need from a legal perspective is that we need permission from the end user that we can* log *their data. So this is a constraint, without that the use case is gone …* (Int-C4)

In a second coding step, challenges and solutions in an alignment type were further grouped into sub-categories. The example above was put into the sub-category 'Data privacy concerns' together with seven other quotes. These sub-categories were elicited by observing commonalities between quotes with the same first level code. This was an iterative process involving all authors and as a final step the interview data was revisited to ensure that all quotes were coded as one of the identified challenges or solutions (second level codes). After this, 19 challenges and 16 solutions remained. These are the main results of this research and are presented in Section 6.

Table 1
Products studied in the three cases.

Case A	Forklifts
Case B	Industrial robots
Case C	Heat pumps

4. Framework development

To analyse the cases, we needed a structured representation of (1) the IoT artefact that the companies had to produce to realise CBM and (2) the surrounding organizational and user-related aspects needed to achieve this. This was achieved through adapting and combining two frameworks: the new technology stack (Porter and Heppelman, 2014) and the work system framework (Alter, 2013). The new technology stack (Fig. 2) provides a way to describe an IoT artefact as a 'stack' with three main layers: the product layer, the connectivity layer, and the cloud layer. The work system framework (Fig. 3) provides a frame for describing the system needed to produce a product or a service.

Below, we first briefly present the two frameworks. Then, we describe how we take the work system framework as a starting point, and adapt it by (1) making simplifications where possible, (2) using the new technology stack to detail the product/service to be produced by the work system, and (3) contextualising the descriptions of the work system elements, and the required alignment between them, to fit the context of this paper.

4.1. Frameworks from literature

The new technology stack presented by Porter and Heppelmann (2014) shows the layered nature of IoT artefacts. As depicted in Fig. 2, it distinguishes between three main layers: the product layer, the connectivity layer, and the product cloud layer. The product layer consists of hardware-level and product-level software. The connectivity layer enables communication between the product and the cloud layer. The cloud layer consists of a product data database, an application platform, a data analytics engine, and cloud-level applications (Porter, 2015).

The work system framework represents a 'work system', defined as a "*system in which human participants and/or machines perform work using information, technology, and other resources to produce specific products/services for specific internal and/or external customers*". The term 'work' is defined as *"the application of human, informational, physical, and other resources to produce products/services"* (Alter, 2013) [pp. 75].

As seen in Fig. 3, the work system framework includes nine elements: participants, information, technologies, processes/activities, product/service, customers, infrastructure, environment, and strategies. The definitions as given by Alter (2013) for each of the nine elements are presented in Table A.2 in Appendix A.

For a work system to successfully reach its goal, i.e., to produce the product/service for the intended customers, the elements of the work system should be 'in alignment' with each other. Five distinct types of alignment are shown in Fig. 3 as arrows linking elements together. For example, participant-processes/activities alignment implies that *"the knowledge, skills, interests, and motivation of the participants should fit with the processes and activities in the work system, and the processes and activities should be appropriate for attributes of the participants*" (Alter, 2013) [pp. 79]. While not explicitly shown in the work system framework, the work system as a whole should also be in alignment with the company-level strategy, infrastructure and environment.

4.2. Integrated framework

To develop the integrated framework, we take the work system framework as a starting point and adapt it to fit the context of this paper. We first simplify by renaming the element 'Processes/Activities' to 'Activities' and combining the three elements 'Strategies', 'Infrastructure', 'Environment' into one category named 'Context'.

Thereafter, we detail to the 'product/service' to be produced by

Table 2
Interviews conducted per case company.

Case	#	Role	Interviewee ID	Total amount of data collected
A	7	R&D manager	Int-A1	6 h
		Service manager	Int-A2	
		Product specialist with aftermarket responsibilities	Int-A3	
		R&D manager	Int-A4	
		Manager Software System Solutions	Int-A5	
		Manager 'Technology Solutions'	Int-A6	
		Head of Group, Embedded software	Int-A7	
B	4	Program manager digital services	Int-B1	4 h 20 min
		Senior principle scientist	Int-B2	
		Senior R&D Engineer	Int-B3	
		User experience designer	Int-B4	
C	4	Senior project manager, R&D	Int-C1	3 h 50 min
		Systems architect	Int-C2	
		Technical support	Int-C3	
		Senior data analyst	Int-C4	
	15			**14 h 10 min**

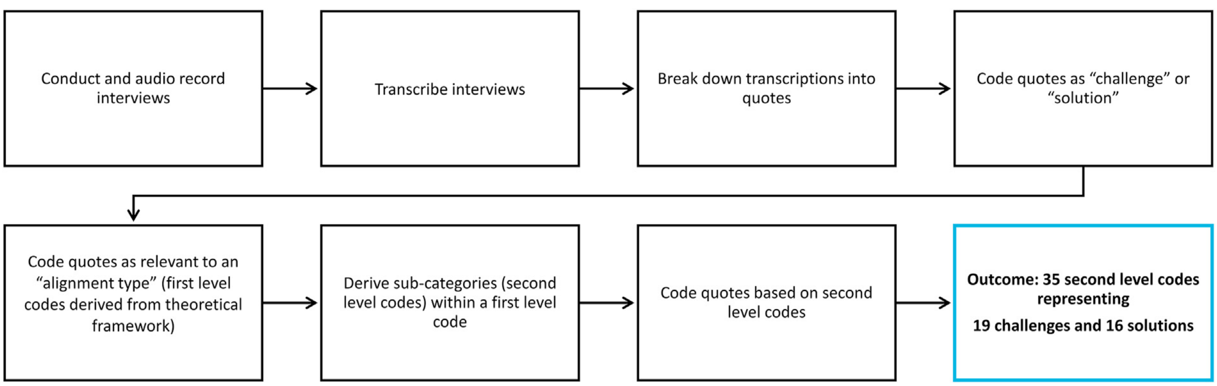

Fig. 1. Steps in the data analysis process.

the work system. We use the new technology stack (Fig. 2) to represent the IoT artefact needed to enable CBM. In order to also include services produced by the work system, and offered to the users of the IoT artefact, we add a service layer on top of the technology stack. This service layer might include, for example, software maintenance, updates, and support.

Based on the above, we formulate the descriptions of the work system elements according to Table 3. We identify the maintenance personnel as the main customers in the work system, since they are the main users of the product/service. This includes roles such as service technicians, service managers, and customer support personnel. However, we acknowledge that there can also be other users of the IoT artefact, for example the end customer (the user of the product to be maintained), or the internal R&D department.

The integrated framework distinguishes between six alignment types, numbered 1–6 in Fig. 4. These alignment types correspond to the five alignment types represented by arrows between work system elements in the work system framework (Fig. 3), and one extra alignment type corresponding to alignment between the work system and its surrounding context. In the context of this paper, we characterize the six alignments types by explaining what is considered satisfactory alignment within each type, as described in Table 4.

5. Case descriptions

5.1. Case A: forklifts

Company A manufactures and sells forklifts to end customers who are operators of, e.g., warehouses and manufacturing facilities. Company A also provides maintenance services to their customers as part of short or long-term rental contracts.

In the recent years, Case A has developed a cloud application that provides the end customers with information about the forklifts they use. Drivers can log in to the application to record driving times, and managers can see productivity data. The application can also be used by maintenance and support personnel to support troubleshooting (IntA3). Through the application, the maintenance personnel can extract reports which show how many hours the forklift has run, as well as the recent error codes that the forklift has produced.

