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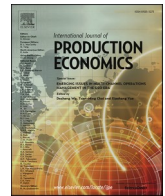
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Smart Maintenance: an empirically grounded conceptualization

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ABSTRACT

How do modernized maintenance operations, often referred to as “Smart Maintenance”, impact the performance of manufacturing plants? The inability to answer this question backed by data is a problem for industrial maintenance management, especially in light of the ongoing rapid transition towards an industrial environment with pervasive digital technologies. To this end, this paper, which is the first part of a two-paper series, aims to investigate and answer the question, “*What is Smart Maintenance?*”. The authors deployed an empirical, inductive research approach to conceptualize Smart Maintenance using focus groups and interviews with more than 110 experts from over 20 different firms. By viewing our original data through the lens of multiple general theories, our findings chart new directions for contemporary and future maintenance research. This paper describes empirical observations and theoretical interpretations cumulating in the first empirically grounded definition of Smart Maintenance and its four underlying dimensions; data-driven decision-making, human capital resource, internal integration, and external integration. In addition, the relationships between the underlying dimensions are specified and the concept structure formally modeled. This study thus achieves concept clarity with respect to Smart Maintenance, thereby making several theoretical and managerial contributions that guide both scholars and practitioners within the field of industrial maintenance management.

1. Introduction

The world is changing at a rapid pace and macro-economic observations indicate surprising developments, including a slowdown in productivity (Syverson, 2017), employment polarization (Autor, 2015), and robust relationships between demographic change and industrial automation (Acemoglu and Restrepo, 2018b). These observations are underscored by technological change. One of the most impactful technologies driving this change is Artificial Intelligence (AI), especially Machine Learning (ML) (Acemoglu and Restrepo, 2018a), coupled with more affordable digital technologies (Syverson, 2017) such as cloud storage and computing power (Byrne et al., 2018). These environmental contingencies require organizational designs that are different from traditional ones (Burton and Obel, 2018), and this is spurring firms to adopt new organizational forms such as networks, ecosystems, platforms and collaborative communities (Gulati et al., 2012; Kapoor, 2018). This development has made the science of organizational design more relevant than ever (Van De Ven et al., 2013; Joseph et al., 2018).

For manufacturing firms, the general question that needs to be

answered is what type of manufacturing that will survive and even thrive in an industrial environment with pervasive digital technologies. For organizational design, this translates to the scientific inquiry of designing organizations that fit with this environment (Burton and Obel, 2018). Achieving fit requires both the design of configurations of mutually reinforcing organizational elements as well as aligning these elements to environmental contingencies (Galbraith, 1974; Tushman and Nadler, 1978). One important aspect of manufacturing firms that requires such design efforts is the plant maintenance function (Bokrantz et al., 2017). The function is expected to exploit capability-enhancing technologies such as ML in order to respond to increasing automation and introduction of digital technologies into production systems (Roy et al., 2016), with expected benefits such as drastic reductions in machine downtime and increased productivity (Lee et al., 2014; Qiao and Weiss, 2016).

However, our research impetus does not stem from directly observing environmental contingencies but from interactions with practitioners within industrial maintenance management and their expressed interests. Specifically, managers of discrete-part and

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continuous manufacturing plants as well as maintenance service providers are interested in discovering how modernizing the maintenance function and operations impacts the performance of manufacturing plants today and in the future. Locally in Sweden, this is referred to as “Smart Maintenance”. As scholars, we suspected that this might reflect maintenance managers’ responses to recent contingencies. That is, organizational design in action. Since organizational design is an applied research challenge (Castañer and Ketokivi, 2018) that rests on a foundation of empirical focus on industrial firms (Lawrence and Lorsch, 1967), we recognized the scientific and practical value to take on this challenge presented to us by practicing managers.

Rooted in this practical real-world interest, this study therefore aims to answer the seemingly simple and deliberately phenomenon-driven research question, “What is Smart Maintenance?”. We derive the answer by adopting an empirical, inductive research approach to conceptualize Smart Maintenance using focus groups and interviews with more than 110 participants from over 20 different Swedish firms. This includes developing the first, empirically grounded conceptual definition of Smart Maintenance and its underlying dimensions, as well as formally modeling the concept structure. By combining a semantic and ontological approach for conceptualization, this paper is the first of its kind within the maintenance realm. Fig. 1 illustrates the structure of the paper.

A theoretical background is presented first, followed by a careful explanation of our research methodology. We then present the core findings at the heart of the paper; the empirical observations and theoretical interpretations. Firstly, we present the data structure that shows our progress from raw data to theoretical, aggregate dimensions. Secondly, we develop a conceptual definition of the focal concept Smart Maintenance and its four underlying dimensions. Thirdly, we specify the relationships between dimensions and model the concept structure. Finally, we summarize the study in our final discussions and present the conclusions and proposed future work.

2. Theoretical background

Given the transition towards an industrial environment with pervasive digital technologies, Roy et al. (2016) postulated a holistic research question for the maintenance field: “How is maintenance going to change in this highly connected industrial environment?” (p. 682). When the interest for such a question increases in both research and practice, a natural and healthy consequence is an increasing number of proposed concepts. This is generally a welcome sign that the theoretical and practical landscape of a field is expanding, and this expansion makes it possible to advance the understanding of what makes certain practices effective. However, as the number of concepts grows, so does the concern for problems due to *lacking concept clarity* (Shaffer et al., 2016). Lacking concept clarity is typically manifested in *concept proliferation* - multiple related concepts with different names but overlapping conceptual domain (Podsakoff et al., 2016). We can observe a multitude of maintenance concepts presumed to fit with this new environment that are used and acknowledged by both scholars and practitioners. With respect to scientific literature, this include but is not limited to ‘E-maintenance’ (Muller et al., 2008), ‘Prognostics and Health Management’ (Lee et al., 2014), ‘Predictive Maintenance’ (Carnero, 2005), ‘Maintenance 4.0’ (Kans et al., 2016), as well as ‘Smart Maintenance’ (Munzinger et al., 2009). With respect to practice, Smart Maintenance is

the primary term used by practitioners in our local firms within the Swedish manufacturing industry, which is also observed in other European countries (Akkermans et al., 2016). To shed further light on the status of concept clarity within contemporary maintenance research, we followed the recommendations of Podsakoff et al. (2016) and surveyed the literature. Since we had good reasons to believe that concept proliferation would be prevalent, we did not focus on an exhaustive review but rather casting a wide net and identifying existing sample definitions of our focal concept and concepts that are related to it (Podsakoff et al., 2016). In Table 1, we provide a list of (a) authors associated with (b) different concepts along with (c) sample definitions and (d) examples of key attributes for each concept respectively.

In Table 1, concept proliferation is clearly manifested in overlapping definitions and key attributes. The data in Table 1 also show that many authors implicitly or explicitly refer to several concepts interchangeably (Fumagalli et al., 2016; Kumar and Galar, 2018) and that key authors drive the development of multiple concepts (Lee et al., 2006, 2014, 2017). Most maintenance scholars are well aware of this situation, and several attempts have been made to tackle this problem. For example, the lack of consensus with respect to an E-maintenance definition motivated the work of Jung et al. (2009). Aboelmaged (2015) reviewed 15 sample E-maintenance definitions in journal publications over an 11-year period and concluded that “there is very little room for clarifying the confusion in the literature as to what constitutes an E-maintenance definition” (p. 620). There are several explanations for this inconsistency, such as country of location (e.g. US/Europe) and shifts between technologies (e.g. from ICT to AI). Nevertheless, Table 1 shows that concept proliferation is an undisputable fact within maintenance research.

Naming or labeling a concept is not equivalent to defining it, and carefully developing conceptual definitions is often ignored (Mackenzie et al., 2011). One of the primary reasons for this ignorance is simply because developing good conceptual definitions is difficult (Podsakoff et al., 2016). At face value, lacking concept clarity might not be perceived as problematic. However, it is the cause of several negative theoretical and empirical consequences. In particular, concept proliferation can lead to diminished creation of cumulative knowledge and confusion between scholars and practitioners (Shaffer et al., 2016). It can also lead to deficient and/or contaminated empirical measures (Mackenzie et al., 2011) that undermine discriminant, nomological and construct validity; in the end delimiting our understanding of antecedents, correlates and consequences of various concepts of interest (Shaffer et al., 2016).

Concept clarity is critical to organizational design and thereby central to our research challenge. The science of organizational design aims to create models of future organizational designs and subsequently analyze their effectiveness empirically (Burton and Obel, 2018). This process thus requires both *creating the concept* (conceptualization) and *empirically measuring it* (operationalization). Because poor conceptual definitions are one of the main causes for invalid measures (Mackenzie et al., 2011), concept clarity is a necessary condition for success in organizational design. In other words, if the effectiveness of an organizational design is to be tested by means of empirical measurement, it must first be properly defined and modeled (Podsakoff et al., 2016). Since the logical first step of organizational design is to create a model of a *future* organizational design, we conceptualize Smart Maintenance by adopting an orientation towards what Corley and Gioia (2011) refer to

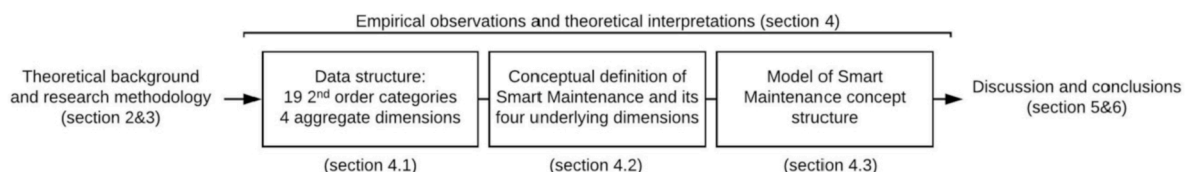


Fig. 1. Structure of the paper.

Table 1
Maintenance concepts.

