Data-based decision-making in maintenance service delivery: the D3M framework

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Abstract

Purpose – This paper aims to present a dual-perspective framework for maintenance service delivery that should be used by manufacturing companies to structure and manage their maintenance service delivery process, using aggregated historical and real-time data to improve operational decision-making. The framework, built for continuous improvement, allows the exploitation of maintenance data to improve the knowledge of service processes and machines.

Design/methodology/approach – The Dual-perspective, data-based decision-making process for maintenance delivery (D3M) framework development and test followed a qualitative approach based on literature reviews and semi-structured interviews. The pool of companies interviewed was expanded from the development to the test stage to increase its applicability and present additional perspectives.

Findings – The interviews confirmed that manufacturing companies are interested in exploiting the data generated in the use phase to improve operational decision-making in maintenance service delivery. Feedback to improve the framework methods and tools was collected, as well as suggestions for the introduction of new ones according to the companies' necessities.

Originality/value – The paper presents a novel framework addressing the data-based decision-making process for maintenance service delivery. The D3M framework can be used by manufacturing companies to structure their maintenance service delivery process and improve their knowledge of machines and service processes.

Keywords Maintenance, Decision-making, Continuous improvement, Service operations, Servitization

Paper type Research paper

1. Introduction

Recent technological evolution has increased competitiveness in the manufacturing sector, forcing companies to find new ways to create long-term relationships with customers who are always more eager to buy products and services tailored to their necessities and requirements. From this perspective, product–service system (PSS) and, in the business-to-business (B2B) market, industrial PSS (IPSS) offerings allow the creation of long-term relationships by providing a combination of product and services (e.g. maintenance) tailored

to customers' needs (Pezzotta *et al.*, 2018) developed as result of a higher integration of customers in the product and service design phases (Wuttke *et al.*, 2019). This transition poses several challenges related to the network organization, the stakeholders' integration and interaction, the way customers experience products and services and the management of all the resources involved in the PSS contract (Meier *et al.*, 2011; Wuttke *et al.*, 2019).

The literature proposes several methodologies (Costa *et al.*, 2018; Pezzotta *et al.*, 2018; Sholihah *et al.*, 2019; Zhu *et al.*, 2015) for PSS conceptualization and design. Yet, there is a lack of insights on how to structure a decision-making process (in terms of phases, methods and tools) to support companies in understanding which, when and how decisions must be made during daily operations for PSS delivery (Medini and Boucher, 2019). The benefits of an integrated design of product and service components vanish if, at the operational level, service delivery lacks the necessary instruments and skills (Brundage *et al.*, 2019; Kumar *et al.*, 2018). Low-quality service delivery, as a consequence of suboptimal operational decisions and information flows, may disrupt the relationships between the stakeholders, resulting in economic losses for the participants. This is emphasized, for instance, when customers interested in machines' availability use different indicators linked to maintenance (e.g. downtime, responsiveness) to select the provider and evaluate the service quality (Sheikhalishahi and Torabi, 2014).

Nowadays, service (and maintenance) delivery still needs to fully take advantage of the smart characteristics of the product and its capability to collect and share data (Pirola *et al.*, 2020). Authors like Brundage *et al.* (2019), Gopalakrishnan *et al.* (2015), Passath and Mertens (2019) clarified that few companies use structured decision-making processes to support maintenance service delivery, mainly because of the lack of reliable data from the field, which affects the final delivery. Other authors (Alexopoulos *et al.*, 2018; Roy *et al.*, 2013) stress the need to use such instruments to improve maintenance service provision and to invest in proper data management and sharing to properly use the feedback collected during maintenance delivery as input for PSS design. These considerations lead to an initial research question:

RQ1. How should a data-based decision-making process for maintenance service delivery be structured in terms of phases, actors and decisions?

As suggested by Ardolino *et al.* (2017), digital technologies might support service delivery improvement in PSS, but only if proper data collection and processing strategies are introduced (Mahlamäki *et al.*, 2016). The lack of structured decision-making processes and tools discussed by Brundage *et al.* (2019) and Passath and Mertens (2019) explains why employees usually capitalize on their experience when making decisions, rather than using data-based decision support tools (Gopalakrishnan *et al.*, 2015). Brundage *et al.* (2019) further pinpointed data quality among the main causes of wrong decisions made in maintenance service delivery processes, stressing the need to develop collection, analysis and visualization methods and tools in support of maintenance decision-making. This input stimulated a second research question:

RQ2. What methods and tools could be adopted to support a data-based decision-making process for maintenance service delivery?

To answer both of the above questions, the paper proposes and verifies a framework to structure a data-based decision-making process, which exploits field and historical data for maintenance service delivery, and that features a double perspective on product and service (i.e. machine and maintenance). In the long term, the adoption of such a framework in companies can create the conditions and knowledge for implementing a decision-making process able to manage and exploit preventive maintenance services. The paper is structured as follows: Section 2 presents the theoretical background of the research. Section 3 illustrates

the research methodology. Section 4 describes the framework and its content. Section 5 depicts the framework verification. Section 6 discusses how the framework can improve maintenance service delivery. Section 7 concludes the paper, delineating future works.

2. Literature review

In recent years, the technological evolution in the B2B context amplified the role of maintenance and the importance of contracts based on machines' reliability (Wibowo *et al.*, 2017). Nowadays, maintenance is no longer seen as a "necessary evil", but rather as an "investment in the future", as a means to increase the machine's useful life and availability, the product quality and to reduce production losses and costs (Manzini *et al.*, 2010).

