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Improving supply chain planning for aftermarket services: challenges with applying product-in-use data

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ABSTRACT

Product-in-use data from connected products are an important driver of enhanced supply chain planning (SCP) and service development for original equipment manufacturers (OEMs). This study examined challenges of applying product-in-use data in aftermarket SCP processes, their interrelation, and how they relate to process and data complexities. In a case study of a heavy truck OEM, empirical data were analyzed concerning three SCP processes. The process and data complexities contribute to explaining the significance of specific personnel, technical, and organizational challenges, for example, IT governance, IT infrastructure, and combining data science and domain competence. Furthermore, technical and personnel challenges cause organizational challenges, and organizational and personnel challenges can be reduced in an interactive circle. Data and technology challenges are especially important in the early analytical phase, where processes are developed, while the importance of organizational and personnel challenges in development phases varies between SCP processes.

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Aftermarket supply chain; big data; advanced analytics; supply chain planning; product-in-use

1. Introduction

As organizations extend their market offerings and business models towards value-in-use (Niu, Deng, and Hao 2020) and aftermarket services (Wagner, Mizgier, and Papageorgiou 2017), the digitally enabled connectivity of products in use has enabled them to collect extensive data about how their products are used (Andersson and Jonsson 2018). The Internet of Things (IoT), smart devices, increased computing capabilities (e.g. faster hardware and smarter software), and the vast amount of internally and externally available data, as well as AI advancements, are key drivers of advanced analytics (Jackson et al. 2024; Kache and Seuring 2017). Data about customers' operation of products (so-called product-in-use data) has not only improved operational processes but also created new conditions for supply chain planning (SCP) processes to respond to new demand patterns created by new offerings (Andersson and Jonsson 2018). Aftermarket SCP processes (the focus of this study), such as demand forecasting, spare part inventory planning, and transport monitoring and planning (Talwar et al. 2021), are challenged by high variability in demand sizes and time intervals (Chien, Ku, and Lu 2023). These processes could therefore benefit from a more effective use of data generated by connected devices from products in use, rather than relying solely on historical demand data, as is common practice in the industry. For predictive maintenance in the automotive aftermarket, the use of predictive models based on product-in-use data could improve the efficiency of the maintenance of vehicles due to less over-maintenance and avoidance of late maintenance causing breakdowns compared to using time-phased or distance maintenance intervals, which does not take into account the degradation of components caused by different usage and age of the vehicles (Bousdekis, Apostolou, and Mentzas 2020). Regarding vehicle monitoring, the purpose is also to avoid costly breakdowns or problems detected by the driver at a late stage, requiring reactive off-road diagnostics and problem-solving.

According to Tabesh, Mousavidin, and Hasani (2019), 85% of big data and AI projects fail. Numerous issues may make big data-enabled processes difficult to implement (e.g. Joshi et al. 2021; Lee and Chien 2022), and 'most existing studies have not effectively addressed practical restrictions' on implementing and using big data-enabled planning processes (Chien, Ku, and Lu 2023). Therefore, big data and advanced analytics are still often just a potential with 'gains yet to be delivered' (Boone et al. 2019). Correspondingly, Boone et al. (2019) reported that understanding the challenges associated with big data usage in aftermarket SCP is crucial for effective demand forecasting. Various challenges related to the use of big data in supply chain management (SCM) are frequently reported in the literature, which initially focused on the data itself, including volume, velocity, and variety (Kuo and Kusiak 2019). Furthermore, most studies have not elucidated how such challenges occur in process-specific contexts within SCM (Lee and Mangalaraj 2022; Talwar et al. 2021) or how they are

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mutually related. One understudied perspective is how advanced analytics challenges emerge from the complexity of data or the complexity of the process in which they are used. Advanced analytics projects often extend over a long time, and several initiatives never extend from the project and pilot phases into large-scale implementation and practice. Tabesh, Mousavidin, and Hasani (2019) emphasized the importance of implementing a big data strategy. Consequently, challenges may differ not only between different types of big data-enabled SCP processes but also between early and late phases of big data implementation and process development (e.g. as identified by Ivert and Jonsson (2011) for advanced planning and scheduling system development and implementation).

Hence, the purpose of this study was to investigate the challenges of applying product-in-use data in aftermarket SCP and how these challenges are contingent on the specifics of the processes in which the data are used and the type of data used. The SCP process and data specifics are characterized as process and data complexities, respectively (Bozarth et al. 2009). *Process complexity* refers to activities, decision-making, and actor involvement, whereas *data complexity* refers to the sources and format of the product-in-use data applied. Challenges may be interconnected between the types of challenges and between process development phases. The purpose of the study was operationalized in the following research questions:

RQ1: What challenges and types of challenges does the use of product-in-use data in aftermarket SCP create, and how are these challenges interconnected?

RQ2: How are these challenges contingent on data and process complexities?

To investigate challenges in SCP, we conducted an in-depth multi-year case study as participatory research in the aftermarket division of a heavy truck original equipment manufacturer (OEM). In what follows, the contribution is shaped by the following. Firstly, we present a phenomenon-based theorization (Schwarz and Stensaker 2014) making use of a research design that creates a close proximity to managerial experience as response to Hasan et al. (2024) account of the limitations of research on big data and advanced analytics within the field of supply chain operations, which is in an 'infancy stage' (Hasan et al. 2024, 60), and predominated by systematic literature review and conceptual work (Chehbi-Gamoura et al. 2020; Stüve et al. 2022; Talwar et al. 2021). Secondly, the research provides further depth into the current scope of big data and advanced analytics in supply chain management (Talwar et al. 2021), with a particular focus on the actual usage and improvement of SCP (Xu et al. 2023). That is, the implications drawn are more about 'how' rather than 'what', stated in five propositions. Thirdly, extending the current manufacturing focus on big data and advanced analytics (e.g. Hasan et al. 2024; Xu et al. 2023), with SCP focusing on traditional operations functions such as procurement, production, distribution, and sales in an aftermarket context. To this end, the research complements the account by Acciarini et al. (2023) on the relevance of big data for business model innovation by offering empirical insight derived from a study of a servitized manufacturing context, i.e. where advanced analytics and SCP serve as a key foundation for the company's extension of their business model.

2. Literature and conceptual framework

This section outlines the characteristics of SCP in an aftermarket context to establish the conceptual foundation and context of the study, and to explain the particularities that emerge when moving from the overall view of big data towards the context of aftermarket services, connected vehicles, and, as the study's focus, product-in-use data. Arising from that foundation, data categories for SCP are described, after which emerging frameworks and key concepts on which the conceptual logic of the study was based are presented and reviewed.

2.1. SCP in an aftermarket context

2.1.1. Aftermarket: more than planning for spare parts and maintenance

The unpredictable nature of demand for maintenance and spare parts is one reason why aftermarket services are more complex than supply chains for finished products (Cohen, Agrawal, and Agrawal 2006). Different maintenance time intervals (Chien, Ku, and Lu 2023) and required response times also contribute to that complexity (Boone, Skipper, and Hazen 2017; Cohen, Agrawal, and Agrawal 2006). For example, a customer who buys capital-intensive products, such as trucks, usually understands that delivery time can be weeks, if not months, but also expects maintenance or repair to be completed in a day, particularly for commercial vehicles, whose downtime is costly and affects the firm's revenue. Additional differences between aftermarket and production supply chains include the number of stock-keeping units (SKUs), the number of distribution points (Jouni, Huiskonen, and Pirttilä 2011), and the varying need to maintain a complicated product portfolio, which is driven to some extent by having to service a specific product for a specific customer during the product's life cycle (Huiskonen 2001). The Demand for maintenance differs across the life cycle and is contingent on the product's use (Boone, Skipper, and Hazen 2017). During its initial phase, a product generates little to no data to inform planning. However, during the mature phase, maintenance demand is relatively stable, but planning for low-frequency items remains challenging. Finally, in the phase-out stage, SCP poses the challenge of finding alternative sources for maintenance operations. At all stages, spare parts are critical, and their unavailability can cause machine failures and prevent planned vehicle operations. Needless to say, the economic impact may far exceed the monetary value of the spare parts themselves (Huiskonen 2001).

2.1.2. Categories of SCP

To maintain customers' requirements for the uptime of their purchased products, SCP sets the foundation for optimizing supply chain performance and can be strategic, tactical, or operational (Stadtler and Meyr 2015). This study focused on the tactical and operational tasks of aftermarket SCP, in which demand is driven by the need to maintain or repair finished products. To meet the customer's requirements for uptime, tactical maintenance planning, which consists of spare parts demand and inventory, supply, and capacity planning, is required. Operational tasks in the field include work order release, resource monitoring, and ensuring the availability of spare parts (i.e. making sure that when a maintenance or repair operation begins, the necessary spare parts, mechanics, and equipment are readily available). Tactical processes to support field locations with spare parts include demand and inventory planning, supply planning, spare part deployment within the supply network, supply and operations planning, and warehouse and transportation capacity planning. The operational task for the OEM consists of releasing and maintaining supplier orders, monitoring inbound and in-transit orders, and releasing and prioritizing customer orders.

To secure uptime, a combined effort between the service provider (maintenance planning) and the OEM (spare parts distribution and planning) is required. Predictive maintenance activities engage the service provider, who is responsible for coordinating services with users and internal resources, ensuring that demand figures are correctly updated, and allocating and ordering spare parts. Meanwhile, the OEM is responsible for ensuring spare parts availability and managing demand and inventory. Demand planning considers both forecasted demand and demand known beforehand (pre-planned demand). Together, the OEM and product owners coordinate the monitoring of products, typically in light of data from connected products in use and technical data, including fault tree diagrams that depict fault codes related to operations and the spare parts most required. Usually, the monitoring process detects emergency conditions hours or days before maintenance or repair is needed, which is why it is considered an operational task.

2.2. Categories and sources of product-in-use data for aftermarket services

Connected devices, such as vehicles, and the extensive use of sensor technology have generated product-in-use data, a new type of data useful for understanding how products are used (Andersson and Jonsson 2018). Aftermarket SCP-specific data, or *product-in-use data*, can be divided into six categories according to its nature and use: operational data, fault codes, sensor data, installed base data, item usage data (Andersson and Jonsson 2018), demand data and external data, the last of which represents factors that impact the underlying demand for aftermarket services (e.g. weather and road conditions and macro-economic factors in the example of vehicles; Table 1). A related taxonomy of big data (Seyedan and Mafakheri 2020) is referred to as supply chain data, but we used the Andersson and Jonsson (2018) product-in-use taxonomy.

The product-in-use data to be applied in SCP for products in use originates from at least types of sources: (1) sources on or connected to the products, which provide operational data, fault codes, and sensor data; (2) maintenance systems, which provide item usage data; (3) manufacturing systems, which provide installed base data; (4) external sources, which provide data about external factors, and demand history of spare parts. Table 1 summarizes the data categories and data source types for aftermarket SCP.

Product-in-use data can also be understood in relation to the 'Vs of big data': volume, variety, and velocity (e.g. Hazen et al. 2014; Lamba and Singh 2017). Whereas volume describes the amount of data, variety refers to whether the data are structured or unstructured, and can be derived from sources such as sales transactions, connected vehicles, or route planning systems (Russom 2011). Finally, velocity refers to the efficiency of collecting and updating data (Waller and Fawcett 2013). Subsequent research has extended the 'V' framework to encompass 4 V and 5 V models (Al-Sai, Abdullah, and Husin 2020; Talwar et al. 2021). Within these frameworks, 'veracity' denotes the quality of data, whereas 'value' pertains to the business insights that can be derived from such data. Recent studies have proposed additional dimensions; for instance, González García and Álvarez-Fernández (2022) introduced 'variability', which refers to temporal changes in data, and visualization, which concerns the clarity and interpretability of data representations.

2.3. Challenges of using product-in-use data in SCP

Despite increased attention to big data, the literature often discusses *what* big data can be used for, that is, its potential, while failing to clarify *how* its use could be increased (Brinch, Gunasekaran, and Wamba 2021). To understand the challenges obscuring the latter perspective and focus on product-in-use data, we reviewed challenges with big data analytics in general and how they affect the conceptualization of big data in the literature, especially reviews, on operations and SCM (e.g. Nguyen et al. 2018; Talwar et al. 2021), or on proposing categories (Chen, Preston, and Swink 2015) and frameworks (e.g. Hasan et al. 2024) of big data analytics.

Table 1. Data categories and sources used in aftermarket SCP.

Category	Example (a vehicle in use)	Source
Operational data	Mileage, running hours, location, and average speed and RPM	Onboard vehicle
Fault codes	Malfunction of critical components and alerts	Onboard vehicle
Sensor data	Oil quality, pressure, temperature, dimension of brake discs, and vibrations	Onboard vehicle
Installed base data	Current and future number of vehicles by type and region	Manufacturing system
Item usage data	Items in specific repair operations, maintenance history, failure rate, and service intervals	Maintenance system
External data	For example, weather, macroeconomics, and geopolitical events	External databases
Demand history	Historic sales data per SKU	ERP system

Source: Adopted from Andersson and Jonsson (2018).