Authors	Concept	Sample definitions	Examples of key attributes
(Hung et al., 2003; Han and Yang, 2006; Lee et al., 2006; Muller et al., 2008; Candell et al., 2009; Jung et al., 2009; Aboelmaged, 2015)	E-maintenance	<ul style="list-style-type: none"> • “Monitoring, collection, recording and distribution of real-time system health data, maintenance-generated data as well as other decision and performance-support information to different stakeholders independent of organization or geographical location” (Candell et al., 2009) • “Leveraging information and internet technologies, the e-Diagnostics/Maintenance system provides equipment supplier’s experts with the capability to remotely link to factory’s equipment” (Hung et al., 2003) 	Diagnostics, Prognostics, Monitoring, Condition-based Maintenance, Decision-making, Integration, Maintenance strategy, Information and Communication Technology (ICT), Remote
(Cheng et al., 2010; Lee et al., 2014, 2017; Tsui et al., 2015; Qiao and Weiss, 2016; Vogl et al., 2016; Weiss et al., 2018)	Prognostics and Health Management	<ul style="list-style-type: none"> • “An enabling discipline consisting of technologies and methods to assess the reliability of a product in its actual life cycle conditions to determine the advent of failure and mitigate system risk” (Cheng et al., 2010) • “Cluster of strategies and techniques that promote condition monitoring, diagnostics, prognostics, and maintenance of a product, machine, or process” (Qiao and Weiss, 2016) 	Diagnostics, Prognostics, Condition-based Maintenance, Health Assessment, Estimation of Remaining Useful Life
(Quinn, 1963; Mobley, 2002; Carnero, 2005; Garcia et al., 2006; Zhou et al., 2007; Lee et al., 2015, 2017)	Predictive Maintenance	<ul style="list-style-type: none"> • “Selected physical parameters associated with an operating machine are sensed, measured and recorded intermittently or continuously for 	Diagnostics, Prognostics, Condition-based Maintenance, Maintenance scheduling, Decision-making

Table 1 (continued)

Authors	Concept	Sample definitions	Examples of key attributes
		<p>the purpose of reducing, analyzing, comparing and displaying the data and information so obtained for support decisions related to the operation and maintenance of the machine” (Carnero, 2005)</p> <ul style="list-style-type: none"> • “Capability to translate raw data into actionable information to facilitate maintenance decision-making” (Lee et al., 2017) 	
(Kans et al., 2016; Kans and Galar, 2017; Algabroun et al., 2018; Kumar and Galar, 2018)	Maintenance 4.0	<ul style="list-style-type: none"> • “Maintenance 4.0 does predictive analytics and suggests feasible solution, with major application in Industry 4.0 and especially on those maintenance aspects that deals with collection of data, its analysis and visualization and asset decision-making” (Kumar and Galar, 2018) • “Maintenance 4.0 utilizes the advanced technologies for the predictive analytics and provides decisions based on feasibility” (Kans et al., 2016) 	Diagnostics, Prognostics, Big data analytics, Maintenance scheduling, Decision-making
(Munzinger et al., 2009; Holgado and Macchi, 2014; Akkermans et al., 2016; Fumagalli et al., 2016; Maritsch et al., 2016; Bokrantz et al., 2017; Macchi et al., 2017)	Smart Maintenance	<ul style="list-style-type: none"> • “A Smart Maintenance tool should provide as much as possible a complete visibility of the asset health status, thus avoiding a need of maintenance operators’ intervention in the nearby of the asset” (Fumagalli et al., 2016) • “Smart Maintenance services are built on field intelligence that is provided by technology either 	Diagnostics, Prognostics, Big data analytics, Self-X capabilities, Monitoring, Remote

(continued on next page)

Table 1 (continued)

Authors	Concept	Sample definitions	Examples of key attributes
		embedded in a product/equipment or facilitated by the use of devices, sensors or any other technology-based tools” (Holgado and Macchi, 2014)	

as *theoretical prescience*. Specifically, we deploy an inductive, empirical research approach anchored in the two core attributes of prescience. Firstly, we direct attention towards future problem domains that are relevant to practice (Corley and Gioia, 2011) (p. 25) by creating a model of Smart Maintenance as a novel organizational design. This is realized through *prospective sense making* – casting ourselves figuratively into the future and acting as if events have occurred, then making sense of those events. Secondly, we focus on *sense giving* – shaping the conceptual conversations of the problem domain in such a way that it informs both scholars and practitioners (Corley and Gioia, 2011) (p. 26). In order words, guiding the scholarly, empirical analysis of the effectiveness of Smart Maintenance as well as solving the practical challenge of designing the organization that satisfies the expressed interest of managers in our local firms.

3. Methodology

We focused on theoretical prescience (Corley and Gioia, 2011) and adopted an inductive, empirical research approach to conceptualize Smart Maintenance. This approach was chosen because conceptualization is generally speaking an inductive endeavor. In fact, when developing definitions for new concepts, the use of inductive techniques are often necessary to adequately flesh out the conceptual domain (Podsakoff et al., 2016). It is therefore important to explicate our reasoning and methodological choices, as well as demonstrate transparency (Ketokivi and Mantere, 2010; Mantere and Ketokivi, 2013; Aguinis et al., 2018). The research process was designed as a large-scale qualitative study aiming to identify the full range of contingencies, responses and performance implications of Smart Maintenance in order to synthesize an empirical research agenda for industrial maintenance management. In the findings section of this paper (Section 4), we report the first part this large study in the form of the empirical data and theoretical interpretations that we use to conceptualize Smart Maintenance. To cover both the depth and breadth of our research approach, whilst at

the same time satisfying both readability and completeness, we provide figures and tables (Figs. 2–3 and Table 2) summarizing our key steps. This is complemented by disclosing specific details about important methodological steps within Appendices A and B.

3.1. Scientific reasoning

To conduct this study, we chose to reason through *theoretical contextualization*, because we embrace the epistemic assumption that we do not all see the same things and that the researcher looking at the data will actively create the generalization. In order words, we see ourselves as *active reasoners* (Ketokivi and Mantere, 2010). This type of inductive reasoning is based on Inference to the Best Explanation (IBE), i.e. abduction, who’s strengths include transparency, openness to explanations, and authenticity to data and the research process. The key characteristic of theoretical contextualization is that theories are an integral part of the reasoning, in which general theories and empirical data are investigated simultaneously (Ketokivi and Mantere, 2010). This reasoning is particularly effective for theory advancement (Fisher and Aguinis, 2017) and fits well with organizational design, in which researchers actively create organizational designs and anchor its explanatory power in a variety of general theories (Joseph et al., 2018). When deploying IBE, it is critical to make the cognitive role of the researchers clear (Ketokivi and Mantere, 2010; Mantere and Ketokivi, 2013). Therefore, we emphasize transparency in our methodological descriptions, as well as in the empirical observations and theoretical interpretations (Section 4).

In line with theoretical contextualization, we identified a set of general theories that could be used to approach the empirical context and arrive at theoretical interpretations (Ketokivi and Mantere, 2010). Contingency theory is the main foundation for organizational design (Joseph et al., 2018), resting on the premise that there is no single best way of organizing (Donaldson, 2001). Contingency theorizing is concerned with achieving fit by both designing *configurations* of mutually reinforcing organizational elements (internal fit) as well as *aligning* these elements to environmental contingencies (external fit) (Miller, 1992; Van De Ven et al., 2013; Joseph et al., 2018). However, despite being one of the most established organizational theories, the limitations of contingency theory are well known (Sousa and Voss, 2008). Inferences about organizational design are therefore typically drawn using a variety of theories (Joseph et al., 2018). Since this paper centers on our conceptualization of Smart Maintenance, we focus here on the configurational approach; identifying an “optimal” configuration that possesses internal fit, taking the environmental contingencies as given (Joseph et al., 2018). To address the limitations of contingency theory, additional theories were introduced as the research progressed to reconcile interpretations with the empirical context, specifically consisting of the Information-Processing View (IPV) (Tushman and Nadler, 1978), the Knowledge-Based View (KBV) (Grant, 1996) and the Resource-Based

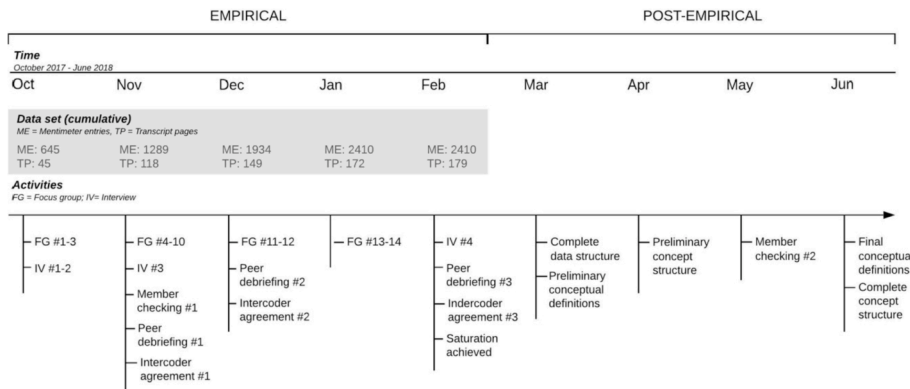


Fig. 2. Timeline overview of the research process.

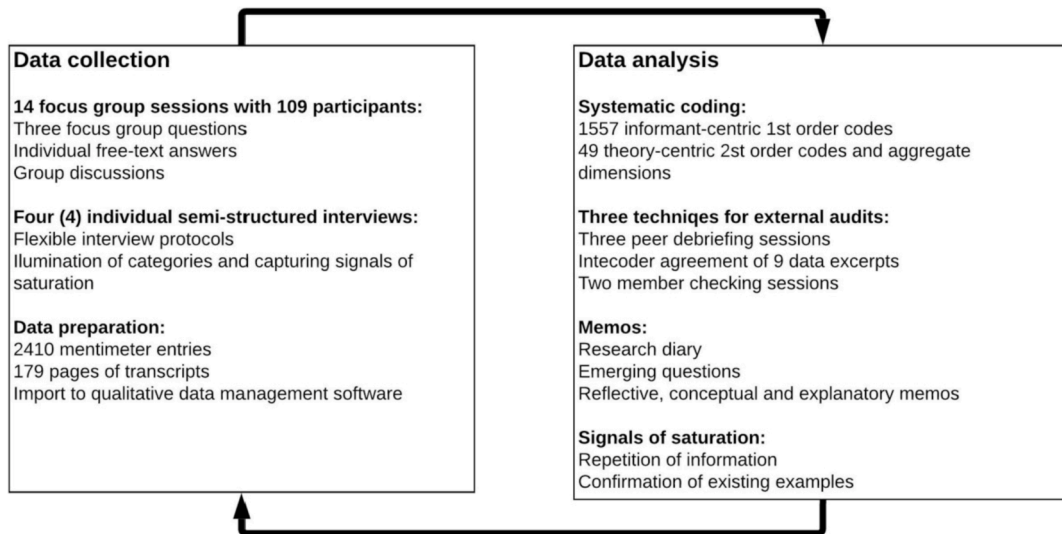


Fig. 3. Summary of process for collecting and analyzing empirical data.

Table 2
Demographic information.

Demographic information about participants		
Characteristics (n = 113)	n	%
Industrial branch		
Discrete manufacturing	15	13.3
Continuous manufacturing	48	42.5
Industrial service	35	31.0
Others ^a	15	13.3
Position		
Manager	48	42.5
Engineer	45	39.8
Technician	10	8.85
Others ^b	10	8.85
Function		
Maintenance	62	54.9
Production	18	10.6
Others ^c	33	34.5
	M (SD)	S (K)
Experience (in years)	15 (11)	0.5 (-0.6)

M = Mean, SD = Standard Deviation, S = Skewness, K = Kurtosis.

^a Includes academia, infrastructure and medtech.

^b Includes researchers and salespersons.