Regarding data analytics to support CBM, the company has started to recruit experts, but is still in an early phase of development.

Looking forward, the interviewees saw the need to develop a failure model, which could prescribe maintenance activities to minimise breakdowns (IntA1). This will require additional data collection from the forklift's operational phase (IntA2,IntA1). The future vision for the cloud application also includes a stronger focus on service planning and coordination, such as automatic dispatching of jobs to service technicians based on their location and competence (IntA2).

5.2. Case B: industrial robots

Company B manufactures and sells industrial robots to a broad range of customers, e.g., in the automotive industry. The company has in-house service technicians who provide maintenance services to the end customers who have opted for that. There is also a support organization, which assists customers remotely.

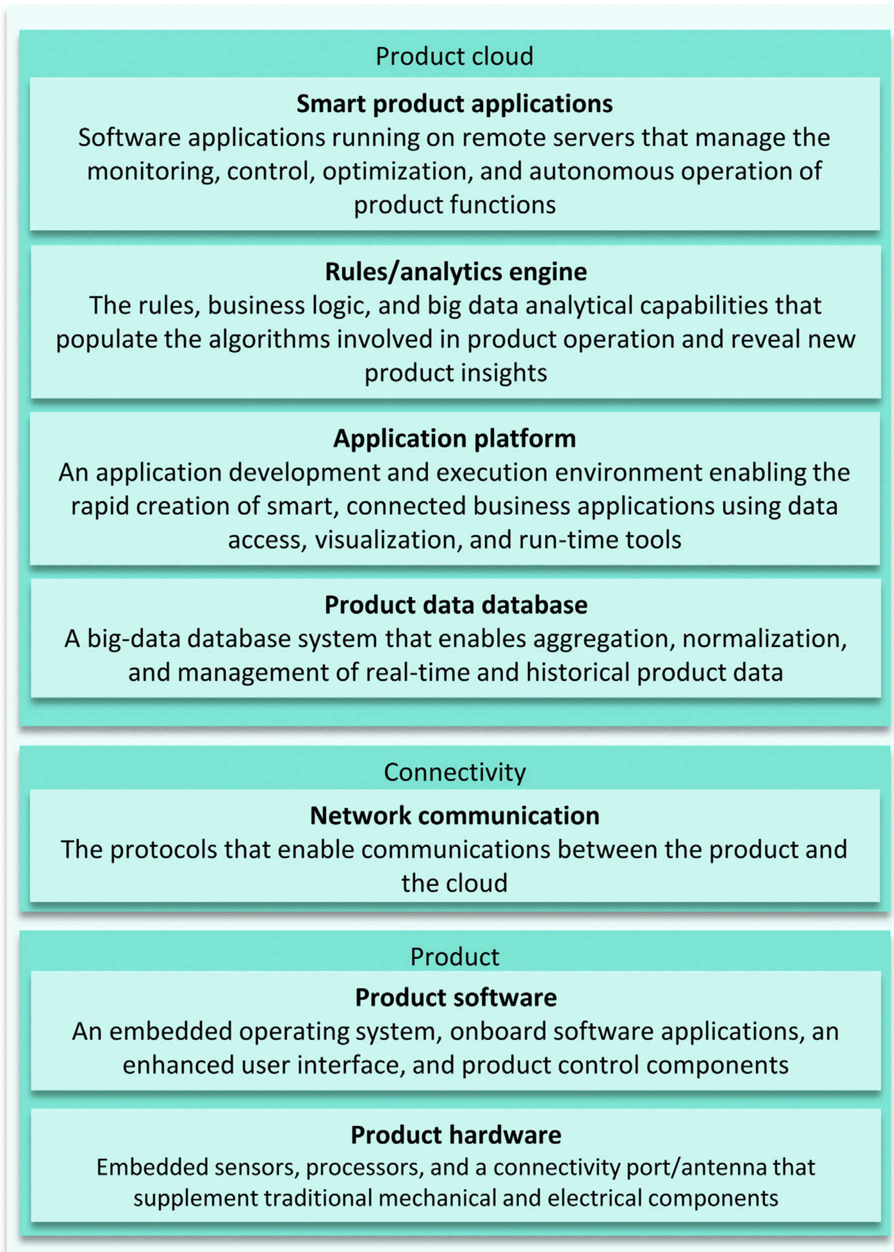

Fig. 2. The new technology stack, adopted from Porter and Heppelmann (2014).

The company has offered services based on connectivity as an add-on to the robots for about 10 years (IntB4). They have developed a web-based application where both the end customer and internal maintenance personnel can log in and get information about the connected robots including alarms and error codes (IntB4). Internally, the main user of the application is the support personnel, who can log in to see and download recent alarms recorded by the robot.

Regarding data analytics, several research projects have been carried out to develop failure diagnostics and prognostics for CBM (IntB3). Moreover, a central data analytics team has been formed to support the different business units.

Looking forward, there is an ongoing project to update the application. The project will make sure that the application is transferred to a new company-central cloud platform and that the user experience is improved (IntB4). Moreover, the vision for the future includes an increased focus on failure predictions, and on prescribing timely maintenance actions (IntB4). Also, there is an ambition to extend the scope of CBM to include the tools used by the robot, or even the whole production line made up of multiple robots.

5.3. *Case C: heat pumps*

Company C manufactures and sells heat pumps to both property managers, and individual households. The company does not offer maintenance-as-a-service directly, but has a long (ca 10 years) warranty which covers maintenance costs. Third party installers perform the actual maintenance activities, with help from the company's support organization (IntC1). There is a drive in the company to reduce maintenance costs, and increase customer satisfaction through increased uptime.

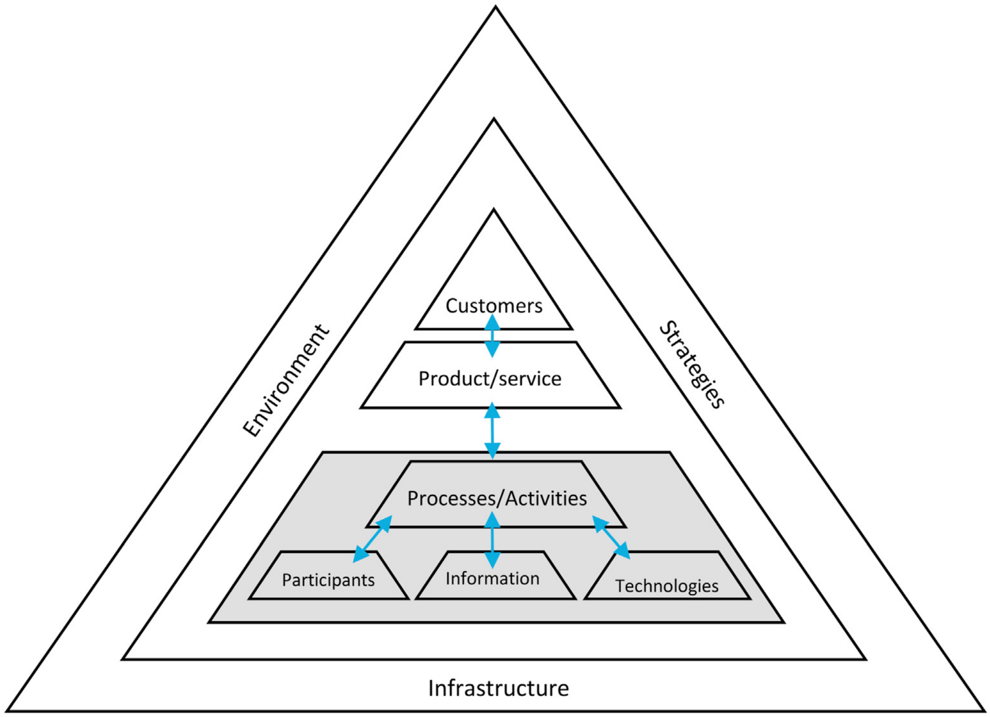

Fig. 3. The work system framework, adopted from Alter (2013).