In the context of big data and advanced analytics, *challenges* refer to obstacles in implementing and utilizing such analytics (e.g. Kache and Seuring 2017), whereas capabilities refer to the resource competencies that enable business insights from these analytics (e.g. Akter and Wamba 2016). To clarify and validate these types of challenges, they were divided into three categories using big data and advanced analytics: organizational, technical, and personnel challenges. Sometimes, data-related challenges are considered a dimension, although the data should be considered as inputs to the analytical process, which can pose various challenges depending on the attributes regarding the big data Vs and due to different data complexities.

organizational challenges are defined by the need to overcome barriers for existing organizations working with traditional methods and data, such as the cultural change aspects of how to transform an organization into a data-driven organization (Barlette and Baillette 2022; Kache and Seuring 2017; McAfee and Brynjolfsson 2012; Tabesh, Mousavidin, and Hasani 2019; Talwar et al. 2021). To accomplish this transformation, Kache and Seuring (2017) and Pansara (2023) emphasized the role of IT governance, which involves setting common goals, defining future directions for big data analytics in supply chains, and ensuring adherence to rules to enable efficient collaboration. Meanwhile, McAfee and Brynjolfsson (2012) acknowledged that coordination and direction for big data initiatives and applications, as well as leadership in terms of communicating a supportive and clear vision, are the most important elements. Barlette and Baillette (2022) emphasized the importance of close cooperation between IT and business departments that traditionally work in silos. Baškarada and Koronios (2017) suggest that domain specialists and data scientists collaborate within the same organizational team. Management awareness and cultural changes are also considered a major challenge by Al-Sai, Abdullah, and Husin (2020) and Lamba and Singh (2017), who stressed the importance of top management's direct involvement in big data projects. Yu et al. (2021) and Al-Sai, Abdullah, and Husin (2020) advocated that a lack of data-driven culture and decision-making will affect the organization's big data and advanced analytics capabilities. Chatterjee, Chaudhuri, and Vrontis (2024) propose that a data-driven culture positively enhances the firm's process development capabilities. Furthermore, organizational challenges refer to the collaborative willingness and ability of actors in the supply chain (Kache and Seuring 2017), which includes compliance with agreed procedures and willingness to share data across multiple organizations. Furthermore, key organizational challenges include developing algorithms that meet the needs of diverse stakeholders belonging to multiple organizations/firms, resolving regulatory issues, and securing stakeholder support (Lim et al. 2018). Regarding inter-organizational challenges, Brinch, Gunasekaran, and Wamba (2021) identified integrative challenges regarding processes composed of poor cross-functional integration of roles, responsibilities, and resources, while Ben-Daya, Hassini, and Bahroun (2019) discussed the organizational challenges of the dynamic, ever-changing business environment, such as the increased demand for integration with suppliers and customers. In a similar vein, Chehbi-Gamoura et al. (2020) and Arunachalam, Kumar, and Kawalek (2018) emphasized the importance of supply chain partners that collaboratively prepare and deploy big data, while Hasan et al. (2024) and Jahani, Jain, and Ivanov (2023) recognize the lack of connection between organizational capabilities and technology.

Technical challenges are required to enable big data and advanced analytics to transform into value, such as new hardware for data storage and processing, and new software for storing, cleaning, preparing, and analyzing massive amounts of data (Al-Sai, Abdullah, and Husin 2020; McAfee and Brynjolfsson 2012; Talwar et al. 2021). Furthermore, big data projects also impose additional requirements on data transmission (Al-Sai, Abdullah, and Husin 2020; Zhong et al. 2016), both wired and wireless, due to the high volume of data, which requires high bandwidth. The additional technical challenges described by Saltz and Shamshurin (2016) include tools for data management and quality, as well as enhanced tools and processes for data integration and security. Regarding technical challenges, Brinch, Gunasekaran, and Wamba (2021) also mention software capabilities such as data visualization, application development and maintenance, and automation tools. Moreover, Ismail, Sengupta, and Amarasoma (2025) recommend adopting cloud platforms to address IT architectural challenges.

The third challenge dimension in the literature regards *personnel competence*, which can be defined as the company's ability to attract people with the necessary skills in big data and advanced analytics and develop human resources in this domain. Without a substantial pool of analytically skilled personnel, it will be challenging to produce valuable outcomes from big data in the supply chain (Talwar et al. 2021). Given the ongoing shortage of skilled professionals (Abtew and Assefa 2023; Baškarada and Koronios 2017), the roles of data scientists and analysts responsible for data cleaning and organization have become particularly critical.

Especially valuable are skilled data scientists with a strong understanding of business needs and people with excellent domain knowledge (Baškarada and Koronios 2017; McAfee and Brynjolfsson 2012). Knowledge about the data used in analytical processes is a challenge (Janssen, van der Voort, and Wahyudi 2017; Roden et al. 2017) because of how it is collected and processed, as well as the value it can bring. Several authors have affirmed the importance of collaborative capabilities; that is, analysts, data scientists, data engineers, and domain experts must combine their skills effectively to create a shared understanding of the problem (Al-Sai, Abdullah, and Husin 2020; Janssen, van der Voort, and Wahyudi 2017; Kache and Seuring 2017).

2.4. Conceptualization and research framework

In an aftermarket context, big data and advanced analytics, in general, and product-in-use data, in particular, can be utilized in various types of SCP processes. The conceptual logic derived from the literature review provides the scope for the study in at least three aspects. First, all aftermarket SCP involves many organizational units and actors. Second, although different types of data are collected from different sources, data collection occurs during the use of individual products. Therefore, the point of reference is not big data analytics but rather product-in-use data, which is often also 'big'. Third, although technology and data quality are wide-ranging, processing product-in-use data for SCP requires human actors, whose involvement is expected to vary across SCP processes.

The key concepts of this research are product-in-use data, SCP processes, process complexity, data complexity, organizational challenges, technological challenges, personnel challenges, and the interconnectedness of challenges. These are defined in the literature section and are related to the two research questions. Here, we elaborate on these concepts in relation to the research framework used in the empirical analysis.

SCP processes are characterized by process and data complexities. Data complexity was defined by Bozarth et al. (2009) as the complexities of detail (e.g. the volume and variety of the data sources and categories in Table 1) and dynamics (e.g. data velocity). Process complexity is also defined as the complexities of details and dynamics. As for activities, decision-making, and actor involvement, the number of activities and interactions between actors (and the extent of their involvement) represent the process complexity of detail, whereas changes in the involvement and interaction of actors represent dynamic process complexity.

Most literature on big data challenges addresses specific issues—such as organizational transformation, management involvement, or technical barriers—and links them to particular applications, while only a few studies (e.g. Brinch, Gunasekaran, and Wamba 2021) take a broader approach. Although it is not explicitly stated in the literature, we expect interconnections between challenges, where a challenge in one dimension can cause challenges in other dimensions. We also expect challenges to differ in significance between different phases of product-in-use data implementation. The two interconnections of challenges were explored. Figure 1 illustrates the research framework. The problem in context is the challenges of using product-in-use data in aftermarket

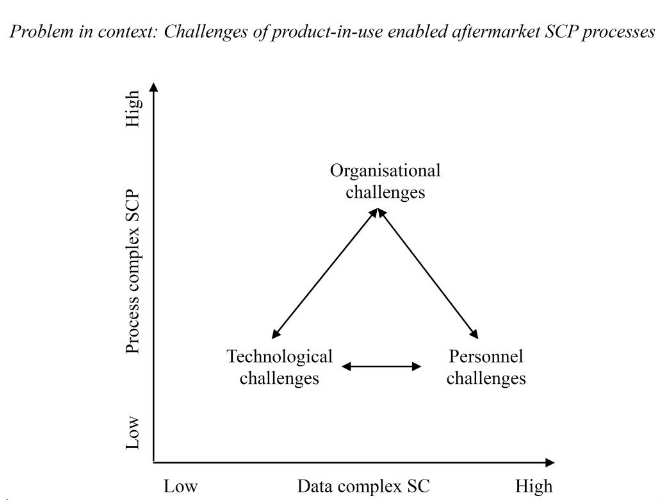

Figure 1. Research framework.

SCP processes. The focus is on investigating what organizational, technological, and personnel challenges exist in SCP processes, which are characterized by different processes (vertical dimension) and data complexities (horizontal dimension), and how these challenges are interconnected.

3. Methodology

Given the purpose of our study and the emergent nature of connected vehicles, product-in-use data, and big data analytics for SCP, a single-case study approach was chosen. Although case studies are encumbered with challenges (Voss, Tsikriktsis, and Frohlich 2002), including a lack of generalizability, we mitigated some limitations by studying three embedded cases, namely three product-in-use SCP processes managed and developed independently of each other within the single case-company: (1) causal-based forecasting, (2) predictive maintenance planning and operations, and (3) vehicle monitoring using product-in-use-data. The context for all three embedded cases regards securing aftermarket uptime for heavy vehicles, while the unit of analysis is different for each embedded case. These processes involve different stakeholders, utilize various types of data, and have evolved as separate initiatives. Given the novelty of the phenomenon, the three processes were chosen owing to their heterogeneity (Van de Ven 2007) in terms of process and data complexity, allowing us to identify and analyze various situations.

Accordingly, the research design relied on multiple data sources. Data were collected over more than two years to determine how the challenges were contingent on the characteristics of the individual SCP process and to capture how the challenges influenced one another. To access the case company, we relied on one research team member's insider status as a manager–researcher (Coughlan and Coghlan 2002) in the company's advanced analytics team. Thus, this study has elements of participatory and interactive research, which promotes the proximity and relevance of the research by understanding the studied processes in detail (Näslund, Kale, and Paulraj 2010). This strategy allowed the research team to investigate a significant phenomenon under rare circumstances (Eisenhardt and Graebner 2007) and enabled a type of longitudinal research design (Voss, Tsikriktsis, and Frohlich 2002), where data were collected and analyzed by following how the three processes unfolded over a period, using product-in-use data and analytics in SCP.

3.1. Sampling and empirical context

The case company, a global OEM of heavy vehicles and machinery, is currently transforming its business model to emphasize revenue streams from aftermarket, product-based services, for example, through uptime service agreements. A significant part of that shift requires developing and using product-in-use data across various SCP processes, chiefly by building on the data afforded by the connectivity of physical products. In that process, using sensor data support the improvement of current process areas and the creation of new ones, which in turn generate new avenues for SCP. The high priority for that process in the case company and the case company's level of experience (Pettigrew 1990), information richness, and direct access were key sampling criteria for the single case. Selecting the three processes to study provides a better opportunity to complement the within-process analysis and to examine the emergence of challenges.

The key actors in an aftermarket supply chain are OEMs and their subsidiaries, service providers, and vehicle users. Here, the OEM is represented by central distribution centres (DCs), whose chief responsibilities are receiving spare parts from suppliers and delivering them to other DCs and service providers in the supply chain; regional DCs, which act as intermediate warehouses and deliver materials to service providers in a region sourced by a central DC; and support DCs, which support service providers in a specific region with emergency orders. Service providers support end customers with services and repair operations, while users are customers (e.g. hauliers) who operate from one to several thousand vehicles. The specific focus of the case study was applications related to SCP that use data from connected vehicles, manufacturing systems, and external sources.

To examine the contemporary phenomenon of using product-in-use data in SCP in the real-life context of the case company, we chose the SCP processes as a collective object of study. After purposive sampling (Miles, Huberman, and Saldana 2014), the three processes were selected on the basis of their high experience level (Van de Ven 2007), that is, processes undergoing development and playing distinct strategic roles to support an already launched business model. All had been initiated, and although the results and experiences from the processes already developed had been put into operational use, the applications remained limited in the number of customers served and spare parts provided. Moreover, guided by theoretical sampling (Miles, Huberman, and Saldana 2014), the three processes can be regarded as embedded cases, selected based on their relevance to the propositions to be developed. The selected processes varied in the number of activities and actors involved (i.e. process complexity), the number of data sources and records, and the frequency of transmission (i.e. data complexity). This sampling choice met the requirements of RQ2 and contributed to enhancing the generalizability of the findings.

3.2. Data collection

To facilitate an in-depth understanding of the phenomenon, which includes challenges and their interrelationships, data were collected from multiple sources and respondents using various methods (Miles, Huberman, and Saldana 2014). Table 2 summarizes the methods and data collection, illustrating how respondents from various functions were engaged and the topic in focus.

First, following the insider approach (Coughlan and Coghlan 2002), evidence was collected through participatory activities such as workshops, project meetings, collaborative idea-generating meetings, informal discussions, and follow-ups, and documented in both formal documents and notes taken by the researcher-manager. This, combined with interviews and internal documentation, enabled triangulation, which contributed to the process validity of the participatory, interactive research design (Elg et al. 2020).