^c Includes academia, R&D, IT and sales.

View (RBV) (Barney, 1991), Transaction Cost Economics (TCE) (Williamson, 1975) and Complementarities (Milgrom and Roberts, 1995). In Section 3.2, Appendix B, and in our findings in Section 4, we further describe how theory was used within our coding procedure, as well as transparently illustrate the fit between our empirical observations and theoretical interpretations (Ketokivi and Mantere, 2010; Ketokivi and Choi, 2014).

3.2. Research design and research methods

We demonstrate our methodological rigor in two steps. Firstly, we explain the overall research design and the chronological steps of the research process. Secondly, we demonstrate the robustness of our empirical evidence by explaining how we sought impartiality in the collection and analysis of empirical data, including careful explications of our coding principles and external audits (Mantere and Ketokivi, 2013). In terms of overall research design, the four-stage process for conceptualization (Identify; Organize; Develop; Refine, p. 169) proposed by Podsakoff et al. (2016) inspired us. Furthermore, the empirical

data collection and analysis deployed four common features of inductive research: theoretical sampling, constant comparison, theoretical coding, and theoretical saturation (Glaser et al., 1968; Strauss and Corbin, 1990). We were immersed in an empirical phase for approximately five months and a post-empirical phase for approximately four months. An overview of the research process is shown in Fig. 2, which illustrates the study's timeline, activities and accumulating data set.

We utilized focus groups and semi-structured interviews for data collection (Podsakoff et al., 2016), two particularly effective methods for capturing respondents' explicit understanding of a phenomenon (Langley and Klag, 2017). The research involved a series of focus groups consisting of a total of 14 sessions with 109 practitioners and academics, as well as four (4) interviews with two academics and two practitioners respectively. Together, these 113 participants represented a total of 22 different firms. Particular emphasis was placed on sampling practitioners, whom we treat as knowledgeable agents who are bound to know more about the realities than researchers (Tracy, 2010; Gioia et al., 2013). In Appendix A, we disclose the specific details of this theoretical sampling strategy. Demographic information about the total 113 participants is summarized in Table 2.

In Fig. 3, we summarize our process for collecting and analyzing data. During this process, we relied on constant comparison, theoretical coding, and theoretical saturation (Glaser et al., 1968; Strauss and Corbin, 1990). This is manifested in simultaneous and cyclic collection, coding, and analysis, where new data are constantly compared to earlier data to enable adjustment of theoretical categories (Glaser and Strauss, 1967). In Appendix B, we disclose the specific details of this process.

For the data collection, we drew inspiration from the approaches of Sonenshein et al. (2014) and Challagalla et al. (2009) and structured the focus group sessions around the following three questions:

- (Q1) *When you think of Smart Maintenance – what attributes comes to mind?*
- (Q2) *What are the consequences of Smart Maintenance?*
- (Q3) *What does absence of Smart Maintenance mean?*

Those three questions aimed to elicit potential attributes, identify consequences and examine the focal concept's opposite pole, respectively (Podsakoff et al., 2016). The focus group research design was pilot tested with one academic and nine practitioners from the target population with an average of 15 years of experience. For each question, the participants first provided anonymous, individual free-text answers using the software "Mentimeter" (www.mentimeter.com), followed by

group discussions revolving around the Mentimeter entries. Approximately three hours were allocated to each focus group session, and the discussions were audio recorded and transcribed. The Mean (M) and Standard Deviation (SD) of the number of Mentimeter entries for each question (Q1, Q2, Q3), weighted by the focus group sample size were: Q1 M = 72, SD = 26; Q2 M = 68, SD = 17; Q3 M = 53, SD = 15. Full transcripts from each session ranged between 9 and 11 single-spaced pages in length. The semi-structured individual interviews were intended to further elaborate specific categories, dimensions or relationships, as well as to act as instruments for capturing signals of saturation (Glaser and Strauss, 1967). The interviews focused on emerging categories and dimensions representing our data (Corley and Gioia, 2004), where flexible interview protocols were used to allow the informants to lead us in the investigation of the focal concept (Gioia et al., 2013). Each interview lasted approximately 40 min and was audio recorded and transcribed. These interviews resulted in transcripts each between 6 and 7 single-spaced pages in length. At the end of the empirical phase, the total sum of qualitative data consisted of 2410 Mentimeter entries and 179 single-spaced pages of transcripts. The data were imported into the qualitative data management software Nvivo (v. 11.4.1).

For the data analysis, we systematically categorized and grouped similar examples from the data (O'Reilly et al., 2012). Specifically, we made use of the methodology proposed by Gioia et al. (2013), and conducted systematic 1st and 2nd order coding aimed at building *data structures*. Data structures provide transparent graphical representations of the progression from raw data to theoretical dimensions, and they represent a key component for rigor in qualitative research (Gioia et al., 2013). The 1st order analysis resembled computational induction (Ketokivi and Mantere, 2010) and consisted of creating codes using informant-centric, in-vivo terms with little attempt to distill these into categories (Gioia et al., 2013). In other words, the 1st order codes represents "facts" from the point of view of the informants (Van Maanen, 1979). The 2nd order analysis utilized theoretical contextualization (Mantere and Ketokivi, 2013) informed by relevant theories (Section 3.1). This consisted of seeking similarities and differences in the data and grouping 1st order codes into more abstract categories using established theory-centric terms. Moving from 1st order codes to 2nd order categories is about move from raw informant data to theoretical interpretations, whilst at the same time reducing the data to a more manageable number of categories (Gioia et al., 2013). In other words, the 2nd order categories represents theoretical interpretations from the point of view of the researcher, explaining the pattern of the 1st order codes (Van Maanen, 1979). Once a workable set of 2nd order categories was available, they were distilled even further into aggregate, theoretical dimensions. The process was also complemented with the use of various memos, specifically using a research diary to log emerging questions and create reflective, conceptual, and explanatory memos (Hutchison et al., 2010). This continued until theoretical saturation was reached at the 2nd order category level. We paid attention to signals of saturation in the form of repetition of information and confirmation of existing categories (Suddaby, 2006). We considered theoretical saturation to be achieved when the conceptual domain of the focal concept was adequately fleshed out (Podsakoff et al., 2016). In summary, a total of 1557 1st order codes were created from the entire pool of collected data ($n_{Q1} = 691$, $n_{Q2} = 495$, $n_{Q3} = 371$).

Consistent with theoretical contextualization, we expected different researchers to potentially interpret some informant terms and passages of text differently (Ketokivi and Mantere, 2010; Gioia et al., 2013). Therefore, we iterated three techniques for external audits throughout the research process to increase the trustworthiness of our data, strengthen our own confidence in the results, and assess the reproducibility of our coding (Lincoln and Guba, 1985; Gioia et al., 2013). Each technique was repeated three times; initiated at points in time where a substantial amount of new 1st order codes and 2nd order categories had been constructed (their timing in the sequence is illustrated in Fig. 2). Firstly, the principal coder developed 1st order codes and 2nd order

categories by unitizing and coding the data (Campbell et al., 2013). The coder then engaged in peer debriefing (Corley and Gioia, 2004), discussing the emerging codes with an external researcher acting as a "devil's advocate" who reviewed the coding and posed critical questions. Through negotiated agreement, codes and categories were revised and clarified. Secondly, an additional external researcher was provided with unitized but un-coded versions of random sample data excerpts from each of the three focus group questions, respectively, and was instructed to assign each 1st order code to a 2nd order category. Inter-coder agreement was then calculated with the proportion agreement method (Campbell et al., 2013). In cases of coding discrepancies, the two researchers engaged in discussions to reach consensus and revise the coding accordingly. Thirdly and finally, both the tentative analysis and the final findings were member checked (Lincoln and Guba, 1985; Creswell and Miller, 2000; Tracy, 2010) with industrial managers, who acted as judges of the credibility and consistency of our interpretations.

4. Empirical observations and theoretical interpretations

Our empirical observations and theoretical interpretations are presented in this section. First, in Section 4.1, we provide our data structure consisting of 19 2nd order categories and 4 aggregate dimensions (Fig. 4). It is important to note that the data structure is not a causal model where the arrows specify the directions of relationships between the codes, categories and dimensions. Therefore, during this stage, the empirical content is given plausible theoretical interpretations without formally specifying relationships between the dimensions. Thereafter, in Section 4.2 and Section 4.3, we use the findings to conceptualize Smart Maintenance using two approaches. Firstly, we use a semantic and definitional approach to develop a conceptual definition of Smart Maintenance and its underlying dimensions (Sartori, 1984) (Section 4.2). Secondly, we formally analyze the relationships between the dimensions and use an ontological and causal approach to specify the concept structure of Smart Maintenance (Goertz, 2006) (Section 4.3). The two approaches complement one another in achieving concept clarity (Podsakoff et al., 2016).

4.1. Data structure

Fig. 4 shows the data structure that includes the four dimensions that constitute our focal concept (dimensions 1–4). The structure represents the positive pole of the concept and consists of data from focus group question Q1: *When you think of Smart Maintenance, what attributes comes to mind?* The positive pole of concepts is what appears in models, propositions and theories (Goertz, 2006). To demonstrate our empirical observations (headings labeled *Dimension*), we provide 1st order exemplars in the illustrative data structures and offer additional structure in text by highlighting key informant quotes that make up our data. Note that while only two exemplary 1st order codes are provided for each 2nd order category, the complete data set consists of over 1500 1st order codes (see Section 3.2). To demonstrate our corresponding theoretical interpretations (headings labeled *Theoretical interpretation*), we provide relevant data-to-theory connections that explicate our theoretical interpretation of each dimension. In the last part of this section, we present the empirical observations and theoretical interpretations of the opposite pole.