Table 3
Elements of the integrated framework, adapted from Alter (2013).

Work system element	Description
Product/Service	An IoT artefact which supports CBM. The IoT artefact has a product layer, a connectivity layer, a cloud layer, and a service layer.
Customers	The main customers of the product/service are service technicians, service management, and customer support. Other customers can be, for example, the end user of the physical product and the R&D department.
Activities	Activities needed to produce the product/service include, but are not limited to, the design and development of cloud applications, data analytics models as well as the setup of data collection, transfer and storage. Activities also include the development of services such as software maintenance, updates, and support.
Participants	Participants involved in the activities are, for example, user interface designers, application developers, data analysts, and embedded software engineers.
Information	Information used by the participants in the activities includes feedback from the customers, as well as data collected by products in the field.
Technologies	Technologies used by the participants when performing the activities include tools for data collection, transfer, and processing.
Context	Using Alter's definitions for Infrastructure, Environment, and Strategies (see Table A.2 Appendix A), the context includes the overarching strategies of the company in which the work system is embedded, the organizational, cultural, competitive, technical, regulatory, and demographic environment surrounding the work system, as well as resources used within the work system, but managed outside it.

Almost all heat pumps currently sold can be connected to the internet. However, the company only collects data from customers if the service technicians cannot solve the problem and therefore contact customer support. Then, the company sends a request to the customer asking for permission to monitor their system for fault diagnosis purposes (IntC1). If accepted, the customer support can see the error codes produced by the heat pump. It is also possible to activate additional data logging, if needed (IntC4).

Regarding data analytics, the company has started to move towards predictive analytics, by putting together a specific team in charge of developing data-driven models to predict failures (IntC4).

Looking forward, there is an ongoing project to develop an application for the service technicians to be able to troubleshoot more easily, receive alarms remotely, and better plan and prepare for maintenance visits (IntC1). The project also involves extending the data available to the customer support team (IntC2).

6. Results

A total of 19 challenges and 16 solutions were extracted from the case data. The challenges and solutions are distributed across the six alignment types in the framework, as seen in Fig. 5 and Fig. 6, respectively. Below, we describe the observed challenges and solutions per alignment type, illustrated by examples from the cases.

6.1. Information-Activities alignment

The challenges within this alignment type relate to collecting the right data at an appropriate quality. In all three cases, data is being collected from products in use. However, the data is not always appropriate and useful for the purpose of CBM (IntA1). Limited accuracy and time resolution of the collected data were mentioned as specific challenges (IntC2, IntB1), as was the fact that the data did not include all the parameters known to affect the

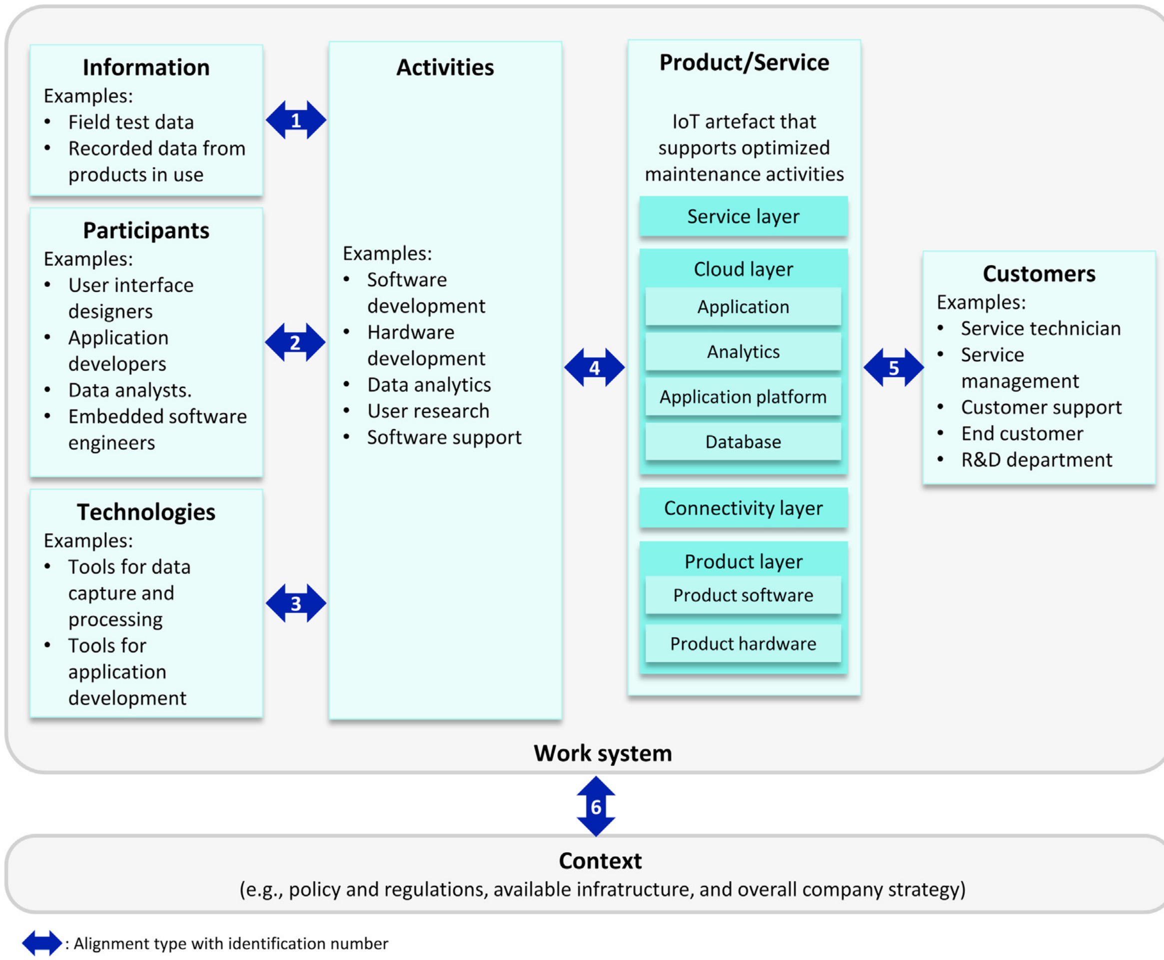

Fig. 4. Integrated framework for analysing the company cases, based on Alter (2013) and Porter and Heppelmann (2014).

Table 4
Explanation of satisfactory alignment, for each alignment type in the integrated framework.