Second, to gain further depth and validation, 17 semi-structured interviews were conducted to understand the challenges of using product-in-use data, both in general and for each of the three SCP processes under investigation. Addressing the application of causal-based forecasting, the first seven interviews were conducted with individuals involved with demand and inventory planning, developing connected solutions, inventory optimization, and vehicle service management. As knowledge about the SCP processes and product-in-use was being developed during the study period, another seven interviews were conducted to discuss the other two product-in-use processes (i.e. predictive maintenance and vehicle monitoring) with individuals involved with spare parts sales, service management at three retailers, truck monitoring, and advanced analytics. The interview themes were derived from the literature review, and the questions were structured around four themes: problems with the *potential* of the studied processes, problems with the potential of *using* product-in-use data, and challenges with *developing* and *implementing* the applications. The interview questions were refined after discussions at internal workshops, where participants were shown our preliminary insights and results and asked to share their views on the experiences and forms of progress being analyzed in the project. To validate the customer's perspective of the emerging results, three internal sales personnel and three external service managers responsible for maintenance or repair at workshops were interviewed.

Third, to gain additional insight into the topics addressed in the first seven interviews, we performed observations of demand and inventory planners and their work with causal-based forecasting concerning service parts (e.g. forecasts with one or several explanatory factors instead of pure demand history as input). Fourth, secondary evidence was used to gain further insight. A video describing the vehicle monitoring process was also reviewed to understand the operational context. Internal documentation (e.g. project reports and presentation materials) with tentative results from causal-based forecasting projects was reviewed to further illuminate challenges with causal-based forecasting. Finally, because some of the applications were at an early stage of development, either planned or as pilots, some data were collected at internal workshops, all lasting 2.5 hours and held regularly. During the ongoing development and implementation of the three processes, weekly management meetings provided opportunities to follow up on specific issues identified in discussions with managers in advanced analytics, regarding requirements for analytical tools, methods, data sources, and analytical skills.

To better understand the challenges in the evolution of the three processes and how managers addressed these, as well as to create conditions for an iterative approach to analysis that encourages changes in researchers' and

Table 2. Overview of the data collection: methods, respondents, time, and topic.

Data collection method	Respondents (roles)	Duration	Time	Topic
Interview	Project Manager, Initial Forecasting	1.5 HOURS + several shorter follow-up sessions	2019	Causal-based forecasting opportunities and challenges, and experiences from (failed) projects
Interview	Business Logistics Manager	1 Hour	2019	Prerequisites for successful predictive maintenance and monitoring, and focus on the aftermarket process (OEM, dealer, and customer)
Interview	Data Scientist, Connected Solutions	1 Hour + 30 min. follow-up meeting	2019	Challenges regarding causal-based forecasting and predictive maintenance based on experience
Interview	Vehicle Monitoring Manager	1.5 Hours	2019	Process overview, including problems and challenges to enhance the process. Focus on process complexity.
Interview + meetings	Demand and Inventory Planning Manager	2 Hours + several recurring discussions	2020–2025	Challenges regarding causal-based forecasting and predictive maintenance based on experience
Workshop	Vehicle Monitoring Team	4 Hours + follow-up via e-mail	2020–2021	Technical focus and personnel/ organizational challenges regarding vehicle monitoring
Workshop	Supply Chain Developers	7 × 2–3 Hours	2020–2025	Experiences and challenges on data complexity, modelling, and challenges from a personnel analytics competence point of view
Interview	Service Manager – Dealer 1	1.5 Hours	2020	Challenges regarding predictive maintenance from a dealer and end *customer* focus
Interview	Service Coordinator – Dealer 1	1.5 Hours	2020	Challenges regarding predictive maintenance from a dealer and vehicle *operator* focus
Interview	Service manager and spare parts manager, Dealer 2	2 Hours	2020	Challenges for minor/medium-sized dealers regarding predictive maintenance
Workshop	Connected Solutions Team	3 Hours	2018	Challenges and opportunities for generic machine learning/AI development based on product-in-use data
Interview	Manager Predictive Maintenance Development	2 Hours	2022	Experience and scope of the predictive maintenance portfolio (involved components)
Interview	Project Manager, Advanced Analytics	1 Hour	2023	Experiences from a great number of explorations regarding advanced analytics
Interview	Technology manager, advanced analytics	1 Hour	2023	Technological challenges + personnel challenges regarding IT staff
Interview	Director, Advanced Analytics	1 Hour	2023	Organizational, staffing, competence, and cultural transformation
Interview	Regional Business Logistics Manager	1 Hour	2023	Recent updates on the predictive maintenance process
Interview	Manager, Spare Parts Sales	1 Hour	2023	Recent updates on the predictive maintenance process + still existing challenges
Interview	Manager, Service Coordination	2 Hours	2023	Details regarding updates in the predictive maintenance process

participants' understandings (Elg et al. 2020), data were collected over a period of more than 2 years. By this time, we could identify challenges, analyze their interactions, and observe how they changed as a result of investments in new technology, organizational change, or the development of human resources and capabilities. Moreover, as the processes cut across the organizational structure, individuals from multiple functional areas were interviewed (LaPlaca, Lindgreen, and Vanhamme 2018), including data analysts, supply chain planners, and managers in functions involving customer interface (e.g. logistics and aftermarket services). These respondents, together with continuous dialogue with the researchers throughout data collection, contributed to both the democratic and dialogic validity of the interactive research design (Elg et al. 2020). Table 3 illustrates interaction modes that served this purpose, including the frequency, time, and topic in focus at these touchpoints.

3.3. Data analysis

Guided by abductive reasoning (Kovacs and Spens 2005), the analysis began with the three SCP processes from the case company as overall categories. However, their data and process complexities were derived from the literature. The analysis then described each process and identified the key challenges regarding the development and usage of each process. From the principles of thematic analysis (Miles, Huberman, and Saldana 2014), three main categories

Table 3. Additional data collection and validation through participatory interactions.

Interaction mode	Duration or extent	Time	Topic
Participation in numerous explorations regarding causal-based forecasting	Average 2–3 hours/week	2019–2025	Explorations regarding regression-based forecasting using several explanatory factors, classification methods to forecast new parts, and so on.
Participation in numerous meetings regarding predictive maintenance	1–2 Hours/meeting	2019–2025	Updates on process, methodology, analytical models, challenges, and predicted components.
Participation in management meetings with the advanced analytics team	2.5 Hours/week	2019–2025	Organizational topics such as ways of working, cultural transformation, communication, competence development, roles to acquire, budget issues, and priorities

emerged: organization, personnel, and technology. The data were coded and analyzed (Flick 2014) and broken down into subcategories that emerged from the empirical analysis and were related to the potential actors involved in the aftermarket service encounter. The study by Andersson and Jonsson (2018) on causal-based forecasting served as the starting point for the analysis, which was then extended through inductive coding of the sub-categories, resulting in four sub-themes: activities, actors, product-in-use data, and item usage. Table 4 illustrates how each of the three SCP processes was assessed by the involvement of various actors and analyzed using the two dimensions of complexity (process and data).

As shown in Table 4, causal-based forecasting demonstrated high data complexity but low process complexity, whereas predictive maintenance and vehicle monitoring had high process complexity but low data complexity. Whilst the current literature presents ‘data’ as a challenge (González García and Álvarez-Fernández 2022), our analysis takes this a step further by depicting the challenges caused by data complexity. Appendix A provides a chain of evidence in this respect.

To gain a more profound understanding of the interactions between the different actors and how they managed product-in-use data and their activities that were involved in the processes under investigation, the analysis followed an iterative data collection process, which allowed us to investigate the interactions between the challenges as they emerged and the effects of the challenges in each of the three SCP processes as they unfolded during the period of investigation. To this end, for each SCP process, the actor structure, composed of the OEM, user, and service provider, was studied in relation to the exchange of information and the inter-relationships therein.

4. Results

The presentation of results aims to answer the RQs and is structured around the three SCP processes for product-in-use data outlined in Table 4 and the three categories of challenges outlined in the conceptual framework (Section 2.4). First, we analyze how challenges surface in the respective process, followed by a cross-process analysis of challenges. The origins of the challenges are presented in Appendix A. This section provides a summary of the results and within-case analysis per process.

4.1. Within-process analysis of challenges

4.1.1. Causal-based forecasting

The current forecasting process at the case company combines six traditional time-series forecasting methods. Causal-based forecasting methods were analyzed in multiple explorations, where the most promising were piloted and analyzed. Studies involving machine learning models for predicting spare parts demand generated promising results from limited test samples. These studies applied linear autoregressive machine learning models with various exogenous variables (ARX and SARIMAX models), such as cumulative installed base of finished products, mileage, hours, and fault codes generated by onboard sensors, and classification models (random forest) using an installed base with descriptive features. Furthermore, investigations using external data, such as weather and macroeconomic data, have been conducted, although with limited results. For machine learning models using product-in-use data, promising results have been achieved on limited assortments, although further testing is considered a necessity before implementing the models in production.

For causal-based forecasting (see Figure 2 and Appendix A), the identified challenges relate to the core of big data analytics: data complexity (data quality/availability and vast volumes of data across various data types and velocities), which directly affects the technological dimension. Even though the case company implemented a cloud solution to enable analysis across several functional systems, these systems had been developed over many years using different technologies to support specific operational functions. Hence, integrating these data into a new technical solution and developing a feasible solution for advanced analytics are major challenges. Hence, to support further development of causal-based forecasting, an enhanced IT infrastructure with high-performance data storage, transmission, and processing capabilities is required. Data complexity, combined with technological challenges, requires solutions within personnel skills. Regardless of the technological foundation (i.e. based solely on data complexity), the personnel dimension presents the intricate task of data preparation, though cloud solutions can reduce the time and effort required. The same reasoning is valid for the personnel challenge regarding skills in advanced analytics (AI and machine learning, and feature engineering) and data modelling; that is, these competencies are still required, regardless of the technical solution. For the data modelling challenge, there is a firm need for close collaboration between data scientists and domain experts.

Table 4. Process and data complexities of the three SCP processes.

	Process complexity								Data complexity					
			Actors											
	Activities and decisions		OEM		Service provider		User		Product-in-use data			Item usage		
SCP process	Activities	Decisions	Demand and inventory planner	Vehicle monitoring centre	Spare parts manager	Service planner	Hauler	Driver	CVD (wireless)	CVD (by wire)	Install base	Maintenance history	Service instructions	Item demand history
Causal-based forecasting	F	F	X		(x)				x	(x)	x	(x)	(x)	(x)
Predictive maintenance	M	M	X		x	x	X		x			x	x	
Vehicle monitoring	M	M		X	x	x	X	x	x				x	

Note. x: involvement; (x): optional involvement (e.g. to increase efficiency); M: many; F: few.

Several causal-based models have proven to show poor results due to a lack of either statistical, programming, or business knowledge regarding demand forecasting. The technical advancements enabled by cloud solutions aim to simplify advanced analytics. However, because only parts of the data are migrated, the current environment, mainly for data scientists, implies further challenges. The new technical solution put additional requirements on IT infrastructure due to the massive amount of various data with different origins, which in turn put requirements on the personnel dimension regarding data engineering. As reported by many stakeholders working with advanced analytics in the case company, to work efficiently in this complex data environment, well-organized and curated data are essential.

Furthermore, the combined technological and personnel challenges impact the organizational level in terms of building up a competent analytics organization, that is, hiring and developing resources in the competence area, including several new IT roles (e.g. software engineers, data engineers, and cloud developers), and adapting new ways of working such as creating a more agile explorative environment and increasing the coordination and focus on causal-based forecasting initiatives. The learning from working on widespread activities in this domain across different teams is to create a team focused on causal-based forecasting. The last organizational challenge explored for the causal-based forecasting process is that cultural transformation is difficult but necessary, which implies strong executive management commitment (priorities, resources, etc.). Regarding transforming into a data-driven culture, the case company invested heavily in communication and training in advanced analytics. Lastly, the requirement for advances in IT infrastructure and architecture adds additional effort and challenges to IT governance, including compliance, security, regulatory requirements, and resource management of the IT environment.