Dimension 1: Data-driven decision-making. The dimension that permeated all focus group sessions was the role of data for maintenance decision-making, and this was typically the first attribute that came to the informants' minds. In a profession traditionally dominated by decision-making based on experience and intuition, the potential insights embedded in data are today firmly perceived as strong drivers for efficiency. One manager stated, "As we get more and better insights from data, we can discard our old time-based preventive maintenance plans and instead base our decisions on the real conditions of equipment. Less gut feeling and not like the guessing game of today." During our analysis, we identified

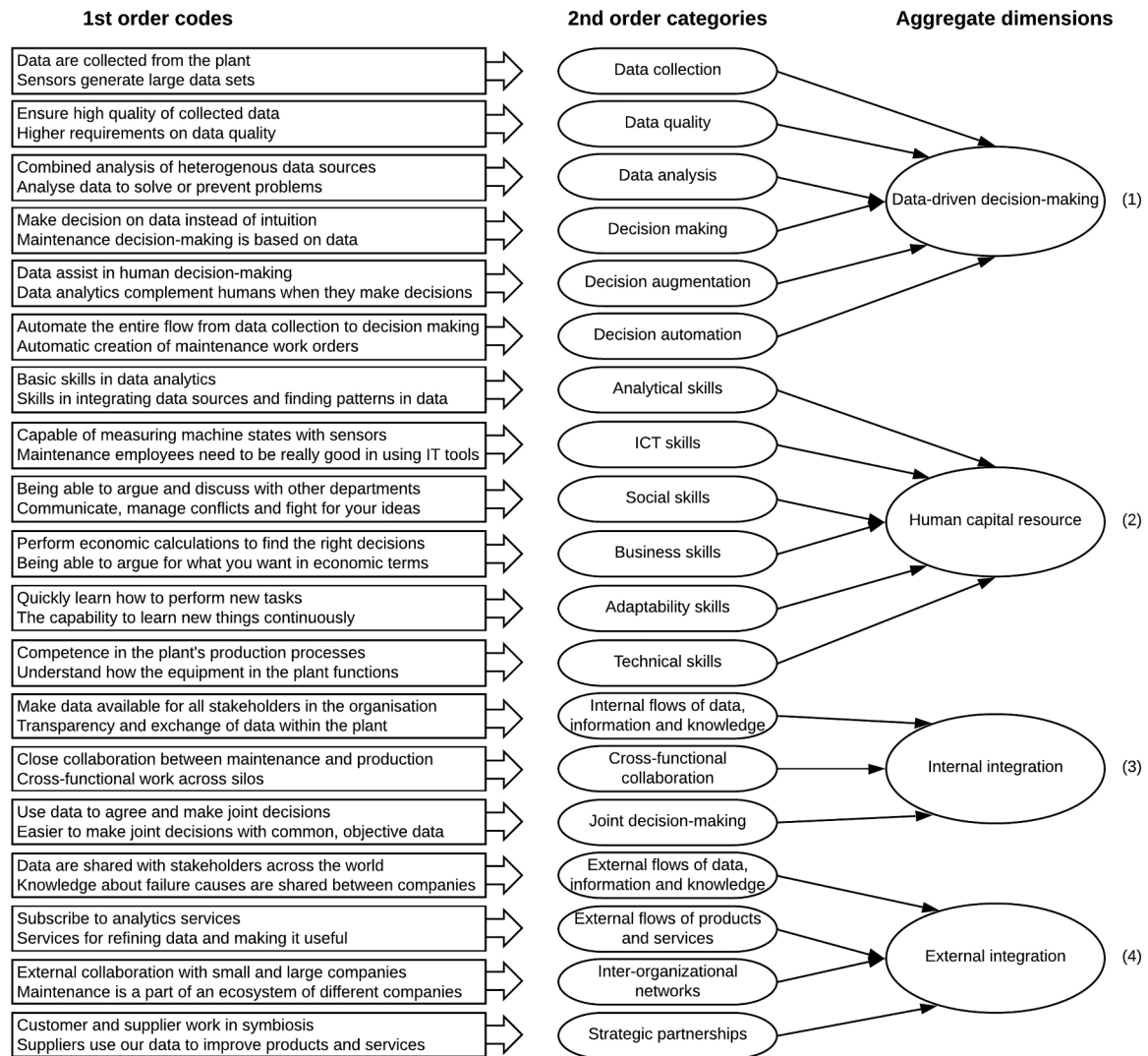


Fig. 4. Data structure from Q1: the core dimensions of the focal concept.

four simplistic but distinct categories in the process of moving from raw data to real value: data collection, data quality, data analysis and decision-making (Fig. 4). In fact, what is often missing in accounts of data-driven maintenance practices is whether these actually impact decision-making. The first three categories - (data) collection, quality and analysis - are means, not ends. They are also straightforward. It is impossible to base decisions on non-existing data, no algorithm can transform bad data into sharp, insightful knowledge, and there is no learning from data without analysis. However, just because it is available, analyzing high quality data does not automatically lead to a state where decisions are indeed data-driven. Too often data remain unused, or the analyzes are not deemed insightful enough, resulting in a state where decisions are still driven solely by intuition and experience. As one participant explained, “This is what happens today. We collect data, store it in warehouses or lakes, and have systems that analyze it. The data are there, the systems are there, it is all there. But the bottleneck is how decisions are made, because the data are never used and there is no value created out of it.” The informants thus asserted that the real key to understanding successful value creation from data is to study how it drives decision-making.

During our constant comparison of empirical data and emerging theoretical categories, we noted that although a single latent variable consisting of the degree to which data is used for decision-making would constitute a useful empirical proxy, it would not capture the full

conceptual domain. Instead, it was evident from the informant responses that data-driven decision-making does not come in one, single form and that there is no universal solution for all decision situations. In contrast, data-driven decisions appeared to consist of two major categories: decision automation and decision augmentation. Decision automation reflects how computers, more specifically advanced algorithms such as ML systems, substitute decision-making tasks previously made by humans. The participants provided plenty of examples of decision tasks susceptible to automation, but most attention was given to automating the prediction and prescription of maintenance actions for specific equipment, “The most important part is to generate decisions automatically so that the equipment tells you when a maintenance action is needed before a breakdown occurs.” In contrast, decision augmentation reflects what is complimentary between algorithms and human judgement. The participants clearly expressed that the choice is not dichotomous, “You cannot discard expert knowledge just because we have better possibilities for measurement. The value comes from synergies between data and experience.” This informant’s observation signifies how algorithms are not synonymous with absence of human judgement. Assumptions are both implicitly and explicitly encoded in algorithms. A practical everyday scenario is that humans specify the evaluation function, followed by releasing the algorithms on their quest to maximize that function. However, despite acknowledging that some decisions will be superior with complementary human judgement, the informants seemed prone to

extensively delegate decision tasks to ML systems, “We are going to rely on data and algorithms and that is what needs to be acted upon. What is common sense today is not going to be followed, we are going to follow whatever the computer says.” The bottom line is indeed the lack of universal solutions and the considerable challenge of task allocation; some decision tasks are fit for automation whilst others are only fit for augmentation.

Theoretical interpretation: Data-driven decision-making. Theory on decision-making is both prolific and varied, but a widely-held assumption stemming from the behavioral theory of the firm is that of bounded rationality. Bounded rationality implies that there are cognitive limitations to intendedly rational decision-making (Simon, 1997). Because of bounded rationality, individuals facing information loads use means to simplify their cognitive decision-making, such as coping with the cost of information processing by satisfying with sub-optimal decisions (Cyert and March, 1963). With this assumption as an onset for organizational design, the IPV depicts organizations as information processors that deal with uncertainty by means of gathering, interpreting and synthesizing information for decision-making. Consequently, at the core of IPV lies the intent to improve decision-making by designing organizations that exhibit fit between their requirements and capacities for information-processing (Galbraith, 1974; Tushman and Nadler, 1978). Our empirical findings of the *Data-driven decision-making dimension* are interpreted using the IPV. We theorize that, in part, higher levels of automation and production system designs that rely on computer science, information, communication and advanced manufacturing technology, are causing maintenance tasks to be increasingly complex and exhibit stronger reciprocal interdependence with the variability of the production flow. As a consequence, maintenance tasks are therefore highly uncertain in the sense that they are difficult to predict and plan with minimal interruptions of production flow. This is increasing the maintenance function’s information-processing requirements. In concurrency, environmental contingencies such as rapid advancements of ML, more powerful and affordable computing power, and the explosion of available data sharply reduces the cost of information-processing. Our empirics thus reflect both the response to, and outcome of, these contingencies in order to increase the maintenance function’s information-processing capacities. Taken together, our conceptualization of data-driven decision-making reflects an attempt to achieve fit between the maintenance function’s requirements and capacities for information processing.

However, our empirical findings also indicated the diversity of decision task allocation (automation vs. augmentation). This relates to the substitution vs. complement debate of AI (Autor, 2015). Examining our data with the IPV may shed further light on this topic. Decision tasks with low predictability exhibit high uncertainty, thus implying that better decisions would result from better predictions (Galbraith, 1977). Prediction is exactly what ML excels at, in many cases far surpassing human performance, thus implying a high value in substitution of prediction tasks. For maintenance, that includes e.g., prediction of component failures and correspondingly planning maintenance actions with minimal interruption of production flow (given that the decision function can be clearly defined over time and trained on sufficient data). However, there are decision tasks with system-wide functions, indescribable features or continuously changing behaviors, such as classifying a production system’s maintenance-critical resource. For such tasks, the returns from ML predictions are less impactful and more value would stem from human judgement, meaning that insights gained from data would result in better decisions because of complementary (augmentation), rather than substitution (automation) effects. Given this lack of universal solutions, in combination with the signals of extensive delegation of decision tasks to ML systems, there is a possibility of task misfit, where some maintenance decision tasks are substituted with ML although a complementary augmentation would have been better, and vice versa.

Dimension 2: Human capital resource. Given the strong emphasis on

data-driven decision-making, it was not surprising that another emerging dimension squarely focused on the capacities of humans. Despite the informants’ belief in the potential of data, they strongly argued that the most important input to production and the main source of value creation will continue to be humans and their implicit and explicit knowledge, “In the end, you have to remember that not everything is zeroes and ones. We cannot only focus on the digital, because our work is out in the plant; that requires competence.” Our informants noted that advancements in technology put new requirements on the workforce. In particular, they argued that a critical caveat for the success of Smart Maintenance is a mismatch between technology and skills, “We have to perform our tasks in a different way with the help of data, so we need to develop our competencies. It is a completely different set of skills compared to 10–15 years ago.” In light of this mismatch, our participants explained the content of new skill requirements, which we could distill into six broad categories: analytical, ICT, social, business, adaptability and technical skills (Fig. 4). While it might be clear to psychologists, our informants did not make conscious distinctions between knowledge, skills, abilities or other characteristics (KSAOs). However, the responses were primarily task-focused. We therefore focused our coding on *skills* - the level of proficiency and capability to perform specific tasks (Nyberg et al., 2014).

Analytical skills reflect an understanding of how to collect and use data, the capability to analyze data, as well as how to decide what actions to take on the basis of data. However, the informants emphasize that maintenance employees are not required to be data scientists. They instead require basic data analytics skills and need to be capable of communicating with data scientists for advanced tasks. ICT skills reflect the capability to make information technology valuable in the daily work, by proficiently using an array of information systems that are integrated into the manufacturing plant. Social skills reflect the interpersonal capability of communicating and collaborating with internal and external parties, building knowledge in networks and arguing for the value of maintenance. In fact, several informants claimed that the historical neglect of the maintenance area is in part due to maintenance employees’ lack of proficiency in communicating, debating and showing facts to the rest of the organization. Business skills reflect the capability to understand the relationship between downtime and cost or revenue, including economic considerations for maintenance actions and being capable of ‘speaking the language’ of accountants. The respondents argued that due to maintenance employees’ incapability to translate engineering decisions into accounting terms, they consistently lose arguments with the financial department. Adaptability skills reflect the dynamic capability of adapting to technological change, continuous learning, and quickly developing the proficiency in new tasks. Finally, the respondents argued that vast technical skills are critical; the capability of working hands-on with the plant’s production processes and equipment as well as the proficiency in applying maintenance fundamentals.