To understand the status of the research linking decision-making, Industry 4.0, PSS and maintenance, a literature review of studies published between 2011 and 2020 was conducted (Figure 1), using the Scopus and ISI Web of Knowledge databases to ensure multidisciplinary coverage. Both journal and conference papers related to "Engineering," "Computer Science," "Business, Management, and Accounting" or "Decision Science" were included. Multiple queries were run using the operators "AND" and "OR" and searching the keywords and related synonyms (e.g. PSS, product-service, product service system*, product-service-system*, servi*i*ation, functional produc*, IPSS*, extended-produc*, extended produc*, decision making, decision* making, decision-making, decision*-making, Industry 4.0, Industrie 4.0, smart manufacturing, cyber physical system*, CPS, maintenance), in the "Article Title, Abstract, Keywords" fields.

The papers were framed according to categories such as decision-making level (e.g. strategical, tactical and operational), perspective adopted (e.g. process, activity) and decision purpose (e.g. scheduling, residual useful life (RUL) estimation). Most of the papers in the dataset deal with operational-related issues and adopt an activity perspective, focusing on a single step of the maintenance service delivery process. They feature a variety of methods and tools for data analysis and exploration and deal mainly with planning, scheduling, failure identification and RUL estimation.

In the domain of planning – which refers to the identification of tasks, tools and resources necessary for interventions (what and how) – ABC analysis and analytic hierarchy process (AHP) (Gopalakrishnan *et al.*, 2015), failure mode effect and criticality analysis (FMECA)
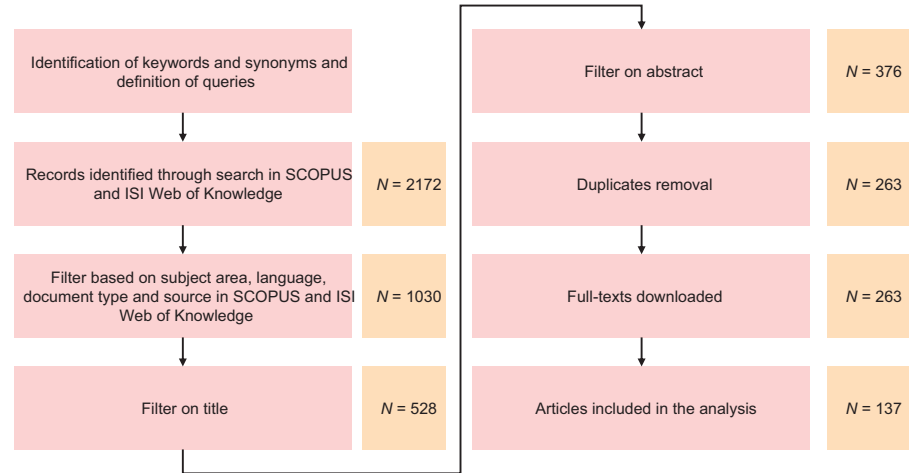
(Candón *et al.*, 2019), genetic algorithms (Upasani *et al.*, 2017), general optimization algorithms (Chang *et al.*, 2019), a combination of methods like k-means and NSGA-II (Chang *et al.*, 2019) or other supporting tools such as those discussed by Mourtzis *et al.* (2020) are proposed. Two main approaches can be identified: one more oriented to define criticalities (e.g. FMECA, ABC and AHP) and one more focused on optimization (e.g. genetic and optimization algorithms).

Notably, health status prediction research has been found to grow with the introduction of machine learning (ML) (Carvalho *et al.*, 2019). Examples can be found in studies by Calabrese *et al.* (2019), Behera *et al.* (2019) and Selak *et al.* (2014), which used artificial neural networks and decision trees, gradient-boosted trees and random forests, and support vector machine, respectively. Similarly, simulation is used to analyze faults and estimate the RUL (Guizzi *et al.*, 2019). While ML approaches are data-intensive, simulation models require fewer data to perform analyses and return results. An extensive analysis of the application of simulation for process optimization (e.g. in maintenance service delivery) is also found in a study by Mourtzis (2020).

In the domain of scheduling – which defines the times of the intervention (when) (Kallrath, 2002) – the literature is dominated by optimization-based approaches, which, for instance, combine genetic algorithms and particle swarm optimization (Upasani *et al.*, 2017), or use general optimization models (Li *et al.*, 2015).

Issues related to the implementation of data-based decision-making approaches are also highlighted. Mahlamäki *et al.* (2016) provided a list of problems, such as missing information, wrong codes, typos, out-of-date or duplicate records and others, affecting the exploitation of data for decision-making. Brundage *et al.* (2019) and Fargnoli *et al.* (2019) underlined the opportunity to improve maintenance service delivery by appropriately collecting, classifying and reusing maintenance data. Tang and Liao (2021) outlined decision-making methods exploiting big data, detailing the necessity for a structured approach guiding data collection, analysis, visualization and decision-making.