Alignment type	Explanation
1. Information-Activities	The information that goes into the activities provides satisfactory input to the participants to perform the activities needed to produce the product/service.
2. Participants-Activities	The participants are able and willing to perform the activities needed to produce the product/service.
3. Technologies-Activities	The technologies available to the participants enable them to perform the activities needed to produce the product/service.
4. Activities-Product/service	The activities are well coordinated and aligned towards the goal of delivering a consistent product/service.
5. Customer-Product/service	The product/service satisfies the needs of all relevant customers, and the customers are able and willing to use the product/service as intended.
6. Work system-Context	The surrounding context supports the goal of the work system.

product's condition (IntA1, IntB3, IntC3). In Case C, the latter issue has partly been solved through a strategy to collect more data than initially needed (IntC1, IntC4). However, this solution is difficult to scale up since it requires large amount of data to be transferred, stored, and processed (IntC4).

Moreover, both high quality metadata and labelled data are difficult to collect. Metadata here refers to information about a product in the field other than the actual monitoring parameters (e.g. the size of a house in which a heat pump is installed), and can be important for interpreting the data recorded by the system (IntC2, IntB1). Labelled data is a dataset that contains 'labels' about what actually happened in the field (e.g., if the product stopped working). Such labels are needed to perform supervised machine learning and build data-driven prognostic models (IntB3, IntC4). A specific issue is that metadata and data labels often have to be entered manually, for example by an installer or the end user. The interviewees pointed out a lack of ability and/or incentive among installers and end users to input this information accurately, and in a format that would allow for automatic processing (IntC2).

In Case C, the company has partly solved the challenge of lacking metadata, by asking installers to input metadata through a mobile application when an installation is registered to the warranty program (IntC2, IntC4). Still, many installers either do not report any metadata at all, or report inaccurate information. To collect labelled data, Case A and B monitor products in their own operations, for which they have insight into the products' condition (IntA6, IntB3). Case B also performs tests of their products in lab environments (IntB3). For Case B, faults that happen at the

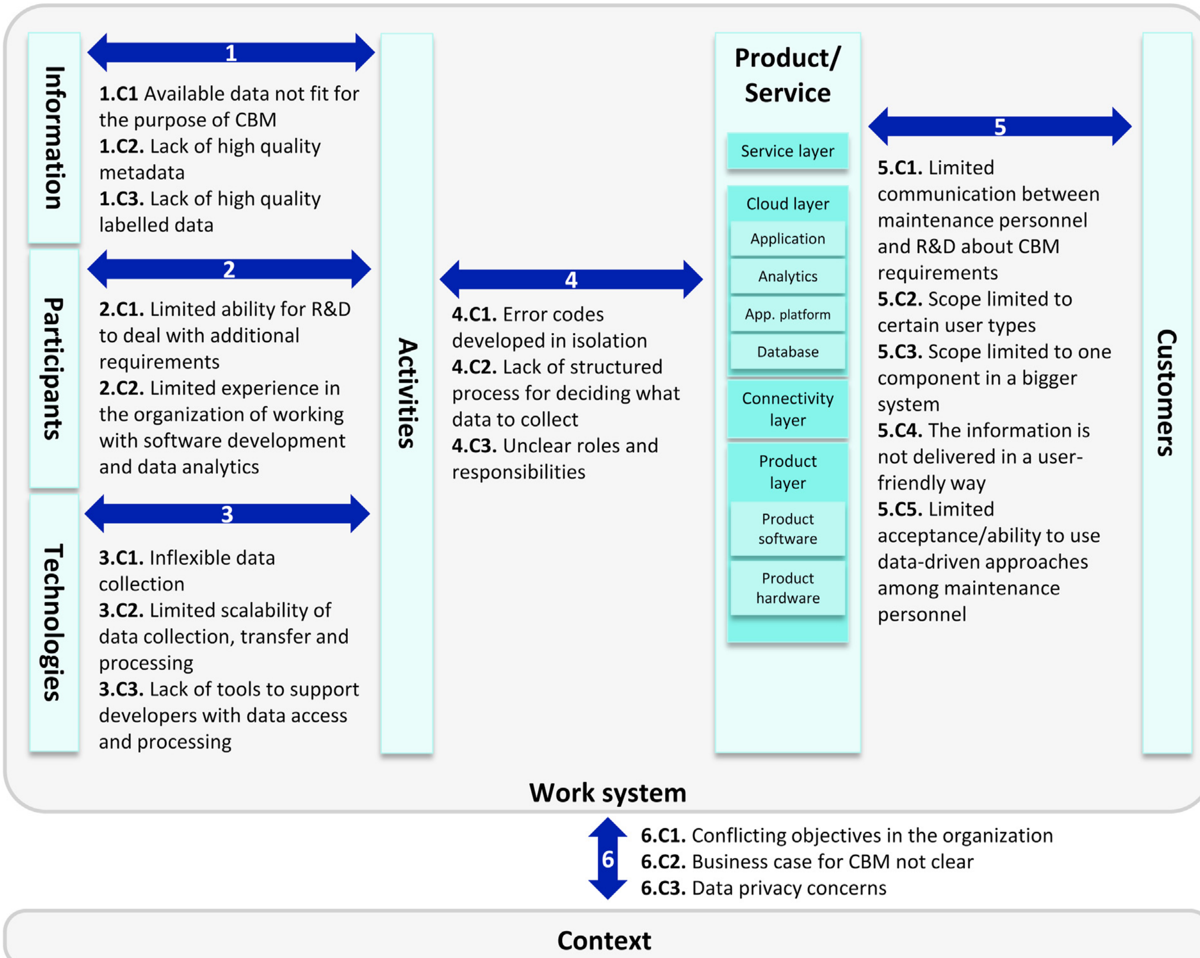

Fig. 5. Challenges per alignments type, as extracted from the studied cases. The numbering used is 'X.CY', where X is the number of the alignment type (1–6), 'C' stands for challenge, and Y is the number of the specific challenge.

customer site during the warranty period are well documented (IntB3) and Case C performs field tests at customer sites when new products are released (IntC1, IntC2). However, to understand product degradation over time, it would be necessary to collect labelled data from the field throughout the whole life of the product. Case C has tried to achieve this through building a web application for service technicians to enter labels about products' condition during maintenance activities. However, the technicians often do not use it, or do not input the data accurately enough (IntC4).

6.2. Participants-Activities alignment

The challenges within this alignment type relate to a lack of time, resources, and experience in the organization needed to meet CBM-specific requirements. CBM requirements are sometimes overlooked if the R&D department is already overloaded with other product requirements (IntB3, IntA3, IntA7). It is especially difficult for the R&D team to develop new infrastructure, such as a cloud platform, while working on sharp development projects (IntB3). Moreover, due to lacking experience with data-driven approaches, some employees do not even consider that these technologies could be of interest (IntB3, IntA1). One way to improve this situation is to work actively with awareness-building in the organization, supporting employees in seeing the value and opportunities of data (IntB3).

In Case B and C, time and resource issues in the R&D team have been reduced by appointing a specific group to manage the cloud platform centrally in the organization. This way, each business unit can build applications in the cloud platform, get support from the central function, and learn from each other (IntC1, IntB3). Similarly, Case B and C have established specialized data analysis teams who support and share knowledge between different business units (IntB3, IntC1).

Another identified solution is to ensure sufficient collaboration between people with more traditional product expertise, and people with data-specific competences. One example is that, when developing failure models, data analysts are supported by product experts about known causes for failure, and important parameters influencing degradation (IntB2, IntB3, IntC4). Another example is that collaboration between hardware development and software development is necessary when software-related requirements imply a need for additional data collection, which in turn leads to a need for changes to the physical product (IntB1).