Theoretical interpretation: Human capital resource. Our interpretation of the human capital resource dimension is rooted in the KBV and RBV (KBV is essentially an outgrowth of RBV towards a theory of the firm). The central assumption of the KBV is that a firm’s primary intangible source of value is knowledge (Sveiby, 2001). This knowledge, along with skills, abilities and other characteristics, resides in the human capital of a firm’s individual employees and creates value when applied (Grant, 1996; Ployhart and Moliterno, 2011; Mayer et al., 2012). This view was the basis for distilling this as a key dimension in our empirical data; human capital will remain a critical resource for value and will not be rendered obsolete because of environmental changes such as advancements in ML. Further, our interpretation draws on recent improvements in the concept clarity of human capital that builds on the RBV (Wright and McMahan, 2011; Nyberg et al., 2014, 2018). Firstly, the *human capital resource* (HCR) is the collective phenomenon that explains how individuals contribute to unit-level outcomes. Our dimension of the HCR is therefore interpreted as a unit-level capacity created from

the emergence of the individual's KSAOs (Ployhart and Moliterno, 2011). The HCR is focused on capacities for producing outcomes rather than the KSAOs themselves, which is aligned with our primary macro-level interest in understanding the maintenance function as a whole. Further, the HCR is accessible for unit-relevant purposes. This means that it exists as a feature of the maintenance function and contributes to the pursuit of the maintenance function's purpose. In addition, the emergence of the individuals' KSAOs to the unit-level HCR is also influenced by the interactions between the individuals, e.g. relationships and social interactions (Ployhart et al., 2014). Secondly, the division between general vs. specific KSAOs is not dichotomous (Nyberg et al., 2018), and the typical RBV perspective that only firm-specific resources are valuable does not always hold (Morris et al., 2017). Instead, the HCR consists of and is valuable because of multiple cognitive and non-cognitive KSAOs that are both context-generic and context-specific (Ployhart and Moliterno, 2011). This is indeed reflected in our data (Fig. 4). The context-generic KSAOs are generally stable and tied to broad domains, such as our categories of social, business or technical skills. In contrast, the context-specific KSAOs are more influenced by environmental change and tied to specific domains, such as our data on specific analytical skills in ML or being proficient in using specific ICT applications (Ployhart and Moliterno, 2011). The key informant observation was the mismatch between technology and skills, which reflects how the HCR is shifting because of the changing task environment. When technological change alters the specificity of KSAOs, parts of the existing HCR may become obsolete, and continuous adjustment of the HCR is therefore needed to regain fit (Lepak and Snell, 1999; Wright et al., 2001). This is what our informant tries to do by explicating the new requirements of both context-generic and context-specific KSAOs for maintenance employees. However, we exercise caution in our precise distillation of the six categories of skills that make up our HCR data for two reasons. Firstly, there is little strong theory about what type of skills that are considered valuable to emerging technologies such as ML, although there are contemporary research streams within labor economics suggesting that this includes various technical, analytical and social skills (Autor, 2014; Deming, 2017). Secondly, we do not have detailed information about the exact task environment of Smart Maintenance. Our key interpretation of this dimension can thus be summarized as follows: The HCR, comprising the capacity created from the KSAOs of the plant's maintenance employees, will remain a key source of value. However, its fundamental requirements are changing in light of rapid technological change.

Dimension 3: Internal integration. ML reduces the price for predictions and shifts the demand towards complementary human capital resources, but technology and skills are nothing without organization. Our informants consistently emphasized this notion and proposed that a central, distinctive characteristic of Smart Maintenance concerns how the maintenance function relates to the internal plant organization. Intense conversations revolved around integration of maintenance with production and the rest of the organization, from which we could distil three categories in our data structure (Fig. 4). Firstly, the participants stressed the significance of information flows, *"I am sure that there are lots of information in the production monitoring systems that could be useful in our maintenance system, like stop times and so on. If we share and combine that data there are probably many interesting conclusions to be made."* By establishing links to other functions, the maintenance function can take part in transparent exchange and utilization of heterogeneous sources of data and information across functional borders. However, several informants highlighted that it is too limited to only focus on data and information while making the point that this dimension is also about knowledge integration. That is, coordination of individuals' specialized knowledge within the plant, *"Even if we have different competencies, we organize ourselves so that these competencies are very far from each other, there are no natural bridges in between. It is about what type of forums you create within the firm, how you come together, how to get value from the knowledge. We have an enormous capital of knowledge at the plant, but it is*

not used in the right way, together."

Secondly, the participants were careful to point out the need for cross-functional collaboration, with one informant expressing it serendipitously, *"Something just hit me now that we are discussing this. It is absolutely impossible to succeed with this without collaborating with production. If it is not firmly anchored with them, it will never work."* The informants vibrantly painted a picture of tearing down the walls between functions and replacing these with more team-work, faster communication, closer connection and better coordination. This category also revealed that a state of achieved internal integration is reflected in high perceived organizational status of the maintenance function, *"Maintenance has always been under prioritized, but now it starts to appear on the agenda of top management and we are perceived with higher status in other functions like production and purchasing."* As the level of integration increases, maintenance progressively constitutes a recognized and active speaking partner with valuable contributions to processes such as production system development, equipment acquisition and design of plant IT infrastructure. Thirdly, the informants realized that it is the expansion of information flows that enables consensus and reduction of conflicts across functions. They emphasized joint decision-making, where shared data constitutes ground truth, *"If we have more facts, we will have less conflicts. If maintenance and production disagree about something, but we have common data about the case, then we will arrive at consensus and make a joint decision."* Essentially, data are perceived as means to reduce subjectivism and arrive at common understandings. Consensus on data enables consensus on decisions, which in turn makes it possible to plan and synchronize maintenance with other processes within the plant.

Theoretical interpretation: Internal integration. Internal integration was one of the dimensions that was formed and saturated early. This is plausibly because integration is one of the most established, researched and practiced concepts in management (Galbraith, 1977), including industrial maintenance (Jonsson, 1999; Chan et al., 2005; Al-Najjar, 2007). Internal integration is distinct from external integration (Fig. 4), and our empirics within this dimension focusses on internal integration in the specific context of plant maintenance. Although integration is understood differently across disciplines, multiple general theories generally converge on its fundamental facets. Structural contingency theory holds that firms respond to the environment by means of organizational design, such as engaging in differentiation of its organization into subunits to respond to environmental uncertainty. But because specialization makes coordination more difficult, differentiation also necessitates integration; the unity of effort among the subunits (Lawrence and Lorsch, 1967). The IPV argues that firms with both differentiated and integrated subunits have higher information-processing capacities (Tushman and Nadler, 1978) because of information transfer across subunits and the ability of the organization as a whole to use such information for decision-making (Galbraith, 1977). Although the KVB perceives knowledge to be distinct from data and information (Sveiby, 2001), the perspective on integration is similar. Because of differentiation, individuals are required to specialize in particular areas of knowledge (Grant, 1996). Different organizational subunits therefore do not possess identical stocks of knowledge (Conner and Prahalad, 1996), requiring the firm to integrate specialists' knowledge into the production of goods and services (Kogut and Zander, 1992; Grant, 1996).

Interdependence is fundamental to integration (Thompson, 1967). For the context of internally integrating the maintenance function with production and the rest of the organization, the two primary types are sequential and reciprocal interdependence. Sequential interdependence is when the contributions of sub-units must be added in a pre-determined sequence, and reciprocal interdependence is when the contributions are mutually dependent to each other (Thompson, 1967). In these two situations, the sub-units are likely to understand how and why they are interdependent (Castañer and Ketokivi, 2018). Our empirics mirror the fundamental facets of internal integration aimed at coping with sequential and reciprocal interdependence, e.g., lateral

relations with other subunits (Galbraith, 1974), status and consensus as reflections of achieved integration of maintenance (Jonsson, 1999), and engagement in practices for transfer and use of data, information and knowledge across subunits (Galbraith, 1977; Grant, 1996). However, with an extended perspective, we argue theoretically that the returns to internal integration of maintenance is amplified because of technological advancements along the entire chain of information-processing. These advancements assist in coping with pooled interdependence, where sub-units act independently of one another but each adding a discrete contribution to the whole (Thompson, 1967). The quantity of data from production systems is exploding because of embedded digital sensors, networks and processors in machines; much of which contain signals of machine characteristics that are indicative of maintenance requirements. This data is comparably cheap to collect, store, and process, yet is also heterogeneous. Traditionally, information heterogeneity stemming from organizational differentiation was managed by investing in interconnected information systems (Galbraith, 1977). Now, embedded digital technologies enable previously non-digital physical artifacts, such as discrete machines, to be interconnected in digital structures. This enables heterogeneous sources of data to be shared more easily and combined across subunits. Given cost-effective labelling of data, this assembled data on multiple production system parameters can then be incorporated into ML algorithms that are capable of providing unprecedented insights about the production system's maintenance requirements. From the perspective of pooled interdependence, these heterogeneous sources of data are not directly dependent one another, and different sub-units might not be aware of why and how these data should be combined. However, if the organization internally integrates and adds the discrete contribution of each sub-unit to this whole, the pool of data can be shared and combined across sub-units to create value.

Dimension 4: External integration. Adjacent to the dimension of internal integration, our informants also guided us beyond the walls of the plant and described a state where the maintenance function also interacts with its external environment. That is, external integration, the fourth dimension in our data structure that consists of four categories (Fig. 4). Firstly, links are extended to the external environment to enable sharing and consolidation of heterogeneous sources of data, information and knowledge with external parties. Particular focus was placed on sharing data, “Data can be shared with suppliers, partners and of course other plants, the point is that information should be available to anyone who needs it.” The informants proposed that distributing and sharing data is a necessity to apply ML at scale and thereby maximize its utility. If not, the acquired knowledge will remain fragmented and scattered among individual plants. With a specific emphasis on compounding knowledge resources across plants, one informant argued that, “Someone who works with maintenance in one plant in one company will always be outperformed by someone who works with the same equipment in more than one plant. There will always be someone outside the plant with more knowledge than you because they accumulate it from multiple plants with the same type of equipment. You can never beat that expertise.” The informants thus inferred that learning about production equipment within one isolated plant is dauntingly slow and easily outpaced by learning through compounding resources. In other words, learning from one single piece of equipment will never outperform learning from thousands of similar pieces of equipment with similar use cases, given that the knowledge is pooled.