Yet, most of the time, maintenance decisions are based on the personal experience of the individual (Potes Ruiz *et al.*, 2014). The adoption of experience-based approaches and, consequently, the scarce adoption rate of decision support tools (Kumar *et al.*, 2018), finds roots in the lack of structured approaches for data collection and analysis (Mahlamäki *et al.*, 2016). In addition to this, available tools do not consider contemporary characteristics of the product and service components and the related complexity (Rondini *et al.*, 2017).
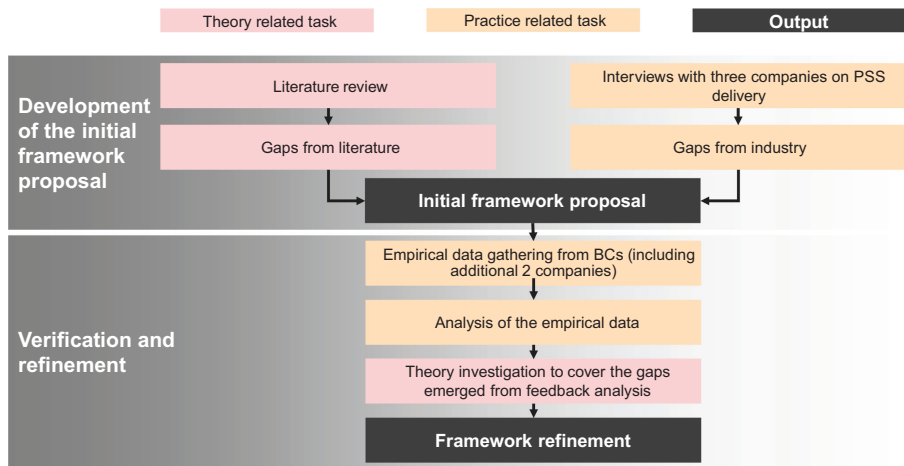
The literature analysis further shows that only a few contributions consider the whole process perspective and combine information from different sources (e.g. service provider and customer characteristics) to support the selection of the maintenance typology, for example, through the use of simulation (Fargnoli *et al.*, 2019), association rules (Xiao *et al.*, 2016) or previous knowledge (Singgih *et al.*, 2019).

The review spotlights the lack of structured approaches, methods and tools to support decision-making in maintenance (Liang, 2020; Passath and Mertens, 2019) by integrating past knowledge with information extracted from data (Brundage *et al.*, 2019; Singgih *et al.*, 2019) and jointly considering the machine and maintenance perspectives. Based on these findings, this research contribution proposes a framework addressing the gaps identified above from the perspective of the (1) phases composing the process, (2) the actors involved and (3) methods and tools supporting decision-making.

3. Research methodology
Figure 2 describes the research methodology adopted in the development of the framework. From a high-level perspective, this was composed of two macro-phases: (1) development of the initial framework proposal and (2) verification and refinement.

3.1 Development of the initial framework proposal

The findings from the literature review were complemented with data gathered by interviewing industrial practitioners on maintenance service delivery to define the initial framework proposal. As the research was focused on the process leading to decision-making in the service delivery process, a *qualitative approach* (Ritchie *et al.*, 2013) was selected. Accordingly, a small sample, composed of three companies, was used, resulting in multiple-case study research (Yin, 2009). Companies had to cover specific characteristics to be selected:

(1) Technological level: Companies must have different technological backgrounds and expertise concerning both the product's technological level and the ability to exploit data collected.

(2) PSS offerings: Companies must have different levels of experience with PSS provision; some should be expert, while others should be new to it.

(3) Sector: Companies should belong to different sectors and produce different products (e.g. balancing machines, automated guided vehicles and circuit breakers).

(4) Location: Companies should be headquartered in different parts of the world (e.g. Italy, China, Northern Europe) to experience different approaches to decision-making and service delivery.

Interviewees were selected with the same approach used for the companies, with actors covering aspects of interest in the maintenance service delivery process – in this case, service managers. Accordingly, the number of employees interviewed was limited (three, one for each company) but sufficient to collect all data of interest (Ritchie *et al.*, 2013). The interviews, lasting 1 h each, were audio-recorded, transcribed and validated by the respondents. Different coding schemes were applied in the data analysis stage, based on keywords related to the research topics (e.g. hypothesis coding and simultaneous coding, Saldaña (2015)) to identify relevant phenomena and trends. The analysis of the information collected from the literature and interviews allowed:

(1) Identifying the framework architecture and main stages;

(2) Defining how the maintenance delivery stage is fed by information generated from products and services; and

(3) Defining the general characteristics of the methods and tools supporting decision-making for maintenance service delivery.

3.2 Verification and refinement
Verification activities were carried out qualitatively in the form of semi-structured one-to-one interviews. This involves two manufacturing companies that did not take part in the empirical data gathering stage: an Italian company working in the oil and gas sector and a European company producing road construction machines. Both companies that satisfy the criteria for case study selection were interested in widening their product-centred portfolio with new maintenance-related services.

A total of eight interviewees (four per company) were selected to verify that the preliminary version of the framework could be used to map all the important activities in the decision-making process for maintenance service delivery. Service managers, technicians, planners, product designers and information technology (IT) managers (identified through opportunistic sampling) provided feedback and ideas on how to optimize the framework structure to improve decision-making for maintenance service delivery, mitigating the risk of wrong decisions. The questions were designed to allow for the collection of further information on the maintenance service delivery process and to test the hypotheses underlying the framework proposal. The results allowed synthesizing suggestions for the framework improvement and the related methods and tools, increasing their applicability in multiple contexts and verifying their contribution to decision-making.

4. The D3M framework
The descriptive study findings above brought about the definition of the dual-perspective, data-based decision-making process for maintenance delivery (D3M) framework (Figure 3). D3M includes activities, methods and tools and combines machine- and service-related data to support decision-making during the maintenance service delivery process mainly at the operational level.