4.1.2. Predictive maintenance operations

In the case company, the service interval and type recommended are based on a service programme offered to customers. In turn, the service offering is based on several parameters pertaining to the specifications and predicted usage of the vehicle in a particular environment (e.g. long haul, distribution, or construction). With these aspects as points of reference, service contracts between users and service providers are based on predictions concerning the vehicle's future use (e.g. mileage per year, load weight, engine hours, and topological factors) and stipulate the interval of maintenance operations and the type of maintenance to be provided. Predictive maintenance workshop maintenance activities in the case company were organized according to a multi-step procedure. Either the workshop or vehicle owner calls for the requested service at least 2 weeks in advance to accommodate the lead time needed for ordering, picking, packing, and transporting the required spare parts. Ten working days prior to the planned service, spare parts are reserved if they are in stock at the workshop or otherwise ordered. The vehicle user is contacted a few days before the scheduled service to determine whether any

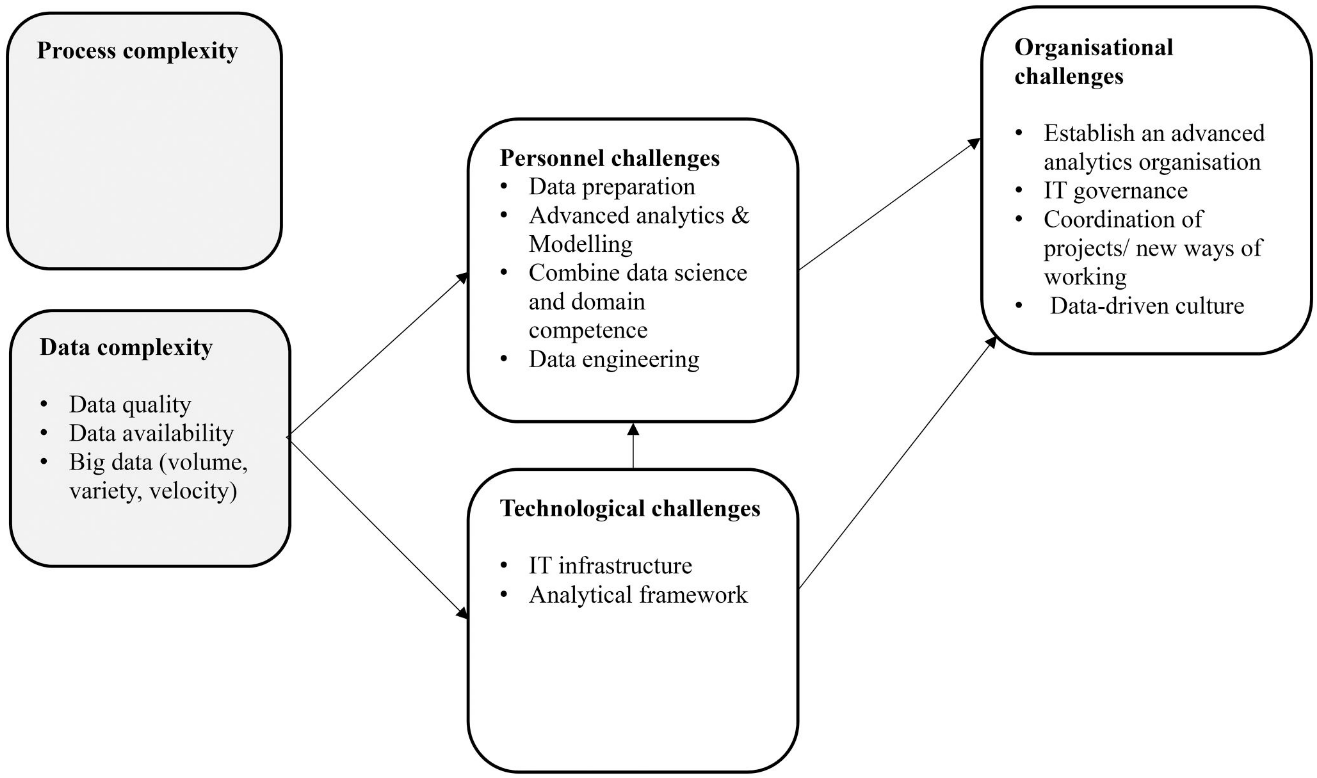

Figure 2. Major challenges and interdependencies in causal-based forecasting.

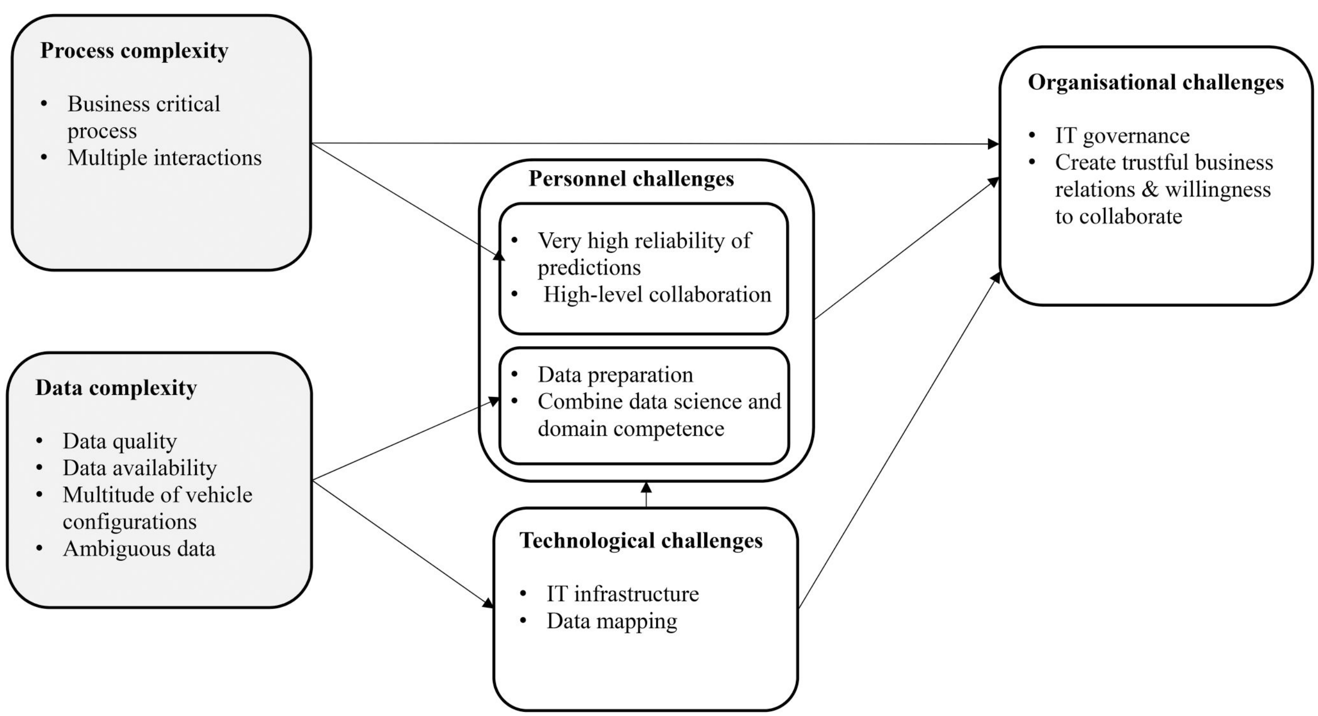

Figure 3. Major challenges and their interdependencies, and pre-planned maintenance.

additional work is needed during the visit. When the vehicle arrives at the workshop for service, the needed spare parts should be available. To enable predictive maintenance for an increased number of cases, predicting the need for replacement parts using product-in-use data is pivotal.

Compared with causal-based forecasting, the challenges of pre-planned maintenance operations are, to a great extent, driven by process complexity (Figure 3 and Appendix A). However, the predictive analytics components are implemented outside the operational systems, which creates challenges in

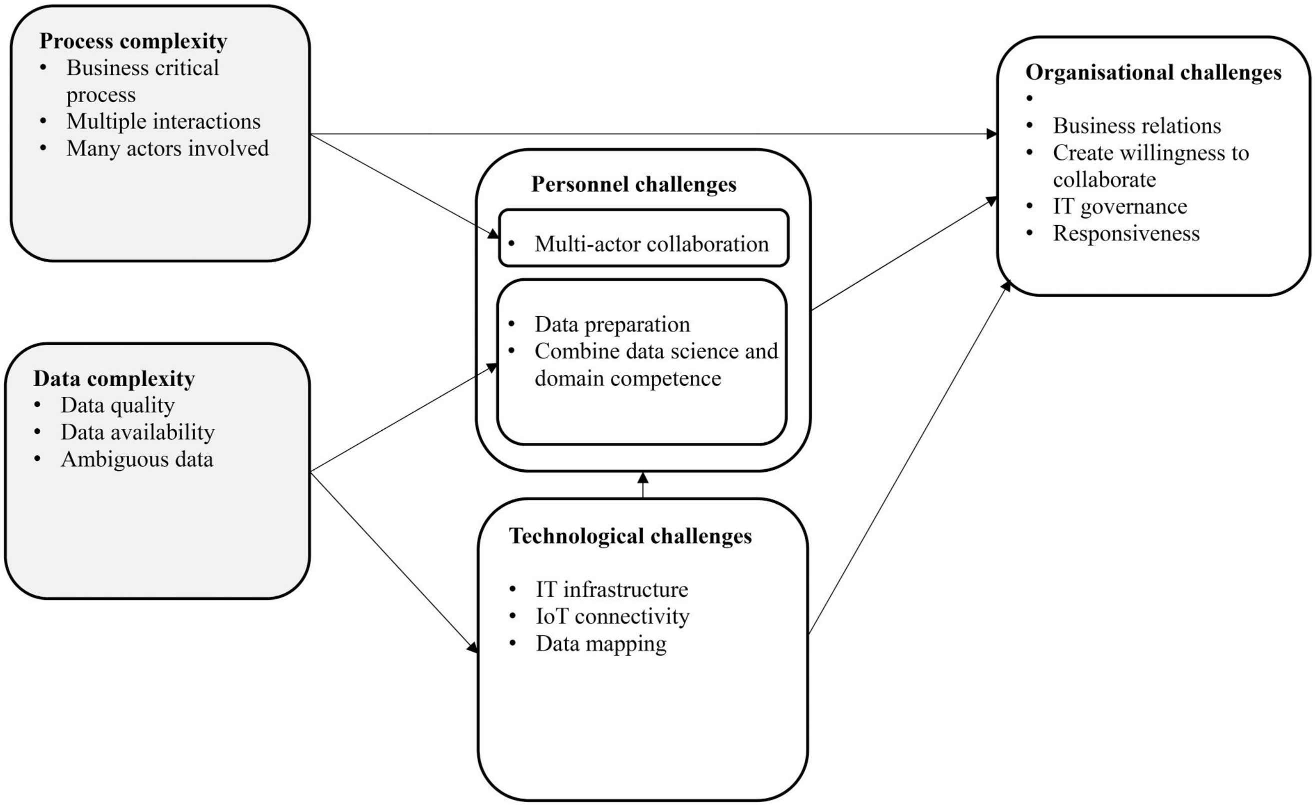

Figure 4. Major challenges and interdependencies regarding vehicle monitoring.

the technological dimension due to the need to integrate the predictive models' outputs into the systems handling maintenance operations (i.e. challenges with IT infrastructure). Furthermore, data quality and availability issues create challenges in the personnel dimension regarding data preparation capabilities, while ambiguous data and the large variation of vehicle configurations (both mechanical and IT-related variations) impose personnel challenges regarding how to interpret the outcome of the predictive models, which require both analytical competence and vehicle maintenance skills; that is, collaborative skills in this domain are preferred. Compared with the data-centric nature of challenges in causal-based forecasting, predictive maintenance becomes more multi-actor in nature, as the challenges relate more distinctly to actors in the service supply chain. Moreover, the challenges are intersectional insofar as they relate to different actor constellations. That is, the main challenges are within the personnel skills and organizational dimensions. The multitude of actions and actors, together with business criticality, creates challenges regarding personnel skills in terms of collaboration and coordination, and from a customer business understanding perspective in the analytics phase. Furthermore, the complex process and the required personnel skills create organizational challenges in business relations among the involved actors; hence, developing strong service coordination capabilities is a critical challenge. The complexity of the process for maintaining high uptime of customers' assets creates challenges in the personnel dimension, given the high reliance on the predictive models' results. High costs can result from both excessive and insufficient maintenance, as well as from scheduling vehicle maintenance when it is not actually needed.

4.1.3. Vehicle monitoring using product-in-use data

Remote monitoring enables the OEM to track the installed base of its products. As each vehicle can be viewed according to its position, potential problems and basic remote diagnostics can be conducted to predict the need for spare parts and recommended services and workshops to visit. In contrast to predictive maintenance, which focuses on replacing spare parts during scheduled servicing, vehicle monitoring primarily aims to prevent costly, potentially hazardous breakdowns in a timely manner. These recommendations are based on heuristic diagnostic algorithms developed by data scientists together with vehicle maintenance engineers.

Vehicle monitoring (Figure 4 and Appendix A) using product-in-use data involves data-related challenges in the personnel dimension due to data quality and availability, and data interpretation issues due to ambiguous data retrieved from connected vehicles. One specific challenge regarding the vehicle monitoring process is missing data due to IoT connectivity, which is critical because of the need for a short response time. Hence, combining data science competence with vehicle engineering understanding presents challenges. Owing to the need to integrate urgent vehicle malfunctions into the systems where monitoring operators work, challenges have emerged that impact the IT infrastructure, such as integrating the suggested activity into the case management system. Moreover, vehicle monitoring shares the multi-actor challenges of predictive maintenance. However, vehicle monitoring faces challenges that relate more directly to the interactions and relationships among actors and their incentives, including the ability and willingness to pay for services and to share data.

Table 5. Complexity, challenges, and challenge causes per SCP process.