The informants thus clearly acknowledged that large parts of the data, information and knowledge necessary to be successful with Smart Maintenance will be distributed outside the boundaries of the plant. This encourages them to establishing organizational structures that enable the maintenance function to absorb such external, heterogeneous and distributed resources. The informants then guided us towards identify the primary locations of these resources and the two major forms of links necessary to absorb it. Firstly, specific and valuable resources will be held by key suppliers. To tap into these resources, strategic partnerships

are sought, “Buyers and suppliers need to invest equally in digital technologies, establish very tight partnerships and understand that symbiosis is needed.” Several examples were given with respect to machine vendors, where the value proposition for the buyer consists of access to technology that enables prediction and prescription of maintenance activities. Correspondingly for the supplier, it consists of access to equipment data from customer plants useful for learning about their equipment to improve product development and develop services based on extended knowledge bases. Secondly, links can also be established with a larger variety of external parties. Many informants were proponents for that the maintenance function being a part of larger networks of firms to enable inter-organizational learning, “We should participate in ecosystems of plants and suppliers at different geographical places. That kind of collaboration and increased transparency leads to that knowledge accumulates within the entire industry.” The bottom line is that if sharing is established in networks, value is indented to return to each participant in the form of more relevant knowledge and better service. Finally, it was common that the informants argued that the establishment of these links, especially with strategic partners, enables an efficient flow of valuable products and services. The participants exemplified this e.g., in the form of shared spare part inventories and subscription to analytics insights, and one plant manager expressed the evolving supplier offerings of result-based maintenance services, “Machine vendors and component suppliers want to offer services. They take care of our data, analyze it, tell us what to do, and we pay for the uptime of equipment.” Integrated products and services are obviously distinct from integration of organizations, but the flow of such products between organizations reflects tighter coordination of buyer-supplier activities and is thus indicative of integration.

Theoretical interpretation: External integration. Integration within manufacturing is typically divided into three dimensions: internal, supplier, and customer; with the last two being jointly referred to as external integration (Zhao et al., 2011). However, since the customer is internal in the context of plant maintenance (i.e., production), integration of maintenance can be meaningfully collapsed into two dimensions: internal and external. Both dimensions are fundamentally about interdependence (Thompson, 1967). Our interpretation of the external integration dimension was achieved by examining the data using the IPV and TCE. The key observation is the informants' acknowledgement that valuable and heterogeneous resources resides within external parties with whom they are inclined to establish various links. Thus, the organizational structure of external integration reflects the need for the maintenance function to access data, information and knowledge residing outside the boundaries of the plant. According to the IPV, organizations as information-processors respond to environmental uncertainty by identifying and absorbing information from the external environment, combining this with information from within the firm, and ultimately utilizing this information for decision-making (Cyert and March, 1963; Tushman and Nadler, 1978). A firm cannot respond to the environment unless it has the ability to identify and absorb external information. Hence, the IPV prescribes that in situations where the processing of external information is critical for internal decision-making, firms should establish information flows that span outside the boundaries of the firm (Tushman and Nadler, 1978).

Additional insights are achieved through a TCE lens. TCE was developed in order to understand complex economic problems. In particular, TCE is concerned with economic exchange, i.e., transactions, in situations where a lot is at stake. TCE focusses on the survival of exchange relationships from the perspective of opportunism (Williamson, 1985). Therefore, many empirical phenomena related to buyer-supplier relationships and contracting are effectively understood using TCE. However, TCE goes beyond merely the make-or-buy decision and is, in a broader sense, a theory of governance (Williamson, 1996). It is particularly important for theory and practice to ask whether our data is indicative of any evolution in the governance of plant maintenance. The traditional setup, albeit simplified, is in line with TCE predictions; use of

hierarchies for activities with high asset specificity (e.g. maintenance of specialized machines that requires knowledge from use) and use of markets for activities with low asset specificity (e.g. repairs of generic machines and overhauls) (Tsang, 2002). Dissecting our data with TCE, we argue that it is indicative of a shift towards a use of a wider range of alternative governance options as a consequence of technological advancements. While hierarchies are efficient for maximizing the deployment of internal resources, they become disadvantageous when there is an increasing need for coordination of external resources (Williamson, 1975).

In our empirical data, we observed three type of alternatives forms of governance where more activities are coordinated with actors outside the plant: strategic partnerships, networks and ecosystems. These types have grown dramatically in recent years (Gulati et al., 2012; Kapoor, 2018) and they all involve coping with different types of interdependence. Firstly, our category of strategic partnerships is an intermediate governance structure, where the intent is to maximize the efficiency of the buyer-supplier flow of products and services while minimizing the transaction costs of governing the relationship (Williamson, 1991). Partnerships based on sharing and joint processes (e.g., using shared equipment data to improve both the buyer's maintenance activities and the supplier's products and services) make both parties more efficient. Successful partnerships are secured by ex-ante stipulation of safe guards against opportunism, such as credible commitment (Williamson, 1983), and the exchange relationship survives over time because of bilateral dependence and equal investments in mutual asset specificity (Williamson, 1985). This bilateral contract includes primarily sequential and reciprocal interdependence because the two parties aim to coordinate and synchronize their respective work processes (Thompson, 1967). Secondly, our category of inter-organizational networks reflects another distinct form of governance (Williamson, 1991); interconnecting with a broader base of external parties, where coordination of resources is achieved through mutually supportive actions such as sharing (Powell, 1987). The particular characteristics of networks is the structure of the ties between parties (Kapoor, 2018) – that the system is not bound together by price signals or control, but by trust in that the parties have resources with mutual asset specificity that benefit from pooling. Networks therefore enable transactions to take place between multiple independent actors; transactions that would not be feasible in either hierarchies or markets (Powell, 2003). Further, ecosystems focus on the type of interdependencies within the network that contributes to the value proposition (Kapoor, 2018). Specifically, networks give rise to pooled interdependencies, in which different actors act independently, yet adding a discrete contribution to the whole (Thompson, 1967). A network aimed at establishing an ecosystem for consolidating equipment data to apply ML at scale is a perfect example of pooled interdependence. The challenge here is to preserve the integrity of the network because the parties might not even be aware of how and why they are independent.

We argue theoretically that this shift occurs in part because digital technologies have the overall effect of making information-processing cheaper and thus lowering transaction costs (Malone et al., 1987), but more so because recent technological advancements enable organizations and also the equipment itself to be directly interconnected. Since the amount of heterogeneous data, information, and knowledge grows much faster outside the boundaries of a single plant and in an increasingly distributed manner, networks continuously expand and thereby incentivizes firms to build digital infrastructures so that the internal organization becomes boundless to the environment (Gulati et al., 2012; Yoo et al., 2012). This large-scale digital interconnection of production equipment is advantageous because of a dramatic drop in transaction costs, resulting in a straight forward prediction from TCE; less use of hierarchies and more use of alternative forms of governance.

Observing and interpreting the opposite pole: The last part of the focus group intended to explore the opposite pole of the focal concept by asking Q3: *What does absence of Smart Maintenance mean?* Throughout

the focus groups. the main reaction from the informants was to respond using the negative pole of the same attributes as in Q1. Since the data reflect the negative pole of the same positive dimensions as in Fig. 4, we do not provide a graphical data structure. For example, in contrast to data-driven decision-making, the informants described a state where decisions are solely based on human intuition and experience. In contrast to the skills requirements forming the HCR, the informants expressed a state where adequate skills are lacking. Similarly, the respondents described states where internal and external integration had not been achieved. From the point of interpretation, the overall pattern of responses across the focus groups indicate that the same attributes are associated with both the presence and absence of the focal concept.

Analyzing this data and explicit theorizing the opposite pole is a critical part of concept-building (Goertz, 2006). Our interpretation of the empirical data suggests that the opposite pole of Smart Maintenance has no clear, independent theoretical existence. In other words, the opposite pole is the negative of the positive (Goertz, 2006). These responses reinforced our confidence that we had indeed uncovered the defining characteristics of Smart Maintenance. This might seem intuitive and it indeed holds as a broad generalization for social science concepts (Goertz, 2006), but this is not always the case (Podsakoff et al., 2016). The conclusions should be used to theorize about the continuum between the positive and negative pole (Goertz, 2006), which we do when model the concept structure in Section 4.3.

4.2. Conceptual definition of Smart Maintenance

Following our empirical findings and theoretical interpretations, we hold the four dimensions of *data-driven decision-making*, *human capital resource*, *internal integration*, and *external integration* as the core dimensions that constitute our focal concept. The concept of Smart Maintenance thus represents a configural organizational design – a tight composition of four interrelated and mutually supportive elements. To sharpen this conceptualization towards achieving concept clarity, we now provide a semantic, conceptual definition of Smart Maintenance as well as each of its sub-dimension. In addition, we specify the dimensionality, property, entity and stability (Podsakoff et al., 2016). We do so on the basis of the uncovered conceptual themes and their interpretation (Section 4.1) while emphasizing cumulative theorizing by incorporating the key tenets of the general theories and existing definitions. For example, our definitions of integration are inspired by Barki and Pinsonneault (2005), who build on contingency theory and TCE, and our definition of human capital resource is inspired by Ployhart et al. (2014) who build heavily on the RBV.

Smart Maintenance is defined as ‘an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies’. Smart Maintenance is a multidimensional concept constituting of the four dimensions of data-driven decision-making, human capital resource, internal integration, and external integration. The property of Smart Maintenance represents a configural organizational design that applies to the entity of a plant maintenance function, and it aims to achieve effective and efficient decision-making and responsiveness to internal and external components. With respect to stability, Smart Maintenance and its four underlying sub-dimensions are conceptualized as being quasi-fixed in the short run, meaning that they are subject to adjustment costs when their levels are changed. This type of stability applies to configurations in general, because the costs associated with changing a system of elements prevents rapid adjustments (Miller, 1992; Brynjolfsson and Milgrom, 2013).

Data-driven decision-making is defined as ‘the degree to which decisions are based on data’. Attributes that manifest data-driven decision-making are effective and efficient maintenance decision-making driven by the internal and external collection and analysis of high quality data and can reflect both augmentation and automation of human decision-making. The property represents decision practices that apply to the entity of the plant maintenance function.

Human capital resource is defined as a ‘unit capacity based on individual knowledge, skills, abilities and other characteristics (KSAO) that are accessible for unit-relevant performance’. The property represents the collective, aggregate stock of human resources within the maintenance function. It applies to the entity of the maintenance function at the unit level but emerges from KSAOs and social processes that exist at the level of individuals, and includes a multitude of cognitive and non-cognitive KSAOs that are accessible and relevant to the maintenance function.

Internal integration is defined as ‘the degree to which the maintenance function is a part of a unified, intra-organizational whole’. Internal integration is manifested in the attributes of frictionless flows of data, information, knowledge and decisions, and close collaboration and synchronization between intra-organizational components. These components refer to independent organizational sub-units and include processes, people and technology, where the attributes of internal integration reflect responsiveness between components. The property represents an organizational structure that applies to the entity of the plant maintenance function.