The D3M framework is composed of two parallel flows – service (i.e. maintenance) and machine-related – aimed at structuring the process for the identification of criticalities in maintenance service delivery decision-making. The framework introduces the capability of merging these inputs in the maintenance delivery stream to support decision-making at the operational level and to collect data for knowledge improvement. The process supported by the framework is highly iterative and generates new knowledge related to operational decisions at each loop. Thus, the framework facilitates the implementation of more advanced maintenance services, such as predictive maintenance, by integrating multiple data sources, both real-time and historical, in the decision-making exercise. Notably, the analysis of aggregated operational data is also aimed at improving decisions at tactical (e.g. maintenance policies' update) and strategic (e.g. resource dimensioning) levels.

4.1 The machine stream
The first stage in the process is dedicated to the *identification of the machine critical components* and considers that the definition of "criticality" varies according to the company's interpretation (e.g. the longest downtime, expensive repair, high failure frequency). Depending on how knowledge is structured inside a company, on machine complexity and on data availability, different approaches are proposed to support the identification step: from open review meetings (Aromaa *et al.*, 2012) to a dynamic version of the FMECA (Chen *et al.*, 2012). During open review meetings, product and service developers meet physically (or virtually) to share their expertise and knowledge on machine components.
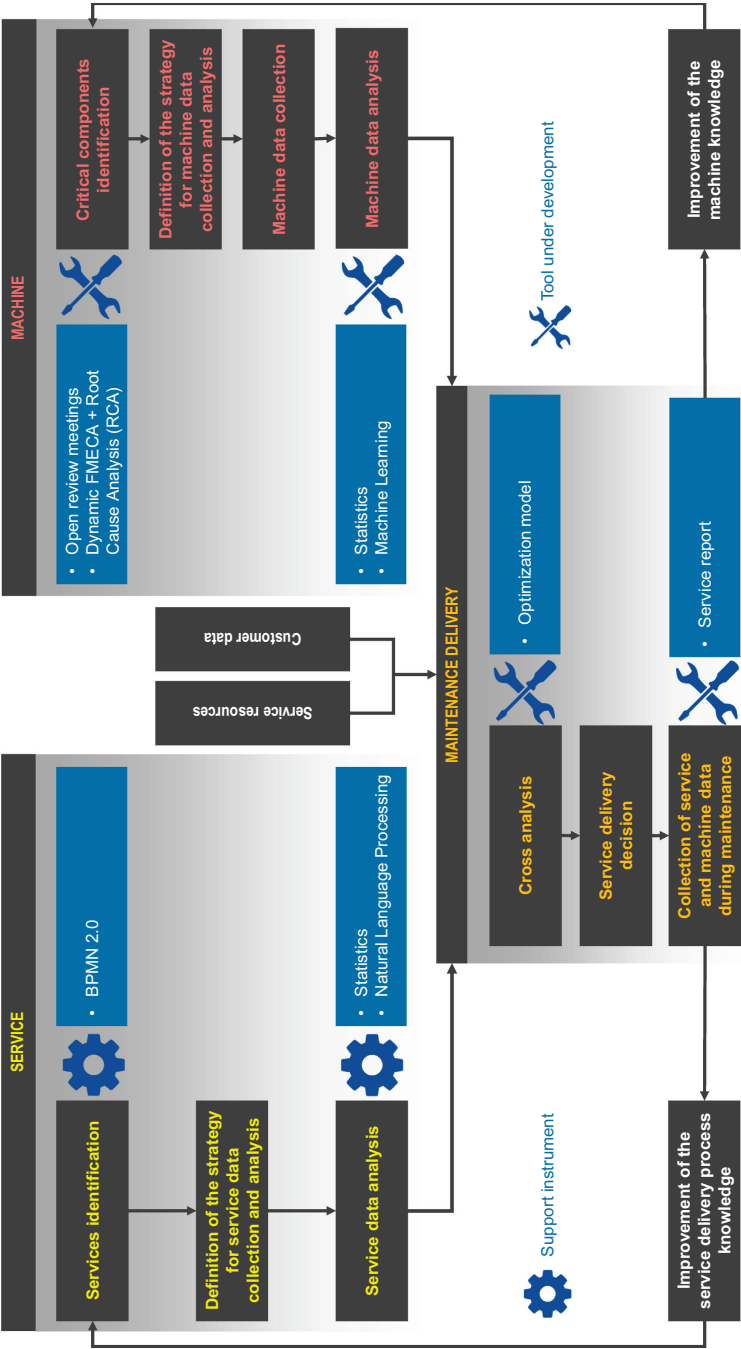
Figure 3.
The D3M framework

This approach fits well for simple systems, for situations dominated by unstructured knowledge and when hardware data are not readily available. The combined use of FMECA and root cause analysis (RCA) (Chemweno *et al.*, 2016) has been further discussed to better document the failures' sources and their effects, both using qualitative scores (i.e. based on expertise) or real data from previous failures. In more sophisticated instantiations, the use of dynamic FMECA (Colli *et al.*, 2019), is suggested. This method consists of updating the components' risk priority number or RPN (i.e. the "criticality" score), defined in the first application of the FMECA during the use phase, to obtain a more accurate vision of the machine criticalities.