6.3. Technology-Activities alignment

The challenges within this alignment type relate to limited flexibility and scalability of data collection and to a lack of tools available for developers. Limited flexibility in data collection means

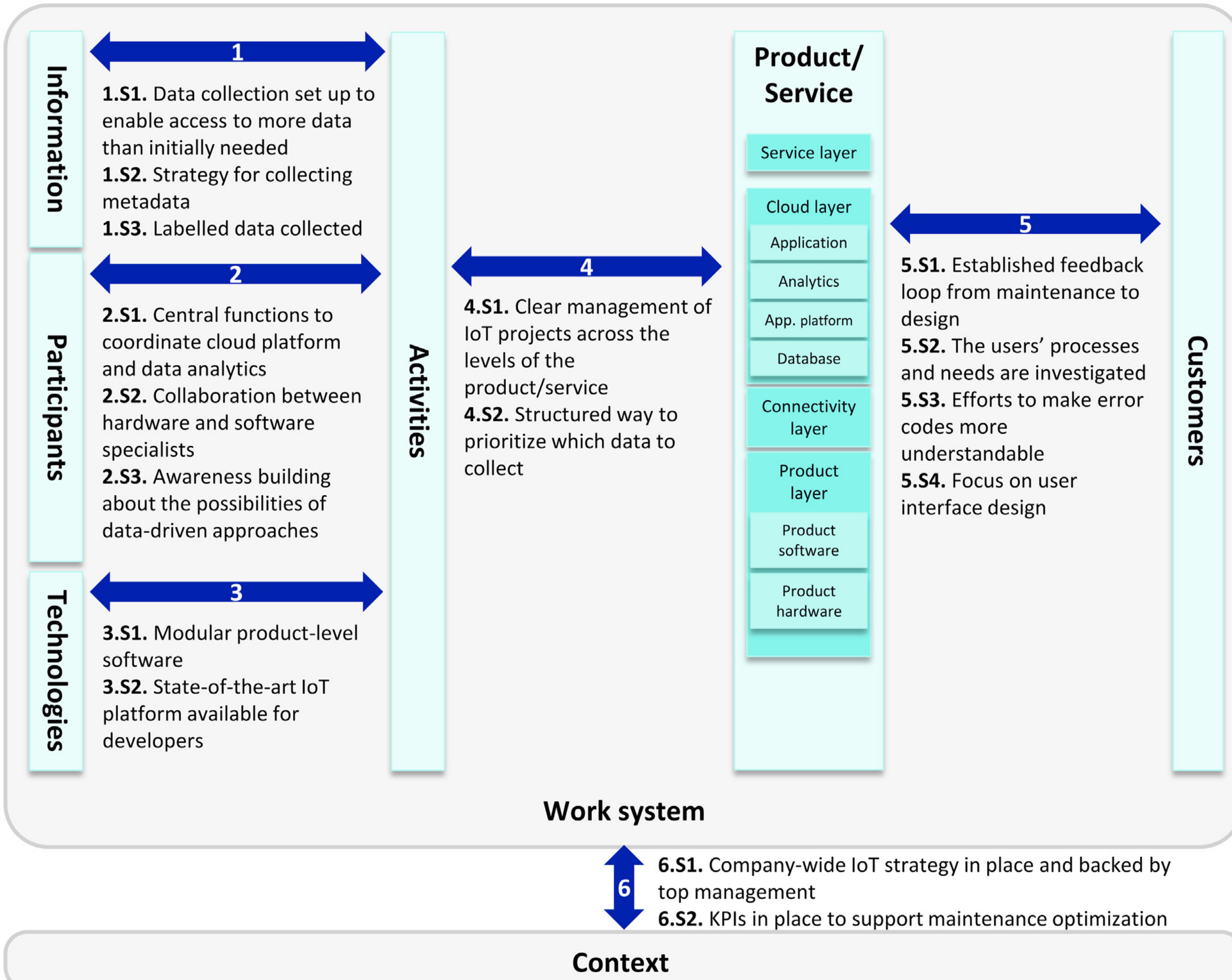

Fig. 6. Solutions per alignment type, as extracted from the studied cases. The numbering used is 'X.SY', where X is the number of the alignment type (1–6), 'S' means solution, and Y is the number of the specific solution.

that it would be difficult to change what data was collected from the products over time. An interviewee from Case B mentioned that if they wanted to add another parameter to be monitored from products in the field, it would require an update of the complete product-level software. This might not be accepted by the end customers, since software updates always involve a risk of introducing new errors. This challenge has been partly solved in Case A, where the data handling unit on the products can be updated separately from other product-level software, enabling collection of additional data without impacting other functionality (IntA6). In Case B, there is an ongoing program to modularize the product-level software (IntB3).

As the number of connected products increase, the scalability of data collection, transfer and processing also becomes a challenge (IntC4). Moreover, one interviewee from Case B highlighted the lack of easy-to-use technical tools and developer environments which could help simplify data access and analysis (IntB3). Both these challenges have been partly solved in both Case B and Case C, through the development of a central IoT platform. The IoT platforms can be used by different business units to build the applications they need. The platforms also offer benefits such as increased data security (IntC2), higher sampling rate, and real time data availability (IntB4).

6.4. Activities-Product/service alignment

The challenges within this alignment type relate to a lack of processes, roles, and responsibilities in the organization to effectively deliver a CBM solution. For example, one interviewee mentioned that there is "*no real ownership of the delivery of useful information to the maintenance team*", and that this responsibility should be made explicit, and assigned to a certain role in the development process (IntA1). More specifically, we found a lack of structure in deciding what data to collect for CBM. Data collection is mainly driven by what is technically possible rather than what is actually needed (IntB4, IntA4, IntA1, IntA2). Similarly, the error codes coming from the products in Case A and C are not developed to guide service personnel when assessing a product's condition, or to propose maintenance actions (IntA1). Instead, the error codes are defined by the software developers for the purpose of testing certain programmed functions (IntA1, IntC3).

The above-mentioned challenges have been partly addressed in Case B by appointing a project manager to lead CBM projects across business functions. Requirements from users of the cloud-level application are collected in a common 'backlog' and sent to the respective teams who implement the request, ensuring feedback of user needs to both software and hardware development (IntB4).

Case B and C have started to address the challenge of lacking structure for deciding what data to collect by (1) prioritizing data from components which fail more often, and which are known to have a high impact for the customers if they fail (IntB3) and (2) by involving the customer support department to help decide which data to collect based on their experience of common issues in the field (IntC3).

6.5. Customer-Product/service alignment

The challenges within this alignment type relate to a lack of user understanding and a limited acceptance among users to adopt CBM solutions. A core challenge is to translate the needs of the service personnel to the data engineers. Reasons for this lacking understanding are, for example, limited interest and ambition of responsible individuals (IntA7), or that actors are ‘stuck’ in established ways of working (IntA1). In Case A, the service team expressed that the data engineers do not take the time to understand how they work (IntA2). On the other hand, the data engineers pointed out that communication was hindered by the fact that the service technicians do not fully understand the specificities of big data analytics (IntC4). One interviewee highlighted that service technicians do not even think about setting requirements for the usefulness of the information that they receive, because they are used to their current way of troubleshooting products (IntA1).