External integration is defined as ‘the degree to which the maintenance function is a part of a unified, inter-organizational whole’. External integration is manifested in the attributes of frictionless flows of data, information, knowledge, products and services and close links between inter-organizational components. These components refer to networks of interrelated firms and strategic partners, and include processes, people and technology, where the attributes of external integration reflect responsiveness between components. The property represents an organizational structure that applies to the entity of the plant maintenance function.

As evident in these definitions, the four dimensions of Smart Maintenance are conceptualized as *state variables*. Organizational elements can be conceptualized as either states or mechanisms (Turkulainen and Ketokivi, 2012). Both are critical to organizational design, but they are distinct. The use of certain mechanisms may lead to states, but presence of mechanisms does not automatically mean presence of states; doing something and being successful in something is not the same thing (Turkulainen and Ketokivi, 2012) (p. 450).

4.3. Conceptual model of Smart Maintenance

To sharpen our conceptualization even further, we now analyze the relationships between the four dimensions of Smart Maintenance followed by modeling the corresponding concept structure. Since configurational organizational designs are compositions of interrelated and mutually supportive elements, achieving concept clarity with respect to such designs requires analyzing the *internal fit* of the elements and answering why they should be achieved jointly. (Miller, 1986; Sousa and Voss, 2008). Complementarities theory is particularly useful for analyzing configurations (Van De Ven et al., 2013). By theorizing interactions among pairs of dimensions that forms a system of internally consistent elements, typologies of complementary configurations can be specified for empirical testing (Milgrom and Roberts, 1995; Brynjolfsson and Milgrom, 2013). Here, the two primary relationships are *substitutable* (S) and *complementary* (C). Substitutable (S) refers to where one replaces the other; complementary (C) refers to where doing more of one increases the returns of doing more of the other (Milgrom and Roberts, 1995; Castañer and Ketokivi, 2018). It is important to note here that complementarities theory is based on an additive *sufficiency logic*. The focus is on identifying configurations in which the returns of implementing all practices is larger than the sum of returns from implementing each practice separately (Milgrom and Roberts, 1995). Configurations can also be analyzed using necessity logic (Fiss, 2007; Dul et al., 2010), in which one element may *enable* the use of another (Castañer and Ketokivi, 2018). This is equally valid and will be an important next step in subsequent research.

Inspired by Brynjolfsson and Milgrom (2013), we approach this

analytically by structuring a matrix of interactions (Table 3) and briefly discussing each pair of dimensions within Smart Maintenance. The configuration as a whole as well as the way each dimension influence the others are all testable empirical propositions.

In Table 3, each dimension appears in both a row and a column (1–4). To verify the configuration, we can neglect the lower half of the table and the diagonals (colored in grey) because the structure is symmetric and based on pairs of interactions (Brynjolfsson and Milgrom, 2013). Firstly, we analyze the relationship between data-driven decision-making and human capital resource (1,2). Data-driven decision-making both substitute (automate) and complement (augment) the human capital resource, because ML primarily substitute for the human task of prediction whilst complementing judgement. Within an occupation, computers in general, and ML in particular, substitute human for some tasks while complementing other tasks (Autor, 2015; Acemoglu and Restrepo, 2018a). Secondly, the relationships between data-driven decision making and internal and external integration (1,3 and 1,4) are both complementary. Both internal and external integration increase an organization’s information-processing capacity (Galbraith, 1974; Tushman and Nadler, 1978). This increased capacity improves the organizations ability to gather, interpret and synthesize information that can be used for decision-making (March and Simon, 1958; Cyert and March, 1963). Thirdly, the relationships between human capital resource and internal and external integration (2,3 and 2,4) are also complementary. Since different organizational sub-units possess different stocks of knowledge (Conner and Prahalad, 1996), the role of the organization is to integrate specialists’ knowledge (Grant, 1996). This knowledge resides within the HCR, and value can therefore be leveraged by integrating the HCR internally with other functions within the organization as well as externally with suppliers and networks (Kogut and Zander, 1992; Sveiby, 2001). Fourthly and finally, the relationship between internal and external integration (3,4) is complementary because internal integration strengthens the effect of external integration. High performance can be achieved by achieving internal integration first, followed by external integration (Koufteros et al., 2005; Flynn et al., 2010; Zhao et al., 2011). For example, suppliers can provide external information that is useful for internal, cross-functional problem-solving (Wong et al., 2011). Further, with the advent of networks and ecosystems, the internal organization can no longer be decoupled from the actors outside the boundaries of the plant (Gulati et al., 2012; Yoo et al., 2012; Kapoor, 2018).

With this analysis, we have verified the configural, complementary nature of Smart Maintenance. The final step in our conceptualization is therefore to formally model the concept structure. We do so by adopting the ontological and casual approach developed by Goertz (2006). It is ontological because it focusses on the fundamental, constitutive elements of a phenomena, and it is causal because it focusses on identifying which elements that hold causal power. This approach acknowledges that the most prominent conceptualizations are both multidimensional and multilevel. Therefore, the modeling of concept structures involves three levels: *basic*, *secondary* and *indicator* level. The basic level is cognitively central because it contains the collective term we use for communication. The secondary level is the constitutive dimensions of the basic level concepts, and this is where multidimensionality and causal power appear. The indicator level is usually where data collection occurs because this level is specific enough to gather empirical data (Goertz, 2006). Using this approach, we model the concept structure of Smart Maintenance in Fig. 5, followed by explaining our theorizing at each level.

To explain Fig. 5, we move from left to right and begin at the indicator level. Since we have defined the four dimensions as state variables, we do not explicitly theorize about the mechanisms that corresponds to the indicator level. For example, our empirical observations and theoretical interpretations of the data-driven decision-making dimension are indicative of that there are no universal solutions and that there are multiple ways to achieve the same organizational state. Therefore, we

Table 3
Relationships between the four dimensions of Smart Maintenance.

	(1)	(2)	(3)	(4)
(1) Data-driven decision-making		S, C	C	C
(2) Human capital resource			C	C
(3) Internal integration				C
(4) External integration				

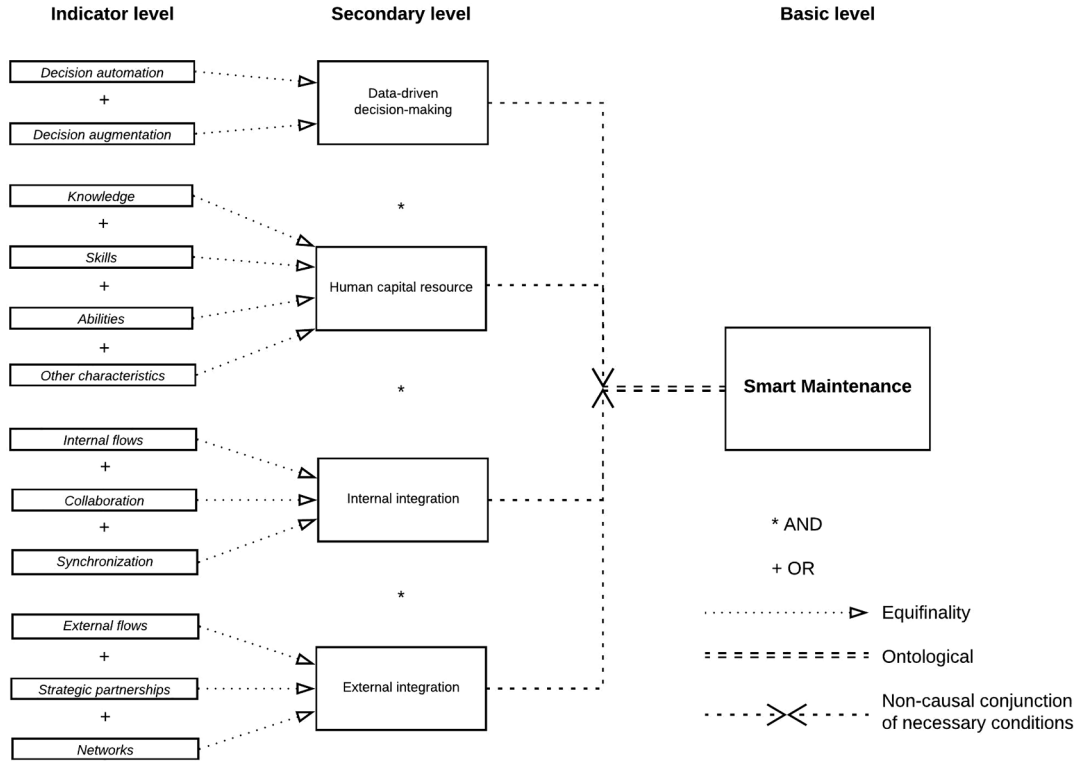


Fig. 5. Smart Maintenance concept structure.

model the relationship between the indicator level and secondary level as being one of *equifinality*. This means that at the indicator level, there exists multiple, equally effective mechanisms that may lead to the organizational state at the secondary level (Sousa and Voss, 2008). For the purpose of graphical illustration, we display a sub-set of variables from Section 4.1 and recognize that mechanisms at this level are important avenues for further research. Following Goertz (2006), we illustrate this by using dotted arrows and the logical conjunction OR.

We then direct attention to the secondary level. Since Smart Maintenance is a configuration, the four dimensions represent a system of mutually reinforcing elements. Following Goertz (2006), we illustrate this using the logical conjunction AND. This also means that Smart Maintenance has a necessary and sufficient concept structure. This structure follows the rule that an object qualifies for membership if and only if all attributes are present (Goertz, 2006; Podsakoff et al., 2016). In other words, Smart Maintenance has been achieved if and only if all four dimensions have been achieved, and if one of the dimensions has zero value, then it implies a zero value of Smart Maintenance at the basic level. Further, a clear conceptualization of the opposite pole is critical for this level (Goertz, 2006). Based on our observation and interpretation of the opposite pole in Section 4.2, we concluded that the opposite pole is the negation of the positive; the positive pole is when the four dimensions have been achieved, and the opposite pole is when the four dimensions have not been achieved (Goertz, 2006; Podsakoff et al.,

2016). However, we conceptualize the relationship between the two poles not as dichotomous but as a continuous. Achieving the four dimensions is a matter of *degree*, as also indicated in our semantic definitions. Moving from an existing organizational design to Smart Maintenance involves a long-run transition executed in a series of short-run equilibrium steps (Brynjolfsson and Milgrom, 2013). It is therefore useful to observe not only the negative and positive end of the spectrum but also borderline cases that are in the process of moving from one equilibrium to another.

Finally, the relationship between the secondary level and the basic level is *ontological* – a matter of identity, not causation (Goertz, 2006). This has several important conceptual and empirical implications. First, the basic level term Smart Maintenance in itself holds no causal power, and the relationships to the secondary level dimensions are non-causal. Instead, the four dimensions *constitute* what Smart Maintenance is. Following Goertz (2006), we illustrate this conjunction of non-causal necessary conditions with dashed arrows forming a four-way combination of the secondary level dimensions. Further, while the basic level term Smart Maintenance serves a critical cognitive function in scholar-to-scholar communication and collaboration between scholars and practitioners, the secondary level dimensions should be the focus for empirical research. It is the four dimensions of Smart Maintenance that hold causal power and thereby play the central role in hypotheses and explanations.