In the *definition of the strategy for machine data collection and analysis* stage, the company pinpoints the data to be monitored and how to gather (e.g. source, frequency, granularity) and analyze them. Ensuring data quality is paramount, as it affects the subsequent analysis stage (Mahlamäki *et al.*, 2016) and the selection of the data analysis algorithm: matching data features, approach and scope of the analysis (Sala *et al.*, 2018). Based on the results, the company identifies which and where to place sensors to collect data, trading off benefit, cost and effort in the installation process. The company must then select the type of sensor to be installed and then evaluate data collection feasibility to avoid problems that could bias the analysis and, in turn, the introduction of predictive maintenance policies based on health status prediction.

During the *machine data collection* stage, data from the machine are collected and categorized according to known parameters and stored for easy retrieval. The data set has to be updated whenever something changes (e.g. location of a customer) to ensure profitable exploitation and avoid misinterpretation (Emmanouilidis *et al.*, 2019).

In the *machine data analysis* stage, the company uses the data gathered to predict the health status of critical components and to plan countermeasures, depending on the maintenance policy adopted and the available skills. The D3M framework proposes the use of both simple statistics and ML. The first is aimed at summarizing information on data (descriptive statistics) and at inferring trends or assumptions on the analyzed population (inferential statistics). Indeed, many researchers have discussed the benefits of using ML in maintenance analyses (Carvalho *et al.*, 2019; Ruiz-Sarmiento *et al.*, 2020) to draw patterns from the dataset to determine the components' status and create prediction models (Williams and Rasmussen, 2006), merging real-time and historical data (to define the thresholds representative of the level of degradation for the component).

4.2 The service stream

The goal of the *services identification* step is to map the maintenance services currently offered by the company, both remotely and on-site. These can include simple consultancy, spare parts provision and on-site corrective, preventive or predictive maintenance intervention, requiring the involvement of different resources for their execution. Each maintenance typology has its strengths and weaknesses and differs in terms of intervention costs, time required and more. All these aspects must be known and evaluated to select the best solution for all stakeholders. BPMN2.0 (Aagesen and Krogstie, 2015) is proposed as a process mapping technique to describe all the activities, actors, decisions and tools involved in such a process. Based on the mapping, the company can identify what data to collect and where, or the activities in the process that do not create value and, thus, must be modified or removed.

The *definition of the strategy for service data collection and analysis* stage encompasses the identification of the relevant information to collect during an intervention. As for the machine stream, the company has to consider the trade-off between relevance and ease of data gathering, understanding how to collect data without affecting the service quality.

The third stage, *service data analysis*, focuses on the analysis of the aggregated data collected from various sources such as service reports or Electronic Performance Support System (EPSS) to synthesize the service performance and the resources involved. Although the report template is designed to be intuitively populated as well as to facilitate data extraction, technicians can add textual information or pictures that cannot be inserted as preformatted text or selected from drop-down menus, as discussed in the following sections. The analysis of the service report can be performed in different ways, depending on the technology and skills available in the company. Statistics can be used to extract information and knowledge from the numerical data, while natural language processing (NLP) can be further applied to improve the analysis of reports that are particularly text-intensive (Stenström *et al.*, 2015).

4.3 The maintenance delivery stream

The lower section of the D3M framework is intended to merge service and machine data, along with additional process information, to support daily operations decision-making.

The process is triggered by the activation of an "alarm" on a given machine, which activates the collection of information for maintenance decisions. The *service resources* item contains all the information needed to identify the most suitable technician for an intervention. This includes current schedule, starting location (for the travelling time), past maintenance interventions and technical-related information, such as skills (used to determine the eligibility to execute the intervention) and spoken languages.

The *customer data* item contains additional data related to the location of the customer facilities, type of machine installed, contractual information (e.g. service-level agreement (SLA)) and others.

The *cross-analysis* phase uses service- and machine-related information, in conjunction with service resources and customer-related data, to identify the optimal way to deliver maintenance. A first version of the model is presented in (Sala *et al.*, 2020). The aim is to minimize the number of tardy interventions (i.e. the ones delivered/completed after the due date established with customer). The model is fed with historical and real-time data, which include information on the machine (e.g. esteemed RUL, failure typology), service alternatives (e.g. available maintenance solutions – technician on the field, remote support and others), the service resources' availability (e.g. technicians' skills, schedule) and the customer (e.g. location, SLA, maintenance skills available in the company). The model mixes the retrieved information and elaborates a schedule where interventions are assigned to technicians in a certain modality (e.g. on field, remote support, machine returned to the supplier), trying to reduce the number of requests satisfied after the due date (e.g. minimum between esteemed RUL and SLA).

In the *collection of service and machine data during maintenance* stage, the framework proposes a service report structured in a way that allows an easy filling to collect all the important information related to the service and the machine defined in the previous phases. It is a functional tool that favours data collection, extraction and analysis and is easily adaptable to the company's needs. The service report is composed of multiple sections dealing with intervention information (e.g. customer, technician, intervention number), activities executed and worked components, billing information and spare parts used. The reports feature a link to the FMECA, where technicians can select components from a set of drop-down menus or enter their specific serial numbers.

Eventually, the D3M framework proposes an approach based on continuous improvement, knowledge creation and sharing. Aggregated data from three layers are periodically analyzed to enhance the maintenance decision-making process at the operational, tactical and strategic levels.

(1) Operational: The aggregated data are used for updating reference values in the intervention schedule, identifying activities affecting the delivery performance and understanding how to improve the maintenance service delivery process and resolution approach (e.g. remote, on-field).