Causal-based forecasting	Pre-planned maintenance operations	Vehicle monitoring using product-in-use data
Data and process complexity		
Data complexity Data quality Data availability Big data (volume, variety, and velocity)	*Data complexity* Data quality Data availability A multitude of vehicle configurations Ambiguous data	*Data complexity* Data quality Data availability Ambiguous data
Process complexity Minimal complexity	*Process complexity* Business-critical process Multiple interactions	*Process complexity* Business-critical process Multiple interactions Many actors involved (call centre, driver, vehicle owner, and service provider)
Challenges		
Organizational challenges Establish an advanced analytics organization IT governance Project coordination and ways of working Data-driven culture	*Organizational challenges* Trustworthy business relations IT governance	*Organizational challenges* Trustworthy business relations Willingness to collaborate (follow recommendations and share data) IT governance Responsiveness
Personnel challenges Data preparation Advanced analytics and modelling Combining data science with domain competence Data engineering capabilities	*Personnel challenges* Data preparation Combining data science with domain knowledge Very high reliability of predictions required High level of collaboration	*Personnel challenges* Data preparation Combining data science with domain knowledge Customer business understanding High level of collaboration Process coordination
Technology challenges IT infrastructure Analytical framework	*Technology challenges* IT infrastructure Data mapping	*Technology challenges* IT infrastructure Data mapping
Challenge causes		
Data complexity is the primary driver and causes personnel and technological challenges. In addition, technological challenges cause additional challenges in the personnel dimension. The personnel and technological challenges, in turn, cause challenges on the organizational level.	Personnel challenges are caused by process and data complexities, as well as technological challenges, which are also driven by data complexity. Process complexity, personnel challenges, and technological challenges drive organizational challenges.	Personnel challenges are caused by process and data complexities, as well as technological challenges, which are also driven by data complexity. Process complexity, personnel challenges, and technological challenges drive organizational challenges.

4.2. Summary and cross-process analysis of challenges

In a cross-process analysis (see Table 5), we compared the identified challenges and commonalities and differences across processes, including the common and unique types of challenges and the interdependencies between them. The results revealed challenges associated with product-in-use data for advanced analytics for each of the three applications.

4.2.1. Common challenges

4.2.1.1. Data-driven challenges. The analysis revealed that two drivers of challenges in the data are common across all three applications: data quality and availability issues. In the technological dimension, challenges related to IT infrastructure are common to all three applications, primarily due to data complexity. Data integration across all three processes poses challenges for the IT infrastructure (e.g. data lakes for data storage, services for advanced analytics, and tools for data transmission), while hardware-related challenges include storage and processing capacity.

4.2.1.2. Data and process complexity-driven challenges. In the organizational dimension, IT governance is identified as a common challenge, although this challenge has slightly different causes for the applications. In all three applications, causality stems from data complexity via the personnel and technology dimensions. However, for complex process applications, process complexity enforces the challenge regarding IT governance. As a result, when handling data from multiple sources—whether used by different parties or characterized by high complexity (big data)—it is essential to ensure reliability, effective management, and the efficient use of IT resources. Other common challenges pertain to data preparation (i.e. correction, imputation, and cleaning) and to combining domain and data science knowledge. Both belong to the personnel dimension and are a consequence of data and process complexities.

4.2.1.3. Process complexity-driven challenges (common for predictive maintenance and vehicle monitoring). There are also common challenges for the two process-complex applications (preplanning and vehicle monitoring). Process complexity is the primary driver of the challenges associated with complex process applications. The main process-related challenge drivers are the business-criticality of the processes and the numerous interactions required within these processes.

The first observed common challenge driver for the two applications is the interpretation of ambiguous data, such as sensor and geographic data, which is affected by software and model versions. To interpret such data and make reliable analytical outcomes, the analyst or data scientist must have considerable product knowledge (mechanical and IT technical). In the personnel dimension, the two common challenges for these two processes, caused by process complexity, are the need to immerse in the understanding of the customer's business and for a high level of collaboration, which requires the development of analytical tools that fit many different stakeholders, who can have different needs of the output from the analysis and capabilities of understanding the outcome. Due to process complexity, common organizational challenges arise for predictive maintenance and vehicle monitoring processes, primarily stemming from the need for external customer collaboration. Difficulties in achieving trustworthy business relations, efficient service contracts, and high-level collaboration are all common challenges for these two applications. That is, the outcome of the analysis must be trustworthy and enable a willingness to collaborate from the customer's perspective.

4.2.2. SCP process-specific challenges

4.2.2.1. Causal-based forecasting-specific challenges. The analytical challenges in the causal-based forecasting process stand out, particularly regarding personnel challenges due to data complexity. Besides the previously mentioned data quality and availability issues, this process is truly data-complex according to the big data definition (e.g. González García and Álvarez-Fernández 2022; Hazen et al. 2014). For this reason, this process creates greater personnel challenges regarding advanced analytics, due to difficulties in identifying underlying demand drivers and analyzing massive amounts of data. Although improved forecast accuracy can be achieved at one point in time, the life cycle, vehicle usage, and other variables often cause the initially promising model to deteriorate in forecast quality over time.

In addition, technological and application-specific personnel challenges cause challenges in the organizational dimension. These challenges, or new requirements on an agile and data-driven project organization and culture, and new ways of working in the operational departments, are difficult because they involve many roles within the company and require managerial input from all levels. Another challenge concerns the recruitment of new data-specific roles (e.g. data scientists, data engineers, and software engineers) with highly competitive, scarce edge capabilities, as well as the retraining of other personnel to acquire these skills.

4.2.2.2. Predictive maintenance specific challenges. An unique feature of the predictive maintenance process that increases data complexity is the many vehicle configurations, including bills of materials, vehicle usage, and software variants.

In the personnel dimension, the requirement for high reliability in pre-planned maintenance prediction is considered an unique challenge. This challenge stems from the customer's need for trustworthiness, as inaccurate predictions would compromise the uptime of the customer's assets and ultimately impact profitability.

4.2.2.3. Vehicle monitoring-specific challenges. The large number of actors distinguishes the process from the other two. This process becomes highly complex, resulting in a high demand for responsiveness (organizational) to meet customer expectations and the need for a high level of coordination (personnel) to enable effective coordination.

4.2.2.4. Differences between the complex processes. Both predictive maintenance and vehicle monitoring strive for more efficient vehicle utilization by decreasing unplanned downtime, but differ in the timing of their predictions. Urgency puts more requirements on the collaboration capabilities for vehicle monitoring than on predictive maintenance, where the customer has more time to react and plan, with less effort to follow the recommendation. The urgency or need for responsiveness is another difference regarding the challenges between the two processes. As both predictive maintenance and vehicle monitoring can be categorized as complex from a process perspective but less complex from a data perspective, most personnel and organizational challenges stem from the complexity within the processes, especially those related to business relations and collaboration. We label these as implementation challenges; hence, they relate to the usability of the analytical outcomes of these processes.

4.2.3. Interconnectedness of challenges

Here, the common causalities between the challenges are presented first, followed by the unique causalities. Several data complexity-related challenges are common across applications. Although data complexity varies across applications, it always poses personnel and technological challenges. In all three applications, technological challenges also cause or boost personnel challenges. Furthermore, personnel and technological challenges drive challenges in the organizational dimension.

There are also some common challenges. On the dimensional level (type of challenges), the causalities for both predictive maintenance and vehicle monitoring are the same. In contrast to causal-based forecasting, we examined additional causalities for the two complex processes. The first is the causal relationship between process complexity and organizational challenges, and the second is the impact of process challenges on personnel challenges. To summarize the causalities, the data complex process (causal-based forecasting) faces challenges caused by data complexity, either directly or indirectly linked to another challenge dimension. The process-complex processes naturally face challenges caused by process complexity, even though they also deal partly with the same data-driven challenges as the data-complex process. However, as described in the detailed cross-case analysis, the challenges differ in both detail and severity.

The causal-based forecasting process started with data scientists and forecasting domain experts exploring data from operational databases. After several years, a cloud solution with ingested data from the same systems was implemented. However, only parts of the data were ingested into the new cloud solution; hence, the challenges regarding causal-based forecasting due to data complexity were somewhat still the same. As the organizations Advanced Analytics has evolved, with more data-related roles, a shift to a more agile way of working, and improved coordination of activities, expectations for improved causal-based forecasts have increased.

Regarding the predictive maintenance process, the most significant modification over the years was the integration of predictive maintenance proposals into a single screen for service coordinators. This advancement had a positive impact on trust and collaboration from the customer side and reduced process complexity by reducing collaboration-related issues for the service coordinator.

For the monitoring process, which has been operational for several years, the accuracy of identifying urgent faults has increased over time, thanks to learning from within the process. The implemented cloud-based solution could lead to the development of more advanced machine learning and AI models in the future.

5. Results

In this section, we further discuss the identified challenges in relation to their underlying reasons and interconnectivity (Section 5.1) and how the challenges relate to process and data complexities (Section 5.2). We also reflect on challenges in relation to the process development phases and the specific aftermarket context (Section 5.3).

5.1. Common challenges and their interconnectivity

To answer RQ1, we analyzed the findings summarized in Figures 2–4 and Table 4 with respect to interconnectivity.

All three processes involve using data from onboard electronic control units, whose mechatronic systems in vehicles, with additional data sources such as repair and maintenance data, bill-of-material data, and other vehicle-specific data, cause technical challenges, including the need for advanced data infrastructure (e.g. data lakes and tools for data transmission), hardware-related challenges (e.g. storage and processing capacity), and implementation of new analytical platforms (e.g. Microsoft Azure or Amazon Web Services). In turn, those technical challenges cause other challenges in the organizational dimension, including the need to meet state-of-the-art requirements for data governance, enable collaboration (e.g. establishing an end-to-end approach), and promote the coordination of initiatives and projects, as essential parts of creating a data-driven culture (Yu et al. 2021). Other studies (Hasan et al. 2024; Jahani, Jain, and Ivanov 2023) acknowledge the impact of technological challenges on organizational challenges, but do not provide a detailed analysis of specific technological challenges and their corresponding organizational challenges, or of how context influences them. Our findings provide some further details, and we formulate our first proposition as follows:

Proposition 1: *Technical challenges cause organizational challenges when developing product-in-use data-driven SCP processes, independently of the levels of process and data complexities.*

Another important finding concerns the relationship between organizational and personnel challenges that affected the ways of working at the case company. Instead of revealing traditional gate-controlled IT projects with a strict division of competencies, the findings show that advanced analytics projects require individuals with a strong ability to work in flexible and collaborative ways, possessing a thorough understanding of the requirements of other roles (Chehbi-Gamoura et al. 2020). The three processes studied here clearly require competencies in SCP, vehicle maintenance, vehicle operation, and data science. Waller and Fawcett (2013) emphasized the need for SCM data scientists to possess a combination of domain-specific and analytical skills. Kache and Seuring (2017) identified that aspects of organizational governance, integration, and collaboration present key challenges for big data processes. However, given the difficulty, if not impossibility, of locating all-around ideal data scientists with the required skills, Baškarada and Koronios (2017) proposed creating data science teams that pair personnel knowledgeable in data science with those with domain-specific knowledge.

We observed that personnel challenges in combining the two types of knowledge led to organizational challenges. From an organizational perspective, the challenges require strong governance, for example, to make the correct priorities on which projects and explorations to perform, as well as evaluation criteria to start such initiative, and also, an emphasis on end-to-end processes, extensive collaboration, and work agility, that is, a culture clearly geared towards data transformation (e.g. Baškarada and Koronios 2017). Furthermore, the findings showed that the data-driven transformation must be supported, if not led, by company executives, for example, to secure resource allocation for data-driven projects and explorations, and to integrate such initiatives into the company's priorities and strategy. Furthermore, Lamba and Singh (2017) emphasize top management's ability to create an organization that meets the need for big data, including funding for the required IT-related roles.