5. Discussion

Using an empirical research approach in collaboration with more than 110 participants from over 20 different firms, we have brought clarity to the question, “*What is Smart Maintenance?*”. Specifically, by adopting an orientation towards theoretical prescience (Corley and Gioia, 2011) and employing a multitude of general theories, we have inductively identified an array of conceptual variables that can be empirically measured. Based on this, we have conceptualized and defined the concept of Smart Maintenance and its four underlying dimensions as a configural organizational design.

We make several *theoretical contributions* - findings that are scientifically useful by advancing the rigor of an idea and/or enhance its potential to be operationalized and tested (Corley and Gioia, 2011) (p. 17–18). In other words, those that contribute to cumulative research efforts (Antonakis, 2017). Firstly, our empirical observations and theoretical interpretations brings theoretical precision to the four dimensions of Smart Maintenance. The dimensions are thereby now in a suitable position for being operationalized. To this end, applying surveys to develop psychometric measurement would be most effective. Secondly, carefully developed conceptual definitions are rare within maintenance research (as evident in Table 1), and our semantic definitions therefore advance the field towards concept clarity. We have thereby dramatically reduced the risks for deficient and/or contaminated measures (Mackenzie et al., 2011). In addition, to the best of our knowledge, formally using an ontological and causal approach for modeling the concept structure is the first within the maintenance realm. In fact, combining the semantic (Sartori, 1984) and the ontological approach (Goertz, 2006) in a single study is rare even within considerably more mature fields such organizational science (Podsakoff et al., 2016). Thirdly, with respect to the specific novelty criterion within organizational design, a novel design is one that embodies new solutions to the basic problem of organizing that contrasts to the solutions used by existing organizations (Gulati et al., 2012). While each of the four dimensions are not novel empirical phenomena in themselves, combining them into a configural organizational design certainly is. We do not radically reinvent, we incrementally expand and make our understanding of empirical phenomena more precise. Fourth and finally, answering our research questions also brings clarity to the meaning of the word “Smart Maintenance” itself. As a basic level term, Smart Maintenance serves an important cognitive and communicative function for scholars and practitioners. While it might smell like managerial hype, the four dimensions that constitute what Smart Maintenance is hold causal powers and thereby constitute legitimate objects for scientific inquiry.

We also make *practical contributions* – findings that can be directly applied to the problems practitioners face (Corley and Gioia, 2011) (p. 18). In other words, those that inform policy and practice (Antonakis, 2017). By conceptualizing Smart Maintenance as an organizational design, we inform practice in the form of solving the practical challenge of organizing the maintenance function for environments with pervasive digital technologies. In particular, our parsimonious conceptualization of the four dimensions of Smart Maintenance is useful, understandable and inspiring to practitioners (Corley and Gioia, 2011). The results from this study can therefore be used as the foundation for developing long-term maintenance strategies, especially on managerial level. For example, specifying Smart Maintenance as a configuration stresses the need for maintenance managers to view organizational design from an holistic perspective – covering not only novel technologies for decision-making but also the role of humans and social interactions. The complementarities between the four dimensions tell managers to focus on implementing all four dimensions jointly, rather than dedicating all available resources on optimizing single dimensions. Since the importance of the maintenance function is increasing, it is important to adopt this type of strategic approach to maintenance management. Finally, the clear conceptualization enables the development of valid measurement

instruments, which could e.g. be used as benchmarking tools that further support the strategic development of maintenance.

However, despite this array of theoretical and practical contributions, there are limitations to our study that call for further research. Firstly, since we focussed on Smart Maintenance based on the interest of practicing managers in local firms, a detailed comparison of our focal concept and those who are related to it is beyond the scope of this study. From Table 1, it is clear that concept proliferation is an undisputable fact within maintenance research. We therefore call for the noble task of conducting such a comparison with further depth to establish whether some concepts are redundant. This would advance concept clarity within the maintenance field as a whole. Secondly, since we have conceptualized the four dimensions as organizational state variables, there is a need for conceptual refinement with respect to the mechanisms that lead to these states. The starting point for this inquiry is equifinality (Fig. 5). To this end, we urge scholars to directly build on our work and identify both individual mechanisms that are suitable in certain environments (external fit), as well as which configurations of mechanisms that are more effective (internal fit) in achieving the four dimensions of Smart Maintenance. Thirdly, we have conceptualized Smart Maintenance within the boundary conditions of the manufacturing industry. However, it is possible that also the overall meaning of the term Smart Maintenance is contingent on the environment, thus inviting for further research on pluralist conceptualizations of Smart Maintenance in other areas of application (e.g. infrastructure maintenance).

6. Conclusions

By observing industrial maintenance managers’ interest in responding to recent environmental contingencies, we recognize the scientific and practical value in bringing conceptual clarity to the concept of Smart Maintenance. Therefore, we apply an orientation towards prescience in the form of an inductive, empirical research approach. By working closely with practitioners, we make empirical observations and theoretical interpretations that serve as the basis for conceptualizing Smart Maintenance. Specifically, we develop a conceptual definition of *Smart Maintenance* as ‘an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies’, as well as definitions for the four underlying dimensions of *data-driven decision-making*, *human capital resource*, *internal integration*, and *external integration*. Furthermore, we analyze the interrelationship between the dimensions and formally model the concept structure. These findings achieve concept clarity with respect to Smart Maintenance, thereby guiding the scholarly field of industrial maintenance management as well as enabling more efficient industry-academia collaborations.

Owing to our use of several general theories encompassing strategy, organization and economics, we introduce novel perspectives that chart new directions for maintenance research. Specifically, we bring theoretical precision to the four underlying dimensions of Smart Maintenance as a configural organizational design of the plant maintenance function. This offers a novel way of modeling the conceptual and empirical nature of phenomena within industrial maintenance management. We hope that this will inspire other maintenance researchers to contribute to cumulative research efforts with respect to Smart Maintenance, which we are convinced will greatly benefit both scholars and practitioners within the field.

Declaration of competing interest

None.

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Appendix A. Details about sampling strategy

All participants were chosen based on purposive sampling (Lincoln and Guba, 1985), with the criteria that they had the necessary theoretical knowledge and practical experience of the particular topic (Eisenhardt and Graebner, 2007). To achieve heterogeneity, participants were sampled from 22 different firms, covering e.g., discrete and continuous manufacturing, consultancies, industrial service providers and IT-system vendors. Some focus groups were comprised solely of participants from one firm, while other groups included participants from a variety of firms. The unit of analysis was the manufacturing plant - which we ensured that all participants were in agreement with. Inspired by Corley and Gioia (2004), we began by sampling managers of each firm, then used a snowball recruitment approach, where the managers recommended and invited a variety of suitable participants from their respective firm. We primarily targeted three positions: managers, engineers and technicians. The aim was to achieve a collective understanding of the focal concept at different organizational levels. Higher management holding major decisional roles in terms of organizational design, are likely to possess knowledge of the firm's strategic priorities and are critical informants since organizational design is endogenous to managerial choice (Ketokivi and Mcintosh, 2017). Engineers and technicians possess vast domain knowledge and are immersed in the daily work at the plant, thus being central to understanding the problem-solving activities of practitioners. Further, we primarily targeted two functions within the firms: maintenance and production. Maintenance is the primary function of interest in this study because it constitutes the origin of our research impetus. Further, maintenance is most commonly considered to be a sub-unit or direct support function to production. This natural relationship between the two functions motivated us to sample from both of them. However, suitable participants from other positions (e.g., researchers and salespersons) and functions (e.g., R&D, IT and sales) were also invited as seen fit by managers' snowballing strategies. Further, the focal concept was viewed from an organizational lens that inevitably included relationships between an array of positions and functions within a manufacturing plant.

Appendix B. Details about data analysis

During our coding process, we iterated between the empirical data and the general theories (Ketokivi and Mantere, 2010). This means that both the 1st order codes and 2nd order categories are situationally grounded in the data, while the 2nd order categories and aggregate dimensions establish a sense of generality by embodying theoretical abstractions from the general theories (Ketokivi and Choi, 2014). We also used the tenets and concepts within the general theories as input for developing the conceptual definition of Smart Maintenance. In essence, each theory allowed us to interpret different parts of the data. Thus, as a set they were sufficient to comprehensively reconcile with the empirical context. Although the theories are formulated for a scholarly audience, they have major pragmatic implications that expand their scope to practical usefulness, hence illustrating fit with our practical, phenomenon-driven research impetus (Corley and Gioia, 2011).

We used three techniques for external audits: *peer-debriefing*, *inter-coder agreement* and *member checking*. All techniques were repeated three times each. Peer-debriefing consists of discussing emerging patterns in the data with other researchers who act as sounding boards, provide an outside perspective, and pose critical questions about the data collection and analysis (Corley and Gioia, 2004). In this study, the peers were department members. Through negotiated agreement during the debriefing sessions, codes and categories were revised and clarified. With respect to formal assessment of the reproducibility of our coding, the standards for assessing inter-coder reliability are not consistent with theoretical contextualization as they are typically used deductively under the assumption that all coders are equally knowledgeable (Krippendorff, 2004). Instead, inter-coder agreement aims to enable multiple coders to reconcile potential coding discrepancies for the same unit of text; discrepancies which may occur due to e.g. idiosyncratic knowledge bases. However, little work has been done to determine how to perform such assessments in a standardized manner in an inductive setting (Campbell et al., 2013). When multiple individuals code entire sets of data, one common approach is to apply some form of consensus coding (Nag and Gioia, 2012). However, this study employed one main coder. We therefore strived to ensure that this single knowledgeable coder was reasonably confident that the coding would be reproducible by other equally knowledgeable coders, if they were available (Campbell et al., 2013). An additional external researcher was provided with unitized but un-coded versions of random sample data excerpts from each focus group question, respectively, and was instructed to assign each 1st order code to a 2nd order category. Inter-coder agreement was then calculated with the proportion agreement method, which does not consider agreement by chance but is suitable for exploratory studies like ours (Campbell et al., 2013). In cases of coding discrepancies, the two researchers engaged in discussions to reach consensus and revise the coding accordingly. The three repetitions thus included coding of a total of nine excerpts. All of these consistently resulted in above 80 percent level of agreement which is well in line with previous examples (Campbell et al., 2013). Member checking is critical technique for establishing credibility by allowing the participants of the study to react to the data and interpretations (Lincoln and Guba, 1985). In this study, both the tentative analysis and the final findings were presented to industrial managers who acted as judges of the credibility and consistency of our interpretations. They were asked whether the categories and aggregate dimensions made sense and whether the interpretations were accurate. Based on their comments, the coding was clarified and revised (Creswell and Miller, 2000).

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