(2) Tactical: This layer refers to decisions related to the definition of maintenance policies for machines and components. Data are used for updating the thresholds that determine the components' health status, understanding failure causes, updating FMECA RPN values or modifying maintenance policies.

(3) Strategical: The aggregated data are intended to support decisions related to strategic modifications to improve company performance (e.g. workforce modification, new service offerings, improvement in machine design).

5. Verification results
The section discusses the results of the verification phase, the D3M framework evolution and the benefits and barriers that could be encountered with its implementation, as emerged from the interviews.

5.1 Structure of the D3M framework
The intentions of the D3M framework were found to be well aligned with the company's long-term goals during the verification activities. As highlighted by one of the respondents: "[. . .] the solution you propose has a lot in common with what we are trying to do. We would like to have a stricter dialogue between the design and service departments. Such a framework would be helpful to manage the maintenance requests and their scheduling".

Concerning the machine stream, respondents confirmed the necessity for a strategy guiding data collection and analysis as proposed in the D3M framework: "We have a lot of products. So, to follow all of them and to be able to make anything out of that data, I think you need to have a good strategy on how to collect them. You can get tons of data, but then when you need to do some analyses, they need to be in the correct form, so this is something you need to consider".

The D3M framework is intended to be flexible, scalable and adaptable to the company's constraints, needs and data availability. As emerged from interviews, some companies are not always able to collect and share data from machines (due, e.g. to privacy or limited capabilities of the sensors). Even in cases when available data only come from maintenance delivery and not from machine functioning, the D3M framework produces benefits and creates knowledge (e.g. by analyzing failure rates, spare parts usage and maintenance performance): "[. . .] I think that information like the ones related to spare parts usage could be helpful to improve the warehouse management and identify the machines that suffer the most for certain failures". Spare parts orders' monitoring could be used to flag the design department about problems in the machine (e.g. if too many spare parts are bought too frequently). Such analyses would be useful to establish countermeasures in terms of service offering (e.g. new maintenance contracts, training courses).

Only a few companies were found to organize periodical meetings among departments to discuss intervention results. Yet, there is a wide consensus among the interviewees on the necessity of adding this activity to their operations to improve maintenance processes and create new value and knowledge. For some respondents, communication is, in many cases, unidirectional: "Today, we share information about the interventions with the design department, but this is unidirectional. We are not informed when new components are installed or about the best way to maintain them. [. . .] We receive indications only if we ask".

The D3M framework was well appreciated by the respondents for its ability to facilitate such dialogue across departmental boundaries. Providing evidence on failures that happened during the life of the machine can help designers improve its design and performance. Similarly, designing the machine with consideration for the maintenance intervention requirements would improve its delivery.

5.2 Methods and tools

5.2.1 Dynamic failure mode effect and criticality analysis and open review meetings. Most of the companies interviewed were interested in dynamic FMECA, as proposed in the D3M framework. Respondents agreed on the opportunity to improve the critical components' identification and use it as a means to increase spare parts sales. RCA was also considered a useful add-on to capture failure events caused by the wrong behaviour of neighbouring components and sub-systems (e.g. milling spindle excessive wear due to errors in the positioning sensor). Besides FMECA, some companies organize open review meetings for the identification of critical components, as they consider exploiting the designers' experience to be easier and timesaving.

5.2.2 Machine learning and statistics. The companies interviewed performed data analysis to some extent but mainly without a defined strategy or approach. Some were trying to set up an infrastructure able to (near) real-time monitor machines, while others would like to use ML to determine components' health status based on real-time data without having experience with ML: "I think ML could be really useful to make additional analyses. As of now, we are mainly working with traditional statistics approaches to monitor the behaviour of our machines; we would like to introduce ML analyses, but we have no experience in using it".

The D3M framework suggests two alternatives for data analysis, considering the companies' skills and aims. Statistic approaches are suggested for companies without strong data analysis skills or large databases, given that ML requires these features. Alternatively, the D3M framework proposes the adoption of ML. In both cases, the selection of the approach must be coherent with the strategy identified in the previous phases of the D3M framework.

5.2.3 Optimization model. The interviewed companies managed intervention allocation manually, without supporting tools. All the respondents agreed on the usefulness of a tool and on considering both historical and real-time data to schedule service interventions. Planners agreed on the usefulness of a database listing the technicians' competencies to facilitate the selection:

> It could be very useful to have something like this when I am occupied with other activities. Having data on the usual intervention length would facilitate the job for my substitute.

5.2.4 Service report. All the interviewed companies filled out service reports after each intervention, even though most of them used text-intensive reports in an unstructured format. They all agreed on the necessity to simplify the filling phase while ensuring information completeness, thanks to the service report proposed in the D3M framework. One of the suggestions was to substitute, in the service report, the (current) critical components' selection based on FMECA with the components serial number (if any). One of the companies suggested making the service report available on an app and adding QR codes to identify machines and components.

A strength identified was the spare parts section: "It would be good to create a link between aggregated spare parts sales and machines and have a tracker. I never thought of this".

Suggestions were also related to the tracking of the software version installed on the machines as well as to allow attachment of failed components' pictures.

5.2.5 Statistics and natural language processing. The interviewed companies analyzed only superficially service reports, extracting numbers, when possible, but did not analyze text. Data gathered with the service reports represent a source of significant information related to machine use. Statistics can provide quantitative information (e.g. failure frequency or fixing average execution time). The D3M framework proposes improving analyses using NLP for text-intensive service reports:

> The report we use is very text-intensive. We never have the chance to analyse their content because of the way we store the reports, which makes it difficult to find and retrieve them. We have to carry out many activities and we do not have the resources and time to analyse reports.