In our analysis, we also found that the organizational challenges relate back to challenges in the personnel category, i.e. the more data-driven and mature the organization becomes, for example, regarding IT governance and coordination of data-driven initiatives, the less the personnel challenges become. For example, improved IT governance guides the involved personnel on the way of working, including following guidelines and motivating the initiation of new initiatives. Therefore, we formulated the second proposition(s):

Proposition 2: *(a) Personnel challenges cause organizational challenges when developing product-in-use data-driven SCP processes independently of the levels of process and data complexities, and (b) reduction of organizational challenges reduces personnel challenges accordingly.*

5.2. Data and process complexity-related challenges and interconnectivity

Having identified several common challenges and interdependencies, we analyzed and categorized the challenges across the SCP processes in terms of data and process complexity to answer RQ2. For causal-based forecasting, data complexity dominated, whereas vehicle monitoring and predictive maintenance, which require extensive human involvement, numerous activities, and frequent interaction between actors, were more complex in terms of process than in terms of data. The data complexity context brings requirements to a firm's IT capabilities (Al-Sai, Abdullah, and Husin 2020; Talwar et al. 2021). The transformation of IT infrastructure, hardware, software, and analytical tools creates a new environment with additional challenges for personnel developing IT solutions (Janssen, van der Voort, and Wahyudi 2017) compared to traditional IT projects, which follow distinct roles and phases (the waterfall methodology). This dependency is particularly prominent in the data complex process, specifically in causal-based forecasting, where a massive amount of data from multiple data sources, including external data, necessitates the implementation of an analytical framework. Although challenges regarding IT infrastructure advancement also exist for less data-complex processes, the infrastructural challenges are higher for more data-complex processes. To manage these resources efficiently, it is clear that a robust competence in advanced analytics, data science, data modelling, and data engineering is required. A firm can either buy or develop that competence by training existing personnel (or both). Regardless of the chosen method, this is a significant challenge (Abtew and Assefa 2023). Even though more students are graduating in data science and other IT domains, there is still a shortage due to the even higher demand from most industries (Abtew and Assefa 2023). During the last years of the study, the case company worked on developing its capabilities in advanced analytics for the aftermarket domain. During that period, several new IT roles were established, more data scientists were hired, and training programs were implemented for both domain experts and operational planning roles. Despite all efforts, this remains a major challenge due to high personnel turnover, competition between daily operational work and data-driven development, and difficulties in transforming the company's culture throughout. Thus, we formulated the third proposition:

Proposition 3: *Technical challenges cause personnel challenges when developing product-in-use data-driven SCP processes with high data complexity.*

In predictive maintenance and vehicle monitoring, challenges emerged regarding actors' involvement, willingness to collect and share data, and willingness to collaborate in analyzing them, leading to inefficient resource use. Those challenges stem from difficulties with convincing vehicle owners to forgo service-related decision-making and, to some extent, trust the personnel who service their vehicles and the analytical predictions behind the maintenance proposals. Consequently, they are organizationally related challenges. Similarly to Kache and Seuring (2017), we also found that data integration challenges emerged in response to the lack of end-to-end approaches and common standards and interfaces between processes and actors, including the dependency on technical and organizational challenges, as expressed in Proposition 1, which the case company paid attention to and recently put considerable effort on by developing a solution where all needed data for predictive maintenance are presented at the same place. Furthermore, poor supply chain collaboration was shown to relate primarily to limitations in organizational interaction. In that regard, a major challenge is cultivating the willingness to collaborate by relinquishing operational decision-making (Kache and Seuring 2017), which constitutes a combined organizational–personnel challenge (as expressed in Proposition 2); that is, the organizational setup in advanced analytics projects must enable and promote collaboration and involvement of all external and internal actors. Personnel challenges related to coordination can be mitigated by implementing process compliance through effective management decisions and a data-driven culture (Chatterjee, Chaudhuri, and Vrontis 2024; Lamba and Singh 2017; McAfee and Brynjolfsson 2012). However, the challenge regarding the willingness to collaborate and share data is more of a business-related problem that could be partly addressed by building trustworthy partnerships with customers and vehicle users, which the case company has recognized and partially mitigated by increasing the number of service coordinators.

Accordingly, we propose that activities with greater process complexity require greater capabilities in interpersonal interaction and organizational collaboration, both in utilizing operational processes to maximize potential output and in developing processes to increase their efficiency and effectiveness, which create greater challenges. That is, more organizational collaboration is required when implementing big data Processes, which creates challenges for the organization, collaboration, and the understanding of the personnel involved. Thus, we propose the following:

Proposition 4: *The greater the process complexity, the greater the (a) personnel and (b) organizational challenges when developing product-in-use data-driven SCP processes.*

The SCP process with the highest level of data complexity was causal-based forecasting. Causal-based forecasting involves using multiple data sources and substantial time-series data and may employ various forecasting methods. Hence, causal-based forecasting has greater data complexity than predictive maintenance, which uses only a few data sources and involves predicting component failure. For data-complex situations, major challenges relate to the enormous amount of product-in-use data combined with a large number of potential impacting features, which could impact the predictive models differently over time and make the models difficult to interpret (Hazen et al. 2014). High data complexity poses challenges in the technology dimension that create analytical challenges for data scientists and domain experts (Al-Sai, Abdullah, and Husin 2020; Waller and Fawcett 2013). Poor data quality also challenges personnel in data preparation, which requires both domain-specific and data science competencies, as well as in using analytical tools to detect, handle, and correct faulty or missing data. That is, more data science competence is necessary as data complexity increases and, ideally, a well-functioning collaboration between data scientists and domain experts, where the latter can validate both business-related data as well as the results of analytical models. At the same time, data-related challenges, such as data quality or availability, also create organizational challenges, including the continued need for data governance and standardization, as well as increased capabilities in coordination and collaboration. From an organizational perspective, the latter also demonstrates interdependency with the ability to work cross-functionally and flexibly between various internal organizational units. For this reason, the case company, after some years, decided to migrate all causal-based forecasting initiatives under one umbrella. However, the data-complexity-driven organizational challenges are mainly indirect, as they are primarily caused by technical and personnel factors (see Propositions 2 and 3). Therefore, data complexity-driven challenges exert the greatest impact as root causes of additional challenges, corroborating the organizational information processing view of big data (Hazen et al. 2014). Thus, we propose the following:

Proposition 5: *The greater the data complexity, the greater the (a) personnel and (b) technical challenges when developing product-in-use data-driven SCP processes.*

Figure 5 summarizes the proposed interconnectivity between organizational, technological, and personnel challenges of product-in-use-driven SCP processes. Firstly, this clearly shows that product-in-use, and big data and advanced analytics, challenges cannot be understood or managed in isolation, but the focus needs to be on inter-challenge interactions. This has been identified in the literature (e.g. Hasan et al. 2024; Jahani, Jain, and Ivanov 2023), but we extend this literature in a phenomenon-based theorization (Schwarz and Stensaker 2014) by proposing how technological, personnel, and organizational challenges are interconnected. More precisely, we show how personnel and technological challenges are antecedents of organizational challenges, and how technological challenges indirectly affect organizational challenges through their impact on personnel challenges. Thus, personnel challenges also have a mediating effect on organizational challenges. There are also direct mutual effects between personnel and organizational challenges, where organizational developments can reduce organizational challenges, which, in turn, result in reduced personnel challenges. Consequently, organizational development may initiate a virtuous circle where the reduction of organizational challenges drives a reduction in personnel challenges, which in turn drives a reduction in organizational challenges, and so forth. Furthermore, the process and data complexity characteristics clearly differentiate and explain how challenges arise. This has not been emphasized or studied in the SCP or big data literature.

We also find that categories of major challenges differ between SCP processes characterized by different levels of process and data complexity. This has not been emphasized or studied in the SCP or big data literature; however, our findings demonstrate how such complexity perspectives on product-in-use-driven SCP can provide an additional understanding of what and how specific challenges occur. In doing so, we provide further depth into the advanced analytics (Talwar et al. 2021) and SCP (Xu et al. 2023) literature on the actual use of big data analytics and the improvement of SCP. Figure 6 summarizes how challenge categories differ in different complexity contexts.

Technological challenges, no matter data and process complexity, concern the IT infrastructure. The research in this domain (e.g. McAfee and Brynjolfsson 2012; Wamba et al. 2017) highlights the importance of this challenge in complex data contexts. However, our findings show that, for less data-complex processes utilizing product-in-use data, but where process complexity is high, there are challenges in establishing a sufficient IT infrastructure, in addition to processes with high data complexity, regardless of the process complexity. Technology challenges in data complex contexts also concern the analytical framework, i.e. developing a working process and access to appropriate tools and methods for data analysis and model development. Some data analytics literature concerning this subject (e.g. Brinch, Gunasekaran, and Wamba 2021) acknowledge big data tools in generic terms, while others (Al-Sai, Abdullah, and Husin 2020) are more specific and describe the need for particular data management tools, such as Hadoop or Spark (Wamba et al. 2017) or cloud platforms (Ismail, Sengupta, and Amarasoma 2025). In a process complex context, on the other hand, technology challenges concern data mapping issues. This finding, which emerged from our empirical data,

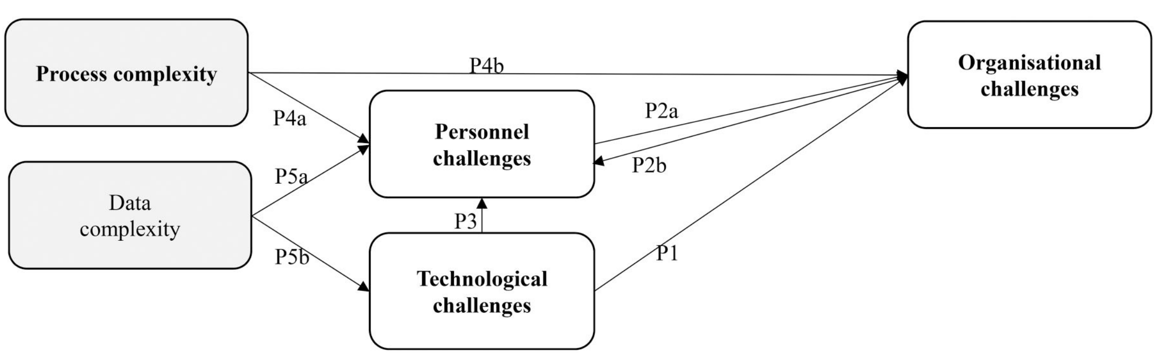

Figure 5. Product-in-use data challenges contingent on data and process complexities.

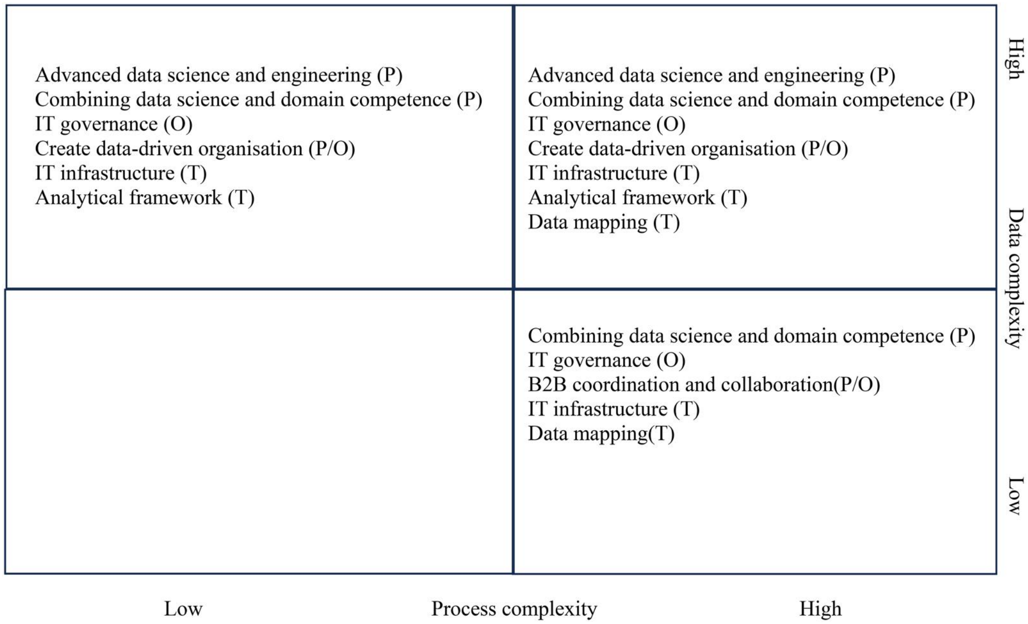

Figure 6. Major challenges from a data and process complexity perspective.

concerns the transmission, relationship, and transformation of data across end-to-end processes and is not discussed in the big data literature, although it is addressed in some data-engineering literature.

IT governance as an organizational challenge is common, regardless of complexity. However, IT governance challenges become more severe and complex as data complexity increases, whereas the most complex challenges in this area concern the management of data accuracy and consistency (Pansara 2023) and are closely related to the volume, velocity, and variety of the data. organizational challenges of generating a data-driven culture are common in situations characterized by high data complexity, as in the causal-based forecasting process, where the demand for the most skilled domain and IT resources, as well as a multitude of personnel resources, was required (data scientists, supply chain development specialists, data engineers, and software engineers). This complex development environment requires management support and data-driven decision-making; hence, a strong data-driven culture is essential. For less data-complex processes, we found that self-organizing, small teams could develop them if they had sufficient technical and domain knowledge. When high process complexity is present, however, the organizational challenges are rather about obtaining commitment and managing coordination and collaboration. Here, the main development challenges concern developing analytical processes that enable users of the outcome to understand and be willing to implement the suggested measures.

Combining data science and domain competence is a personnel-related challenge that exists regardless of process complexity, which aligns with Al-Sai, Abdullah, and Husin (2020) who advocate for multifaceted teams to be successful with big data projects.

In Figure 6, we have summarized the main challenges per data and process complexity. To make the summary comprehensible, some challenges are grouped together. Thus, advanced data science and engineering encompass the previously mentioned challenges of data preparation, advanced analytics, data modelling, and data engineering. In IT governance, we included coordination of data-driven projects. Creating a data-driven organization involves addressing the challenges of establishing a data-driven culture, recruiting data scientists and other IT professionals, and developing the IT and data science competencies for existing staff. B2B coordination and collaboration relate to understanding the customer's business, high-level collaboration, process coordination, building trustful business relations, efficient service contracts, fostering a willingness to collaborate, and service coordination, which are of a personnel and/or organizational character.