Some solutions were found in relation to these problems. In Case B, the application development team perform dedicated user observations and interviews in order to understand the users' needs and pain points. This way, insights are extracted about what information would be useful, and how it should best be presented to the user (IntB4). In Case A and C, the service organization and the development organization hold regular meetings to discuss how to improve product maintainability (IntA3, IntA2, IntC3). While this provides a platform for communication about design for maintenance, the requirements discussed are mainly related to physical product features and not CBM-specific.

A specific challenge is that the CBM solutions do not deliver information in a user-friendly way (IntA3). For example, the service personnel might not understand why certain error codes appear, what they mean, or what action to take based on this information (IntA2, IntA1, IntB4). The same error code can also mean different things for different product models (IntA7). Moreover, support technicians are overloaded with alarms and have difficulties prioritizing between them (IntB4). The interviewees discussed ways to make error codes more understandable. In Case A, the embedded software developers include an information file to all software packages, explaining the error codes. They also use a certain structure for numbering the error codes, and try to keep this structure across product models (IntA7). In Case C, an interviewee mentioned that they always try to make error messages as self-explanatory as possible (IntC2). Case B have focused on reducing unnecessary terminology, using more visuals, and using more consistent terminology (IntB4).

With regards to the limited acceptance and ability among service technicians to adopt data-driven approaches (IntB4), a specific challenge is the limited trust in failure detection and prediction algorithms (IntC4). An interviewee highlighted the importance of keeping the number of ‘false alarms’ from algorithms low, in order to enable higher acceptance rates among service technicians. Interviewees also mentioned that some service technicians are lacking the skills to take advantage of data-driven approaches (IntC2), pointing out a need for additional training (IntA3).

Another challenge is to properly identify and target all relevant users of the IoT artefact. For Case A, a cloud-level application was initially developed for the end customer, partly disregarding the needs of the service organization (IntA5, IntA6). In Case B, a cloud-level application was developed to serve the customer service team (IntB3, IntB4), assuming that they would be the main users. This assumption turned out to be true for small customers, who did not perform any maintenance themselves, but not for big customers (IntB3). Further, there might be other potential users of the IoT artefacts, who are not yet considered. For example, an interviewee from Case A saw the need to add a specific interface towards the back-office service department (IntA2), and in both Case A and B, interviewees saw an opportunity to develop a specific interface towards R&D (IntA5, IntB3).

In Case B, interviewees also discussed that the current CBM solution only monitors the condition of the core part of the product. However, to provide real value to the end customer, the CBM solution should include the whole product, and even the system in which it operates. In Case B, this would mean a solution which considers the condition of the robot itself, the different tools that the robot uses, and potentially even multiple robots in a production line (IntB1, IntB3, IntB4).

6.6. Work system-Context alignment

The challenges within this alignment type relate to conflicting objectives in the organization, uncertainty about the business case for CBM, and data privacy issues. All three cases have an IoT strategy in place at the top-management level. On this level, the companies are thus committed to ensuring that their products can be connected to the internet (IntC1, IntB1, IntA4). However, this top-level vision does not always translate into actual changes in work practices regarding CBM. Conflicting objectives manifest themselves through, for example, that CBM advocates struggle to get buy-in from the organization (IntA1, IntC2) and that reducing production costs is prioritized over reducing maintenance costs (IntA2, IntA1). In Case A, some customers also still pay per service visit, and per spare parts exchanged (IntA3). This creates a mind-set among people in the organization that they make money when they replace parts for customers, which dis-incentivized maintenance optimization.

A possible solution to these issues is to introduce organization-wide key performance indicators (KPIs) that steer toward maintenance optimization and CBM. Case C has introduced a KPI to minimise the number of maintenance visits per installed product (IntC1) while Case A has a KPI to minimise downtime in their customers' operations (IntA5, IntA6).

The challenge of finding a business case for CBM relates to how customers perceive the value of the service (IntC2). Many customers are, for example, more concerned about the buying price of a product than the maintenance costs (IntA2). In Case C, the interviewees said that since their products do not have regulated scheduled service events, many customers do not see the value of optimized maintenance (IntC2). It is especially challenging to communicate the customer value of prescribed, precautionary maintenance activities, which take place before the customer detects any issues with the product (IntC4).

Another challenge for CBM implementation is that data privacy regulations are becoming stricter. Interviewees from all cases describe that they work carefully to comply with data privacy regulations. In Case C, an interviewee highlighted that the changing regulations create a careful attitude, among both employees and customers, which might prevent the use of data which could be compliant and useful (IntC2). This was especially true for large customers, who are particularly concerned about IT security and confidentiality of data (IntB3).

7. Discussion and recommendations

The results show that CBM implementation comes with a wide range of challenges, confirming the previously noted importance of taking a broad and systemic perspective when studying CBM in practice (Golightly et al., 2018; Veldman et al., 2011). It is noteworthy that all three cases display challenges within each of the six alignment types. Moreover, the challenges and solutions within an alignment type are sometimes interrelated with challenges and solutions in another alignment type. As such, targeted interventions within one alignment type can also impact other parts of the system.

Below, we discuss the findings, per alignment type, in relation to previous literature. We combine the challenges and solutions found into a set of 17 recommendations for OEMs aiming to implement CBM (Fig. 7). Each recommendation is formulated to be concise and actionable. Fig. 7 shows how each recommendation links to the challenges and solutions identified in the cases. This way, interrelations within and across alignment types are made explicit. As such, Fig. 7 could support companies in taking concrete action towards more successful CBM implementation, without losing the 'big picture'.

Firstly, the results show that conflicting objectives in the organization is a challenge in CBM implementation (6.C1). This has also been noted by Bokrantz et al. (2020) who saw a need for clear leadership, visions and goals. Rastegari et al. (2013) further pointed out management support as one of the main challenges in CBM implementation. We found that a company-wide strategy for IoT in general is helpful for CBM implementation (6.S1), but that CBM-specific goals and KPIs are important additions (6.S2), confirming similar conclusions by Bouskedis et al. (2020). Based on these insights, we formulate two recommendations:

1. Create a common vision in the organization for CBM.
2. Put in place KPIs which support CBM.

The case companies also struggled to clarify the business case for CBM (6.C2), due to uncertainty about how the CBM solution would benefit themselves and their customers. This challenge has been reported previously by, e.g., van de Kerkhof et al. (2016) and March and Scudder (2017). We further note that the CBM offering might have to be adapted to the needs of different customer types. Specifically, some customers might, for data privacy reasons, prefer to manage their own data storage and processing. As data privacy issues among customers is increasing, and as data privacy regulations are becoming stricter (6.C3), companies need build expertise in this area. Based on the above, we formulate the following recommendations:

3. Clarify the businesses case for CBM.
4. Build expertise in data privacy.

The results further display a need to improve the usefulness of CBM solutions (5.C2, 5.C3, 5.C4, 5.C5). The case companies struggled to identify and sufficiently target all relevant users of the IoT artefact (5.C2) and to decide on a suitable scope the CBM solution in relation to the context in which it operates (5.C3). The latter contextualises the argument made in CBM literature about the importance of developing CBM solutions for multi-component systems (e.g., Alaswad and Xiang, 2017; Olde Keizer et al., 2017). Moreover, we found a challenge in making the IoT artefact's interfaces user friendly (5.C4), indicating a need for more focus on user interface design (5.S4). This confirms previous findings from, e.g., Golightly et al. (2018) who highlighted the importance of user interface design for CBM. Questions about how to make more intuitive interfaces toward service technicians in CBM have also been explored in the field of augmented reality (e.g., Egger and Masood, 2020).