Despite being a relatively new research field, NLP has already shown promising results. A summary of the improvements that followed the interviews is provided in Table 1.

6. Discussion

The introduction of the D3M framework and its related methods and tools aims at creating the conditions for improved data sharing among the stakeholders involved in the PSS contract. The prescribed data collection and analysis process allows practitioners to identify strengths and weaknesses in their decision-making process, assessing how data and information are managed together with the suitability of the instruments currently used. In fact, introducing PSS offerings means that hardware manufacturers would need to deal with several challenges (Wuttke *et al.*, 2019). Such should be addressed not only in terms of PSS design (Meier *et al.*, 2011) but also in terms of methods and tools for data exploitation (Tang and Liao, 2021) and decision-making (Roy *et al.*, 2013), which should be selected and developed in accordance with the characteristics of PSS (Pirola *et al.*, 2020).

The interviews contributed to understanding how companies currently manage decisions and deliver maintenance and shed light on how data from various sources are collected, managed and processed, confirming, in many cases, the problems highlighted in the literature (Brundage *et al.*, 2019; Mahlamäki *et al.*, 2016; Singgih *et al.*, 2019). The D3M framework was used during the interview to map these aspects and picture the current situation in the companies. Then, based on the methods and tools proposed in the D3M framework and the participant's experience, suggestions and improvements were provided to the companies in terms of information flow organization and methods and tools to be adopted. Table 2 summarizes the results of the dialogue, depicting how machines, services and maintenance service delivery processes are currently managed and showing how they could be improved by adopting the D3M framework.

Concerning the *machine* stream, this descriptive study pointed to the lack of structured approaches for data collection and analysis, resulting in poor decisional support to prevent failures. In the *to-be* scenario, the dynamic FMECA represents a step forward in the way companies handle critical components' identification and define strategies for data collection and analysis.

The *as-is* analysis of the *service* stream showed that companies are offering mainly corrective maintenance to their customers, with only a few preventive interventions. The introduction of the D3M framework allows a systematic analysis of service data, increasing the capacity to create new knowledge and, thus, the ability to offer a higher number of preventive interventions.

The *as-is* analysis of the *maintenance delivery* stream allowed identifying gaps related to the tools supporting the planners during the intervention allocation and identification of the machines' problems (Gopalakrishnan *et al.*, 2015; Potes Ruiz *et al.*, 2014). Some companies raised concerns related to the way maintenance data are collected, with service reports not standardized in terms of structure and language, as discussed in the literature review

Focus	Strengths	Weaknesses	The solution adopted/proposed
Framework	(1) Sound structure (2) Enables an approach that fosters a "continuous improvement" working mode (3) It can be used at the strategic, tactical and operational levels depending on the needs	(1) Cost and infrastructure should be carefully considered (2) Data collection may be prevented for security reasons	(1) Contractual clauses should be established with customers considering infrastructure's maintenance and data ownership
Identification of the machine critical components	(1) Dynamic FMECA shortens the problem identification and resolution time (2) Dynamic FMECA improve spare parts management	(1) Dynamic FMECA may be too labour-intensive for some companies (2) Causes of component failures must be carefully evaluated	(1) Open review meetings added as an alternative to dynamic FMECA (2) RCA added to support the identification of the components' failure cause
Machine data analysis	(1) ML supports advanced analyses (2) ML allows the introduction of preventive and predictive maintenance strategies	(1) Some companies do not have the competencies to run ML-based analyses or are not interested in it (2) Preventive maintenance policies require historical data	(1) Statistics added as an alternative to ML
Service data collection	(1) Service report structure (2) Possibility to ease even more the filling phase for companies who are developing an app and a platform able to manage automatically general information	(1) Some companies use serial numbers to track components (2) The software/firmware version is not tracked; it could be useful for problem tracking	(1) Added the possibility to track worked components via serial numbers in the service report (2) Added the possibility to enter the software/firmware version
Service data analysis	(1) Statistics for companies interested in descriptive analyses (2) A competencies database is useful for later decisions and resources improvement	(1) Some companies use text-intensive reports that complicate manual analysis and data extraction	(1) Added the possibility to use NLP
Optimization model	(1) General structure and approach validated (2) Data coherent with the current process (3) Support for planners and substitutes	(1) Contingent factors are not considered (e.g. visa problems)	(1) Added contingent factors to the model

Table 1.
Summary of the validation phase

	Company A	Company B	Company C	Company D	Company E
Location	Italy	Europe	China	Europe	Italy
Product	Balancing machines	Robotics and power equipment	Automated guided vehicles	Road construction equipment	Pumps and equipment for the oil and gas market
Stream					
Machine As-is					
Critical components identification	(1) FMECA to identify the critical components			(1) Critical components identified through designers' experience	
Machine data collection	(1) Few data collected due to privacy constraints (2) Programmable logic controller(PLC) and sensor data available only on the machine (3) Remote data sharing allowed in only a few cases and with few customers		(1) Big amount of data collected (2) PLC and sensor data available on the cloud	(1) Few data collected due to privacy constraints (2) PLC and sensor data available only on the machine	
Machine data analysis	(1) Data processes using basics statistics techniques		(1) Data processed using artificial intelligence (AI)	(1) Data processes using basics statistics techniques	
Machine To-be					
Critical components identification	(1) Dynamic FMECA to improve and keep updated the critical components' identification (2) Maintenance policies' update based on failure rate analysis and updated components' criticality				
Machine data collection	(1) PLC and sensor data available on the cloud for remote monitoring, respecting privacy constraints (2) Identification of data to collect based on the dynamic FMECA update and the critical components' list (3) Implementation of smart sensors and edge processing for data collection, elaboration and sharing (4) Guided procedures for customers for data collection				
Machine data analysis	(1) Unique approach for data analysis based on data availability, company skills and interests				