5.3. Process development-related and SCP process-specific challenges

5.3.1. Process development-related challenges

With the development and practical use of SCP processes, we examined the challenges related to the time at which they occur in process development. Processes involving many human actors and organizations (e.g. vehicle monitoring and predictive maintenance) are critical to business processes and, hence, need to be almost fully developed, tested, and functional before being activated. In this and other cases, external actors who are willing to use the processes must trust the new services first (Kache and Seuring 2017). Analytical results regarding when and where to bring vehicles for maintenance or diagnostics to prevent breakdowns indicated that the reliability of the prediction should be exceptionally high (>95% in our studies). To support the willingness of different actors to collaborate in these new processes, the processes required as little additional effort from external actors as possible. After all, hauliers and service providers are burdened with their own businesses, rely upon vehicles with considerable uptime, and therefore seek to avoid additional burdens as much as possible. For this reason, enhancements to these processes must be seamlessly integrated into the existing predictive maintenance and vehicle monitoring systems. Likewise, our findings indicated that it is beneficial to add process changes as functionalities in existing software. These process-complex challenges align well with those identified in advanced software implementations (Ivert and Jonsson 2011), indicating that development and implementation phases are separate.

Data-complexity-driven technical challenges primarily occur and must be handled early in the analytical development of models and processes, whereas personnel and organizational challenges (e.g. managerial changes) are critical throughout the development and implementation phases (Barlette and Baillette 2022). The main challenges in the early development phase involve: (a) technical aspects, specifically the development of a robust IT infrastructure (Al-Sai, Abdullah, and Husin 2020); and (b) data-related issues, mainly causing challenges in the personnel dimension, particularly the quality and accessibility of data necessary for analysis (Hazen et al. 2014). Further significant challenges that are prevalent during the early development phase include acquiring competence in data science. In the implementation and adoption phase, personnel and organizational issues become the main barrier, overtaking technical problems. Similar challenges are seen in software rollouts, where user adoption and process integration are crucial (see Ivert and Jonsson 2011). High process complexity is the main driver of challenges within organizations during the implementation phase. It results in significant organizational difficulties, such as establishing reliable business relationships and fostering a collaborative attitude among external stakeholders (Kache and Seuring 2017), as well as putting requirements on the advanced analytics applications used in a multi-actor environment (Lim et al. 2018), which creates personnel-related issues about the coordination of complex, multi-actor processes.

For causal-based forecasting, an intra-organizational process at the OEM involving the use of complex data and analytics, a semi-manual, iterative approach to development and implementation was applied, utilizing causal-based forecasting models developed in multiple pilot projects. Due to contextual factors and significant differences in product-in-use data for firms and businesses, it was challenging to apply or find a relevant standardized forecasting model. Initially, solutions were developed using analytical software and frameworks (e.g. Python, R, and Azure), and the forecasting results from these tools were integrated into the existing demand planning system. Following Hazen et al. (2014), a comprehensive effort related to data management and to improve the data quality of such a large dataset was conducted throughout development. Consequently, in identifying feasible solutions, the challenges related to the early phases of model development were primarily driven by data complexity and technical issues. However, organizational and personnel challenges also emerged, including the need to understand how causal-based forecasting could be used in the planning system for receiving demand and to understand business needs from the user's perspective (i.e. demand and inventory planners). In this respect, detailed collaboration and communication seemed to be pivotal between the developers and users of the forecasts. Thus, personnel and organizational challenges were also more important for causal-based forecasting, especially in the later implementation phase.

5.3.2. SCP-specific challenges

Overall, the challenges with causal-based forecasting, which are related to personnel, the organization, or technology, can be characterized as provider-centric (i.e. data owned and controlled by the OEM) and departing from the data used. On the one hand, the challenges primarily relate to the operations of service providers, which fall within the scope delineated by SCM functions (Nguyen et al. 2018) and the intra-organizational capabilities outlined by Arunachalam, Kumar, and Kawalek (2018). On the other hand, although overcoming those challenges may be driven by, or result in, the potential to create value, they can also be primarily associated with 'data first' (Roden et al. 2017), or the discovery of value, in a departure from data instead of business problems or an SCM process. To overcome this, organizations must work with capabilities at the initiation and even the adoption stages to shift from descriptive to prescriptive use of product-in-use data.

The challenges outlined by predictive maintenance operations reflect the multi-stakeholder nature of big data analytics and product-in-use data. Challenges can be related to individual actors such as providers, call centres, maintenance operators, and vehicle users and owners, all of whom can be characterized as 'data-related stakeholders' (Lim et al. 2018). However, our results extend beyond attributing challenges to actors and detailing the inter- nature of data (Arunachalam, Kumar, and Kawalek 2018), considering the intersectional nature of the challenges. In relation to the three categories suggested by Chen, Preston, and Swink (2015), we conclude that the intersectional challenges in the findings for predictive maintenance primarily concern coordination and integration (e.g. service providers and vehicle users or drivers), and learning and improvement (e.g. quality of data from vehicles and data interpretation by service providers). However, the findings do not relate to their third category (process configuration). From the perspective of value creation (Roden et al. 2017), the challenges relate to the discovery and generation of value but remain driven by the providers' businesses and the so-called health and operation (Lim et al. 2018) of vehicles, not the performance of the customers' processes.

Vehicle monitoring using product-in-use data is perhaps the most advanced SCP process, insofar as it abandons the provider-centric approach for the benefit of a firmer stance from a value-in-use perspective (Chakkol et al. 2014). Furthermore, the nature of those challenges could be characterized as somewhat larger than those in the other two categories. First, the challenges related to improving predictions and monitoring vehicle operations require capabilities that entail both predictive and prescriptive analytics, within and across the organizational boundaries of service providers. Such challenges resonate with the capabilities of big data analytics during routinisation and adoption (Arunachalam, Kumar, and Kawalek 2018). Second, challenges such as contract flexibility and customers' willingness to pay for services and share data extend the provider-centric approach of the first two processes, not only by offering a firmer customer-oriented perspective but also by acknowledging the need for flexibility in provider–customer interactions.

5.4. Advancing business model innovation

One of this study's main contributions, as mentioned in the introduction, is to broaden the analysis of big data and advanced analytics from a manufacturing context to an aftermarket, servitized environment. This elaborates upon the analysis presented by Acciarini et al. (2023) concerning business model innovation. Acciarini et al. (2023) review how big data can drive business model innovation. Our study adds practical insights by identifying key challenges that impact the success of these strategic changes.

This connection is most clear in our analysis of applications with high process complexity, such as predictive maintenance and vehicle monitoring. The case company's shift from a traditional OEM to a provider of 'uptime service agreements' exemplifies data-driven business model innovation. Our findings show that the main barriers to implementing this new, service-oriented business model are not solely technical. Instead, they are primarily organizational and inter-relational.

The significant challenges identified, such as establishing 'trustworthy business relations' and securing 'willingness to collaborate (follow recommendations and share data)', are not just SCP issues; they are essential prerequisites for the servitized business model itself. A model that offers 'uptime' rather than spare parts shifts the customer relationship from transactional to relational. The study indicates that if organizational and personnel challenges, such as coordination between stakeholders, trust, and data sharing, are not addressed, the intended value of the new business model may not be achieved.

Thus, our research complements the 'what' of data-driven business model innovation (as outlined by Acciarini et al. 2023) with the 'how'. We demonstrate that the strategic goals of business model innovation are closely tied to the firm's ability to manage the operational, organizational, and personnel complexities involved in data-driven SCP processes. The challenges we highlight are, in fact, the critical hurdles for implementing data-driven servitization successfully.

6. Conclusion

In our study, we investigated how technological, personnel, and organizational aspects represent important challenges in developing and using big data, namely product-in-use data, in aftermarket SCP. From the perspective of aftermarket supply chains, we conclude that the process and data complexities where product-in-use data are implemented contribute to explaining the significance of personnel, technical, and organizational challenges. Furthermore, we propose how technical and personnel challenges lead to organizational challenges, and how organizational and personnel challenges can be reduced through an interactive virtuous circle. We also conclude that data and technology challenges are especially important in the early analytical phase, where models and processes are developed, and that the importance of organizational and personnel challenges in development phases varies between SCP processes.

The generally high complexity of data and organizational aspects in aftermarket contexts poses formidable challenges for big data implementation, regardless of the relative degree of data or process complexity, across specific SCP processes. All processes entail challenges related to data quality, which is derived from complex systems, some of which include sensors in products in use, such as the heavy trucks in our study. The data source originates from different organizations, and data use is typically conducted across organizations, which requires the involvement of several actors and results in complex organizational supply chains. Moreover, the data come in various formats, including both structured and unstructured data (Helo and Hao 2022).

6.1. Theoretical implications

We present a phenomenon-based theorization (Schwarz and Stensaker 2014) contributing to the literature on big data and advanced analytics (e.g. Hasan et al. 2024; Jahani, Jain, and Ivanov 2023) and to the SCP literature (e.g. Xu et al. 2023) by proposing how technological, personnel, and organizational challenges are directly and indirectly interconnected in product-in-use driven SCP, and how challenge-focused organizational development may initiate a virtuous circle. The findings on how process complexity and data complexity clearly differentiate and explain the challenges that occur have not been emphasized or studied in the SCP (e.g. Xu et al. 2023) or big data and advanced analytics literature (e.g. Hasan et al. 2024; Talwar et al. 2021). These complexity perspectives and findings consequently provide additional understanding of what and how challenges occur in different operational contexts. They provide further depth into the empirical literature about actual usage of big data and advanced analytics in SCP. The findings on how challenges arise in different development and implementation phases build on studies of the implementation of other phenomena (e.g. Ivert and Jonsson 2011). They add initial insights about the implementation of advanced analytics-driven SCP – an area with very limited practice and research (e.g. Barlette and Baillette 2022; Wamba et al. 2023).

The research also provides further depth into the current supply chain management scope of big data and advanced analytics in the literature (Talwar et al. 2021), with a particular focus on the actual usage and improvement of SCP. It also extends the current manufacturing focus of big data and advanced analytics with an SCP focus in an after-market context. Empirically studying SCP in an aftermarket context, consequently, brings insights into the general supply chain management literature on big data, advanced analytics, and business model innovations. To this end, the research complements the account by Acciarini et al. (2023) on the relevance of big data and advanced analytics for business model innovation by offering empirical insight derived from a study of a servitized manufacturing context, i.e. where big data, advanced analytics, and SCP serve as key foundation for the company's extension of their business model.

6.2. Implication for practice

The study findings have several implications for practice. First, a firm aiming to utilize big data in general and product-in-use data, in particular, should evaluate the processes for which they consider developing with advanced analytics/AI methods from a process and data complexity view presented above. A recommendation would be to start with processes with moderate data and process complexity, evaluate these challenges, and, step by step, build up the technological, personnel, and organizational capabilities. Second, the organizational dimension of challenges could serve as a foundation for implementing big data analytics in SCP. This would encompass issues such as governing activities involved in big data analytics, funding and implementing relevant data infrastructure, pinpointing strategic directions for focal areas of development, and establishing cooperation within and outside departments, divisions, and companies, and recruit and upskill the personnel resources in data science and business development to seize opportunities related to big data. Third, regarding the technical dimension, the findings show that companies seeking to become data-driven and succeed in advanced analytics for SCP must invest time, effort, and resources in ensuring data availability and quality, data analysis tools, and a data architecture that supports analytics. Such companies should address data quality challenges by implementing data quality assurance with sufficiently skilled analytics resources, including data scientists, statistical experts, and domain-specific analysts (McAfee and Brynjolfsson 2012). Effective and efficient inventory planning, utilizing product-in-use and external data, requires an infrastructure for collecting and storing data. Fourth, developing data science and analytics competencies within the company is urgently needed, as are training business developers and managers to understand the potential opportunities and challenges of big data analytics. Lastly, collaboration or interaction with parties within supply chains should not be underestimated, not least in the aftermarket context. Without the willingness of vehicle owners to share data or follow actions proposed by a prescriptive process, many potential big data applications will fail or, at the very least, not optimize their full potential.

6.3. Limitations and future research

In summary, our study focused on understanding SCP processes not yet fully implemented in practice, except for vehicle monitoring. The case company afforded excellent access to the aftermarket context and ongoing projects seeking implementation. The experience gained from designing and testing various big data analytics-driven SCP projects represented a significant contribution to our findings. However, the study was limited by focusing exclusively on a business actively developing competencies and processes in advanced analytics applied to product-in-use data. Furthermore, because the study focused on the automotive context, future studies should address challenges with product-in-use data in aftermarket supply chains in other industries. This study's focus has been on big data and advanced analytics challenges of SCP in an aftermarket context. Several findings may be transferable to other big data and advanced analytics contexts. It would be interesting to compare findings of this study with challenges of implementing other advanced analytics practices also being in 'infancy stages' (Hasan et al. 2024), for example, generative AI in operations and supply chain management (Wamba et al. 2023). We identified how challenges relate to the process and data complexities of the applications and the process development phases. Our findings reveal development patterns that would be interesting to study in more detail in future research. Despite accommodating the perspective of customers and extending the scope from service providers to other actors and their intersections, the scope of SCP does not reveal evidence of any challenges with using big data and advanced analytics for product-in-use data as a means to advance services (Lim et al. 2018) or capture value (Roden et al. 2017). In this way, SCP becomes more firmly connected to the organization's front-end strategy for solving business problems instead of focusing on data and information processing. Although studying service innovations was not our aim, we identified relevant strands for further research in that direction.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A: Empirical sources of SCP process challenges

Table A1. Causal based forecasting.