The layered view of the IoT artefact presented in our framework further highlights the need to translate insights from user research into design decisions at each layer of the technology stack. Specifically, we identified a need for improved communication between maintenance personnel and data engineers about CBM requirements (5.C1). This relates to the challenge within the activities-product alignment type, which showed a lack of coordination of CBM projects across the layers of the IoT artefact (4.C1). Based on the above-mentioned insights, we formulate the following recommendations:

5. Ensure sufficient communication between data engineers and maintenance personnel.
6. Investigate the processes and needs of all relevant users of the IoT artefact.
7. Actively decide on a suitable scope for the CBM solution.
8. Ensure that the IoT artefact delivers information in a user-friendly way.

An interesting challenge found with regards to usability of the CBM solution was the barrier among service personnel to trust data-driven approaches (5.C5). Akkermans et al. (2016) observed a similar challenge, noting that data-driven approaches are "*not in the genes*" of service technicians. In our study, we found that increased transparency and explicability of algorithms might be important for acceptance, something that has also been mentioned by Bokrantz et al. (2020). Our results did not expose any clear solutions here, but we note that this challenge relates to the identified solution about continuously spreading awareness in the organization about the possibilities of data-driven approaches (2.S3). Based on these insights, we formulate the following recommendation:

9. Combine algorithm explicability efforts with training of maintenance staff to lower the acceptance barrier for data-driven approaches.

The companies also faced challenges related to developing the IoT artefact as one entity. The development of solutions at different layers of the technology stack were generally not well-coordinated (4.C1, 4.C2, 4.C3). We also found a need to clarify roles and responsibilities among the actors in this process (4.C3), something that has been previously noted by, e.g., Ciocoiu et al. (2017). Based on this, we formulate the following recommendation:

10. Set up clear roles and responsibilities for CBM projects, across the layers of the IoT artefact.

Moreover, our results showed a lack of structured processes for deciding which data should be collected (4.C2). This challenge has been noted by multiple other authors (e.g., Lee et al., 2009; Tiddens, 2018; Rastegari et al., 2013) and relates directly to challenges of the Information-Activities alignment type, indicating that the data collected is not always fit for the purpose of CBM (1.C1). Based on this, we formulate the following recommendation:

11. Establish a structured process for deciding which data to collect, and at what quality.

We saw that CBM implementation can be facilitated by building technical solutions which allow for flexible data collection over time (3.C1, 3.S1), and to provide easy-to-use tools for developers (3.C3, 3.S2). Flexible data collection solutions are important as they

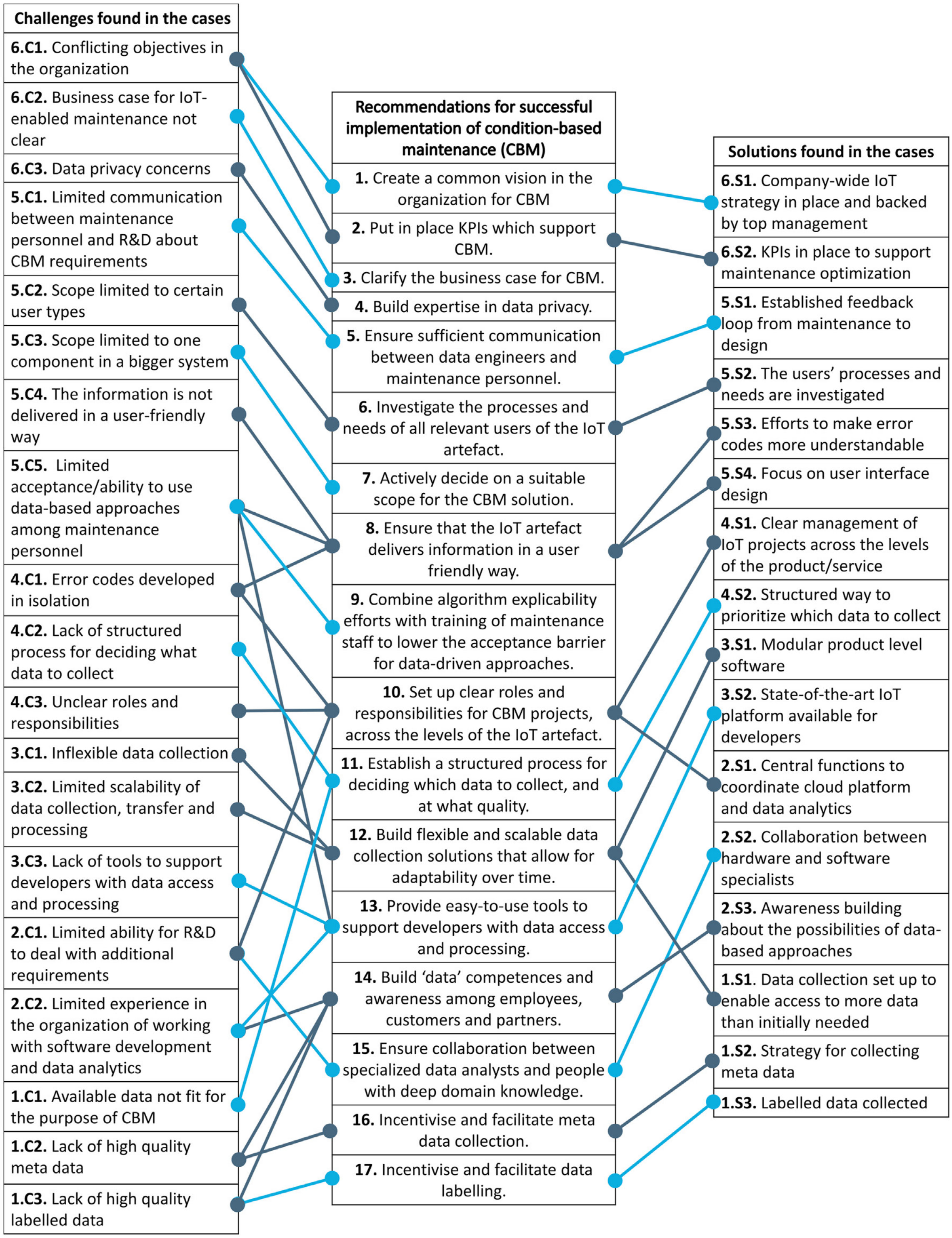

Fig. 7. 17 recommendations for companies wanting to implement CBM, based on the challenges and solutions found from the cases in this research (alternating colouring of the connecting lines for readability).

allow for learning through trial and error, and for adding new parameters to be monitored when needed (3.S1). Moreover, a flexible data collection solution can help companies avoid the sub-optimal solution of collecting more data than they really need (1. S1), a strategy which has limited scalability (3.C2), and can lead to data overload (Akkermans et al., 2016; Jonsson et al., 2010). Based on the above, we formulate the following recommendations:

12. Build flexible and scalable data collection solutions that allow for adaptability over time.
13. Provide easy-to-use tools to support developers with data access and processing.