(continued)

Table 2.
Improvements based
on the D3M framework
introduction for all the
companies interviewed
during the research

		Company A	Company B	Company C	Company D	Company E
Location		Italy	Europe	China	Europe	Italy
Product		Balancing machines	Robotics and power equipment	Automated guided vehicles	Road construction equipment	Pumps and equipment for the oil and gas market
Service As-is	Services identification	(1) Corrective maintenance, few preventive interventions				(1) Only corrective maintenance
	Service data analysis	(1) No analysis of service reports due to lack of time and resources				(1) No analysis of service reports due to lack of time and resources
Service To-be	Services identification	(1) Preventive interventions offered more frequently (exploiting the new knowledge generated)				
	Service data analysis	(1) Automated analysis of service data, thanks to the facilitated extraction from the service report (2) Automatic generation of reports (3) Implementation of NLP approaches to improve the analysis of text-intensive service reports			(1) A unique place for service report storage (2) Basic manual analyses done through pivot tables	
Maintenance delivery As-is	Cross analysis and service delivery decision	(1) Interventions scheduling and allocation based on planner experience				
	Collection of service and machine data during maintenance	(1) No standardized vocabulary in service report (2) Service report filing is not guided (intense use of free text fields) (3) No feedback collected from customers (4) Problem and solution identified based on technician knowledge and expertise				
Maintenance delivery To-be	Cross analysis and service delivery decision	(1) Optimization model merging service and machine data to support the planner and improve intervention allocation				
	Collection of service and machine data during maintenance	(1) Definition of a standardized vocabulary for service reports (2) Mixed use of free text and close-ended fields in service reports to standardize the filling phase (3) Collection of feedback on maintenance (4) Tools to help technicians/customer care identify problem and solutions				

Table 2.

(Brundage *et al.*, 2019; Mahlamäki *et al.*, 2016). In the *to-be* scenario, as suggested by the D3M framework, reports are formatted and standardized to allow proper data collection and analysis. This favours the extraction of new knowledge and improves the allocation of requests to technicians. With the adoption of the optimization model proposed, the number of tardy interventions will decrease, and maintenance management will improve with effects on machines' reliability and corrective and preventive maintenance delivery.

In the long term, new knowledge could support the shift from corrective and preventive maintenance to predictive maintenance. This transition requires the identification of algorithms defining the machines' health status and the introduction of advanced models for failure prediction (Carvalho *et al.*, 2019). Once introduced, machines will send alarms and maintenance could be scheduled with consideration for the esteemed RUL, customer necessities and supplier's constraints, finding the optimum solution.

7. Conclusions and further development

This work presents a new framework proposing a dual-perspective data-based decision-making process for maintenance service delivery at the operational level that uses service and machine data in a structured way.

On the theoretical side, the D3M framework contributes to the research related to the definition of procedures that can guide companies and practitioners in collecting and exploiting data generated during maintenance service delivery and machine working time. The framework answers RQ1 *by identifying* the phases for data collection and analysis on the machine and service sides, the actors involved in the process (e.g. designers, planners, technicians) and the decisions to be addressed (e.g. component's health status, technician identification, intervention schedule, machine and service process criticalities identification). The D3M framework proposes a process that exploits maintenance service data for design purposes, thus addressing one of the gaps mentioned by Roy *et al.* (2013).

On the practical side, the D3M framework proposes a set of methods and tools aimed at supporting the actors in the decision-making process, addressing RQ2. One of the gaps identified through the literature review consisted in the lack of methods and approaches developed for considering a process perspective instead of an activity one. The D3M framework proposes a set of methods and tools, distributed along the framework structure, developed to support facilitated information sharing between them and adopting a process perspective (e.g. optimization model assigning tasks considering customer and provider needs and constraints and real-time and historical data). Being the authors' proposal developed as a framework, one or more tools were suggested in each phase, allowing the companies to choose the ones more suitable for their scopes. This contributes to addressing some gaps raised by Brundage *et al.* (2019), Fargnoli *et al.* (2019) and Tang and Liao (2021), which focused on the necessity of using suitable methods and tools to correctly support decision-making.

Results from the interviews were used to iteratively improve the D3M framework and to detail its theoretical and practical contributions to research. The interviews allowed testing the D3M framework as a mapping tool for the company maintenance service delivery process with the analysis of the current state and the definition of a future state to be reached through a series of improvements and modifications.

Currently, the D3M framework has only been tested at a theoretical level through semi-structured interviews, and this constitutes the main limitation of this work. Moreover, some methods and tools require further elaboration and development to increase their flexibility and efficiency in terms of data management and decision-making support. The next steps will encompass further tests in other companies to continue the validation and improvement

process and, possibly, its complete application. In addition, further tests will be conducted to verify whether the D3M framework could be used as a maturity tool to evaluate the companies' maturity level in terms of data handling for maintenance service delivery.

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