Challenge category	Sub-category of challenge	Impacted by	Empirical details combine quotes with other data
Technology	IT infrastructure	Data complexity	'A vast number of functional source systems, developed over many years, based on different IT technologies (hardware as well as software), cause a major challenge regarding the integration of these systems into the newly implemented cloud solution'. Quote from a data scientist, but similar comments were made by several members of the different causal-based forecasting teams. A large volume of data retrieved from vehicle on-board systems, vehicle maintenance systems, and spare parts catalogue systems, together with the traditional data used for spare parts forecast (demand data), puts very high requirements and challenges on the IT infrastructure in terms of data storage capabilities, data transmission capabilities, and data processing capabilities. Furthermore, these challenges are augmented by different velocities and the variety of data. The above challenge (and corresponding limitations in the available infrastructure) is emphasized by both the technology manager and data and software engineers within the advanced analytics department.
Technology	Analytical framework	Data complexity	'We need to develop a technical solution to test and pilot new forecasting algorithms with associated data to increase the efficiency' (less time spent on data preparation). Stated by a data scientist in a causal-based forecasting exploration. Similar statements are made by other data scientists and domain experts working with forecasting explorations. Although the various causal-based forecasting explorations and pilots employ different features as explanatory variables, it is common to spend most of the time searching for data, understanding it across multiple sources, and cleaning and correcting it. Within the big data framework, a solution is needed to develop causal-based forecasting methods, along with the corresponding data.
Personnel	Data preparation	Data complexity	'We spend the majority of our time (∼80%) with data preparation, i.e. data cleansing, imputation, and correction, in the forecasting explorations' (quote from data scientists in Advanced Analytics) In the cloud-based big data framework, which is currently in rollout phase, some data exists and has good quality, while other data is available but not quality-assured. Additionally, some of the data necessary for causal-based forecasting is still missing. Hence, the burden on data scientists regarding data preparation has decreased, but it has not disappeared. They still spend a considerable amount of time, but less than before, due to some of the data being in one single place, utilizing a single database technology (Reported by data scientists).
Personnel	Advanced analytics and modelling	Data complexity	The large amount of data required to forecast tens of millions of SKUs, for a large installed base with many configuration possibilities (many different bills of material) and a large number of independent variables that can impact the demand, is an excellent challenge for the data scientists regarding big data handling and modelling, i.e. the potential positive outcome of the model, as well as the required computational time and power (and cost) requires

(*continued*)

Table A1. Continued.

Challenge category	Sub-category of challenge	Impacted by	Empirical details combine quotes with other data
			a lot of effort, and, often support from experts in other domains, e.g. software engineer or software architect (Reported by data scientists).
Personnel	Combine data science and domain competence	Data complexity	To succeed in causal-based forecasting, the company needs to develop behavioural and job-specific competencies identified by the personnel involved in developing the analytical pilot studies (i.e. managers, data scientists, and other IT-specific roles, and domain experts). These competencies relate to the ability to develop machine learning and AI methods applied to internal and external data, as well as ensuring the quality of such methods in the forecasting process by evaluating both input and output. To understand the relevance of some of the data (e.g. underlying variables) and the potential impact on forecasts, to specify and develop models and algorithms, test the outcome of the model and evaluate the result, the case companies experience is that the best results are achieved when the main responsible for the model development (usually a data scientist) has enough access to senior domain experts.
Personnel	Data engineering	Data engineering	Driven by technical challenges (mainly IT infrastructure), IT technical roles, particularly data engineering, face challenges due to the transformation of the IT landscape, i.e. the ingestion of massive, varied data from different systems into a cloud solution.
Organization	Advanced analytics organization	Technology & personnel	'It is difficult to find and attract people with the necessary competencies' (Manager, advanced analytics). 'We need to advance the analytical competence for everyone working with forecasting and supply chain planning' (from workshop with advanced analytics team). New IT roles need to be filled, including data engineers, software architects, and machine learning engineers (as documented by the advanced analytics management team). This need was driven by the requirement for dedicated specialists to implement the significant data transformation. Although these roles have been filled (one person per role) since this decision was made (2021), the challenge persists (2024) due to the numerous explorations and pilots ongoing, as well as personnel turnover.
Organization	IT governance	Technology	The numerous data sources with varying data types require advanced IT infrastructure, which in turn poses challenges for IT governance, including routine operations, scalability, and compliance (as discussed in meetings with the advanced analytics team).
Organization	New ways of working	Technology & personnel	There has been a vast number of explorations in the causal-based forecasting domain, carried out by different people and departments, sometimes with a similar scope. The involved parties agreed that this has caused both non-optimal forecasting models and unnecessary work; hence, it was decided to coordinate all forecasting development activities (explorations, pilots, and implementation projects) within a focused team instead of running the development within the functional groups (outcome from a workshop with initial forecast analysts and personnel from the Advanced Analytics team). New agile ways of working are needed, e.g. DevOps (from workshop with advanced analytics team).
Organization	Build a data-driven culture	Technology & personnel	Transformation of the organizational culture, which requires new ways of working, for example, how to coordinate and manage projects and explorations in an agile way, also requires strong management support. Hence, considerable effort is needed to communicate the opportunities that data-driven, causal-based forecasting can generate.

Table A2. Pre-planned maintenance.

Challenge category	Sub-category of challenge	Impacted by	Empirical details combine quotes with other data
Technology	IT infrastructure	Data complexity	Predictive maintenance requires information from the vehicle (sensor data and fault codes) and maintenance history (required spare parts). This process stepwise approach, i.e. developing a predictive model per spare part type, does not require a considerable amount of data, although it requires an integration of the output of the model into the workshop system, as well as an integration of the IoT data from vehicles. Recently, an effort was made to present the required predictive maintenance operations for each vehicle, including operational instructions, required spare parts, and explanatory reasons, on a single screen, which, to a high degree, has limited the IT infrastructure challenge. Before the integration of predictive maintenance data, the maintenance staff (service coordinator, mechanics, spare parts manager) had to spend more time and effort on the process before the actual maintenance work could start, for example, more time on triage and communication with the vehicle owner/driver.
Technology	Data mapping	Data complexity	Data scientists and the manager of service coordination stressed the importance of correct data transmission and relationship and transformation of data between the vast number of involved systems.
Personnel	Data preparation	Data complexity	According to data scientists working with predictive maintenance, the majority of their time is spent on data preparation, i.e. correcting, imputing, and cleaning data, instead of focusing on their analytical tasks. Recent advancements in IT infrastructure, including the collection of more data through cloud-based solutions, have to some extent mitigated this challenge. Also, lessons from previous predictive models that adopted a stepwise approach to modelling and evaluating components one at a time have reduced the severity of this challenge. For example, components whose behaviour and fault frequency change over time have been corrected, and features related to the life cycle and driving behaviour have been added. (From a meeting with the predictive maintenance manager, 2023).
Personnel	Combine analytical competence and vehicle maintenance skills	Data complexity	The wide variety of vehicle configurations, including the mechatronics and software configurations, makes data interpretation difficult for data scientists, e.g. the significance of fault codes and sensor signals. This is considered a major challenge for data scientists and domain experts working together; hence, ambiguous data can be interpreted more effectively when their competencies are combined. (Reported by predictive maintenance data scientist). Over time, as more data have been collected, the understanding of various features, e.g. vehicle age, has improved, and the predictions have become more accurate.
Personnel	Very high demand for reliability regarding predictive maintenance	Process complexity	Both data scientists and service coordinators emphasize the importance of avoiding false-positive errors, i.e. when the predictive model proposes a maintenance operation when there is no need, to avoid unnecessary workshop visits for the vehicle, which limit the vehicle's uptime and potentially lead to over-maintenance costs.
Personnel	High demand for collaboration between the maintenance provider and the vehicle owner	Process complexity	For the maintenance provider, it is of paramount importance to have excellent collaborative skills, given the complexity of the maintenance process and the high uptime requirements from the vehicle owner. We interviewed three service coordinators and a workshop manager and compared their experiences with traditional maintenance planning. They reported a need for close contact with the vehicle owner and driver due to trust issues, as well as substantial effort to align maintenance planning between these two actors. The trust relates mainly to the ability to do the right thing, i.e. to perform the correct operations at the workshop, while alignment refers to the difficulty of finding, in advance, a suitable time slot for both the workshop and the vehicle. However, the recent investment in hiring maintenance managers has the potential to build trustful relations. To perform efficient predictive maintenance, the maintenance coordinators mentioned that understanding and considering the vehicle owner's business are crucial. This includes awareness of the different vehicles' utilization and life cycle. With the recent implementation of service coordinators, this challenge has decreased compared to before, when service coordination was included in other customer-related roles.
Organization		Process complexity and personnel	Interviews with service coordinators report good progress in the efficiency of the predictive maintenance process. However, it

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Table A2. Continued.

Challenge category	Sub-category of challenge	Impacted by	Empirical details combine quotes with other data
	Trustful business relations and willingness to participate in service programs		requires substantial effort, whereas service providers without such a role (mainly cost-related) face difficulties due to extensive multitasking for customer support staff.
Organization	IT-governance	Technology	The technological requirements for integrating maintenance predictions into operational maintenance systems pose challenges in the organizational dimension, specifically in IT governance, i.e. ensuring the effective use of IT tools and data security. Reported by the manager of service coordination.

Table A3. Vehicle monitoring.

Challenge category	Sub-category of challenge	Impacted by	Empirical details combine quotes with other data.
Technology	IT infrastructure	Data complexity	The vehicle monitoring process handles specific reported alerts generated by vehicles with service contracts. This requires handling a large amount of data; however, it is not as much as the massive amount required for causal-based forecasting. This process is not considered complex from a data perspective. However, the vehicle monitoring process also requires integrating the proposed actions into the IT landscape and supporting them with sufficient IT tools and infrastructure (as discussed in the workshop with the Truck Monitor Centre team).
Technology	IoT connectivity	Data complexity	Due to the urgency of reacting to potential vehicle faults/risks, the uptime of the sending system in the vehicle and the IoT infrastructure reliability is very critical (from workshop with Truck Monitor Centre team). This problem relates to either the vehicle's telecommunication device or poor data transmission in the region where the vehicle is located, as reported by a data scientist at the truck monitoring centre.
Technology	Data mapping	Data complexity	Data scientists and the manager of service coordination emphasized the importance of accurate data transmission and the relationships and transformations of data across the numerous systems involved.
Personnel	Data preparation	Data complexity	Data scientists report (from a workshop with the OEM's Truck Monitor Centre) that a large portion of their time is spent on data preparation tasks due to missing data. Moreover, inaccurate data creates challenges for the reliability of predictive models, which require a considerable collaborative effort between data scientists and vehicle engineers to interpret the model's results and adapt the data.
Personnel	Combine data science and vehicle technical competence	Data complexity	Since vehicle downtime potential is based on heuristics, the analytical challenges are not particularly high; however, there are still interpretation issues with the data and the proposed actions, which require combined competencies from both data scientists and vehicle engineers (as determined through workshops with the truck monitor centre).
Personnel	Multi-actor collaboration	Process complexity	Monitoring organizations in both Europe and the Americas emphasize interaction-related challenges, i.e. coordinating several actors via the call centre that interacts with both users (i.e. drivers and vehicle owners) and service providers. With drivers, the correct reasons for generated alerts are determined; with owners, services are coordinated with the transportation schedule to avoid unnecessary downtime. Lastly, the need for spare parts is coordinated with the OEM, a complex process due to the short notice of the need. Accordingly, this creates challenges in the personnel dimension for those working in the process, including multi-actor coordination, collaboration, and interaction.
Organization	Business relations	Process complexity/Personnel	For the OEM to attract as many users as possible to use and pay for the monitoring service, a significant challenge has been convincing vehicle owners of the benefits and value of such services. Hence, it is a challenge to carry out the process efficiently and collaborate, both internally and with customers. I.e. understanding customer business requirements and creating business relationships are part of the organizational challenges, as identified through

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Table A3. Continued.

Challenge category	Sub-category of challenge	Impacted by	Empirical details combine quotes with other data.
			interviews with service coordinators and spare parts managers.
organization	Willingness to collaborate	Process complexity	Another major challenge is the parties' willingness to share data and collaborate. After all, only vehicles with service contracts are monitored. Regarding the interaction among actors, the number of stakeholders, the urgency of correcting monitored vehicles, and the need for many systems, monitoring vehicles is challenging (as mentioned in two workshops with two organizations working on monitoring, one in the EU and the other in the Americas).
organization	IT governance	Technology	The analytical outcome of this process encompasses potential severe errors of vehicles, leading to malfunctions and downtime. The technological requirements for integrating urgent potential vehicle malfunctions from vehicle monitoring algorithms pose challenges in the organizational dimension, specifically in terms of IT governance, i.e. ensuring the effective use of IT tools.
Organization	Responsiveness	Process complexity	Due to the urgency of detecting potential faults, the analytical outcome needs to be designed so that the involved actors know how to handle the problem, i.e. clear instructions, who to contact, and where to seek assistance (from interviews with service coordinators).