We also found that the R&D departments struggled to find the time to develop CBM solutions (2.C1), and that they had limited experience of working with software development and data analytics (2.C2). To overcome these challenges, companies can focus on awareness-building around data-driven approaches (2.S3), and ensure collaboration between data analysts and product experts (2.S2). The latter has been mentioned previously by, e.g., Åkerman et al. (2018) and Hiruta et al. (2019). Based on these insights, we formulate the following recommendations:

14. Build data competences and awareness among employees, customers and partners.
15. Ensure collaboration between specialized data analysts and people with deep domain knowledge.

Finally, we found that the data collected by the case companies was not always fit for the purpose of CBM (1.C1). This relates directly to the lack of structured processes for decided what data to collect (4.C2, covered in recommendation 11). Specifically, high quality metadata and labelled data was lacking (1.C2, 1.C3), partly due to a lack of ability and incentive among installers, service technicians and end customers to input metadata and data labels with sufficient accuracy. As such, this relates to the need to increase the awareness about the value of data-driven approaches (2.S3, covered in recommendation 14) and to the challenge of limited acceptance among maintenance personnel for data-driven approaches (5.C5, covered in recommendation 9). Based on these insights, we add two final recommendations to the list:

16. Incentivise and facilitate metadata collection.
17. Incentivise and facilitate data labelling.

Having presented these recommendations, two important limitations of the research should be mentioned. Firstly, the results build on insights from three company cases. This is a limited data set and more research is thus needed to confirm the findings in other cases. Secondly, the case selection criteria were formulated so that the companies should have an at least a partly implemented CBM solution in place. Had the selection been more strictly limited to advanced cases of CBM implementation, it is possible that other or additional insights could have been captured.

8. Conclusions and future research

The aim of this research was to understand the challenges related to CBM implementation in practice and to extract solutions which companies have applied to address these challenges. Towards this aim, we conducted a multiple case study at three manufacturers who had partly implemented CBM. We proposed an integrated framework, which takes a broad perspective on CBM implementation, integrates technological, organizational and user-related elements, and explicitly considers the need for alignment between these elements. Using the framework to analyse the three cases, we identified 19 challenges and 16 solutions, spanning across the different alignment types. Based on this, we proposed a set of 17 actionable recommendations for practice. Moreover, we showed that some challenges and solutions are interrelated across the different alignment types. This implies that, when proposing a solution to a specific CBM implementation challenge, it is important to also assess its effects on other parts of the system. In the discussion of our findings, we facilitated this by making the interrelations between challenges and solutions explicit.

Our study contributes to the field of CBM with a comprehensive view of implementation challenges and solutions in real-world implementation, from the OEM's point of view. It also contributes with an analysis framework that can be used to derive such insights in other cases. Further, we contribute to CE research by adding a concrete case study to the emerging literature about IoT-enabled circular strategies, which has so far predominantly focused on opportunities rather than implementation.

Future research could build on the findings presented here to study more cases of IoT-enabled circular strategy implementation, eventually building a knowledge base around how to best realise the opportunities of IoT for CE in practice. In particular, given the strong analogies between maintenance and reuse/remanufacturing, the recommendations proposed here might also be relevant for OEMs aiming to implement condition-based reuse and/or remanufacturing. To verify this, future research is needed to understand specific challenges and solutions of such strategies.

CRediT authorship contribution statement

Emilia Ingemarsdotter: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft. **Marianna Lena Kambanou:** Investigation, Methodology, Project administration, Writing – review & editing. **Ella Jamsin:** Supervision, Writing – review & editing. **Tomohiko Sakao:** Project administration, Supervision, Funding acquisition, Writing – review & editing. **Ruud Balkenende:** Supervision, Funding acquisition, Writing – review & editing.

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.

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Appendix A

Table A.1
Interview guide used to collect data from the cases

Questions to R&D	
Context	• What was the idea when designing the CBM solution, what should it be able to do, and for whom? • Was the maintenance service already in place before the development of the CBM solution? How did IoT change the service proposition? • Who owns the cost and benefit of the CBM solution? Do end customers pay a fee for the CBM service? • Who owns the data collected from the CBM solution?
Function	• What functionalities does your CBM solution currently have? • How is this functionality supporting improved maintenance, according to you? • What information and knowledge can be obtained from your CBM solution? • Who uses the your CBM solution, and in what way? • Which information and knowledge is used by whom? • What are current limitations to the solution according to you?
Process	**Development of the CBM solution** • Who initiated the project? • Who was involved in the development process? • Did you use some kind of defined design/development process for developing the CBM solution? If yes, what does that entail? • Which were the main activities in the development process? **Requirements collection** • Whose needs did you consider when collecting requirements? • How and when did/do you collect requirements from the users of the CBM solution? • How and when did/do you collect needs from maintenance personnel to identify requirements? **Design decisions made** • How did you decide what information to show the users of the system, and how to visualise it? • How did you decide what data to collect and how to analyse it? **Evaluation activities** • How was the solution evaluated throughout the development process? • Did you have to make changes to this after the system had been used for a while? Can you describe that process? • How do you work with continuous improvement of the CBM solution? **Improvement potential** • What are your future development plans for the CBM solution? Why is this needed?
Questions to maintenance personnel	
Process	• Was the maintenance department involved in the development of the CBM solution? Can you describe how? • Do you think you/your group should have been more involved in the development of the system? Why/Why not? • Do you have a process for providing feedback to R&D about improvements that you would like to see for the CBM solution?
Use of the CBM solution	• What kind of maintenance activities do you do? • How do you use the CBM solution? • Has your work changed since the CBM solution came in place? How?
Improvement potential	• Is the information that you get from the CBM solution relevant? • Is the information that you get from the CBM solution reliable? • Is the information that you get from the CBM solution sufficient for you to make the decisions that you want to make? • Does the solution integrate well with other systems that you are using? • If you could change something about the solution as it is now, what would it be?

Table A.2
Definitions of the nine elements of work systems (directly from Alter, 2013 page 81)

Processes and activities occur in a work system to produce products/services for its customers. The use of the term "processes and activities" recognizes that the work being performed may not be a set of clearly specified steps. Many important work systems perform organized activities that rely heavily on human judgment and improvisation, are semi-structured, and are better described as a set of related activities.
Participants are people who perform work within the work system. Customers are often participants in work systems, especially in service systems.
All work systems use or create **information**, which in the context of work system analysis is expressed as informational entities that are used, created, captured, transmitted, stored, retrieved, manipulated, updated, displayed, and/or deleted by processes and activities.
Technologies include both tools that are used by work system participants and automated agents; that is, hardware/software configurations that perform totally automated activities
Products/services consist of information, physical things, and/or actions produced by a work system for the benefit and use of its customers.
Customers are recipients of a work system's products/services for purposes other than performing work activities within the work system. Customers of a work system often are also participants in the work system.
Environment includes the relevant organizational, cultural, competitive, technical, regulatory, and demographic environment within which the work system operates, and that affects the work system's effectiveness and efficiency. Organizational aspects of the environment include stakeholders, policies and procedures, and organizational history and politics, all of which are relevant to the operational efficiency and effectiveness of many work systems.
Infrastructure includes relevant human, information, and technical resources that are used by the work system but are managed outside of it and are shared with other work systems. From an organizational viewpoint rather than a purely technical viewpoint, infrastructure includes human infrastructure, informational infrastructure, and technical infrastructure.
Strategies that are relevant to a work system include enterprise strategy, department strategy, and work system strategy. In general, strategies at the three levels should be in alignment, and work system strategies should support department and enterprise strategies.

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