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Adoption patterns and performance implications of Smart Maintenance

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ABSTRACT

To substantiate and extend emergent research on maintenance in digitalized manufacturing, we examine adoption patterns and performance implications of the four dimensions of Smart Maintenance: data-driven decision-making, human capital resource, internal integration, and external integration. Using data collected from 145 Swedish manufacturing plants, we apply a configurational approach to study how emergent patterns of Smart Maintenance are shaped and formed, as well as how the patterns are related to the operating environment and the performance of the manufacturing plant. Cluster analysis was used to develop an empirical taxonomy of Smart Maintenance, revealing four emergent patterns that reflect the strength and balance of the underlying dimensions. Canonical discriminant analysis indicated that the Smart Maintenance patterns are related to operating environments with a higher level of digitalization. The results from ANOVA and NCA showed the importance of a coordinated and joint Smart Maintenance implementation to the maintenance performance and productivity of the manufacturing plant. This study contributes to the literature on industrial maintenance by expanding and strengthening the theoretical and empirical foundation of Smart Maintenance, and it provides managerial advice for making strategic decisions about Smart Maintenance implementation.

1. Introduction

Maintenance is an operations process that is vital to the performance of manufacturing plants of any size and shape. Recently, maintenance has received increased attention as a consequence of industrial digitalization (Silvestri et al., 2020), where novel digital technologies are progressively introduced to the production process (what to maintain) as well as the maintenance process (how to maintain). This new operating environment changes the nature of maintenance as a support process, and the diffusion of novel digital technologies has far-reaching implications for decision-making, strategy, learning, and governance of the maintenance function (Bokrantz et al., 2020b).

Contemporary research streams on maintenance in digitalized manufacturing are both focused on technology development (tools, methods, and techniques to solve maintenance problems) (Florian et al., 2021; Liang et al., 2020; Silvestri et al., 2020; Zonta et al., 2020) and theory development (how and why maintenance works the way it does) (Bokrantz et al., 2020b; Tortorella et al., 2021; Öhman et al., 2021). An emerging proposition that unites these streams is that in operating environments infused by digital technologies, modernizing the maintenance operations through some combination of technology, people, and organization will have positive implications on performance (Roda and Macchi, 2021).

However, to advance maintenance theory and practice in this direction, it is crucial to investigate if such a proposition holds against empirical data. At present, empirical evidence regarding the value of modernizing maintenance operations in digitalized manufacturing is largely confined to exploratory studies (Roda and Macchi, 2021; Silvestri et al., 2020; Tortorella et al., 2022). Therefore, in this study, we build on the theoretical foundation of maintenance in digitalized manufacturing to empirically examine the adoption patterns and performance implications of Smart Maintenance; a concept that consists of the four dimensions data-driven decision-making, human capital resource, internal integration, and external integration (Bokrantz et al., 2020c). Specifically, we apply a configurational approach to study how emergent patterns of the Smart Maintenance dimensions are shaped and formed, how the prevalence of these patterns is influenced by the operating environment, as well as how the patterns of Smart Maintenance are related to the performance of the manufacturing plant.

Through our empirical analysis, we make three contributions to the literature. Firstly, we show that an emergent taxonomy of Smart Maintenance can be developed, reflecting the strength and balance of the four underlying dimensions. Secondly, we show that more advanced Smart Maintenance patterns may be more prevalent in operating environments

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characterized by a higher level of digitalization. Thirdly, we show that manufacturing plants with strong and balanced Smart Maintenance patterns have higher maintenance performance and productivity, as well as that high levels of the four dimensions of Smart Maintenance are individually necessary for a high level of maintenance performance. These insights expand and strengthen the theoretical and empirical foundation of Smart Maintenance as well as provide managerial advice for making strategic decisions about Smart Maintenance implementation.

2. Theoretical framework and hypotheses

We begin by establishing the theoretical framework of the study. We first present the definition and dimensions of Smart Maintenance, followed by deriving our hypotheses about adoption patterns and performance implications. The resulting theoretical model and empirical scope of the study are thereafter summarized and visualized in Fig. 1.

2.1. Definition and dimensions of Smart Maintenance

The concept of Smart Maintenance reflects an emergent research stream that originates from the empirical analysis of industrial firms whilst at the same time resting on the historical evolution of the maintenance discipline. Through a bibliometric analysis of almost 800 articles, Roda and Macchi (2021) uncovered the evolutionary path of maintenance concepts from 1985 to 2020. They observed rapid growth of the Smart Maintenance concept in recent years (since 2014) and underlined its significant role in maintenance theory and practice. While there exist multiple definitions of Smart Maintenance as well as definitions for the same or similar concepts (Huang et al., 2019), Roda and Macchi (2021) emphasize that the current benchmark and the most suitable foundation for cumulative knowledge creation is the definition by Bokrantz et al. (2020c). Here, Smart Maintenance is defined as "an organizational design for managing maintenance in environments with pervasive digital technologies" (p. 11) and encompasses four underlying dimensions: data-driven decision-making, human capital resource, internal integration, and external integration. The formal concept structure along with definitions and descriptions of the four dimensions' conceptual contents are extensively outlined in Bokrantz et al. (2020c) and Bokrantz et al. (2020a). In short, data-driven decision-making is "the degree to which decisions are based on data"; human capital resource is a "unit capacity based on individual knowledge, skills, abilities, and other characteristics that are accessible for unit-relevant performance"; internal integration is the "degree to which the maintenance function is a part of a unified, intra-organizational whole"; and external integration is the "degree to which the maintenance function is a part of a unified, inter-organizational whole" (Bokrantz et al., 2020c) (p. 11).

In this study, we adhere to this conceptualization for three reasons. Firstly, it meets established criteria for good conceptual definitions (Podsakoff et al., 2016), which allows for obtaining valid empirical scores that can be used for our research goal of examining adoption patterns and performance implications. Secondly, it originates from practice and the experience of working professionals, which allows for conducting research that captures the engagement of practitioners (Von Krogh et al., 2012). Thirdly, it has gained rapid acceptance in academia (Roda and Macchi, 2021; Tortorella et al., 2021), and the clear specification of the meaning and structure of the concept allows for accumulating a body of evidence through empirical research.

2.2. Configurations of Smart Maintenance

Theory on organizational configurations is instrumental in helping managers in making strategic decisions about Smart Maintenance implementation. We adopt the configurational perspective that views organizational designs as sets of commonly occurring constellations of interrelated elements that are believed to exhaust a fraction of a given population of organizations (Miller, 2018). This particular configurational perspective focuses on capturing patterns among organizational elements (Hinings, 2018) and rests on three foundational theses: (1) that it is important to distinguish between different types of organizations, (2) that the elements of an organization will group thematically, and (3) that a reasonably small set of configurations may encompass many organizations (Miller and Mintzberg, 1983). The goal of such configurational research is to develop parsimonious and robust configurations that are useful for classification (Hinings, 2018). Specifically, the aims are to provide descriptions of organizations that resemble each other along important dimensions; explanations for organizational success or failure; and predictions of which sets of organizations will be successful under given circumstances (Short et al., 2008). The two most common types of configurations are typologies (conceptually driven classification schemes) and taxonomies (empirically generated classification schemes) (Miller, 2018). This type of configurational research has been critical for theory development within Operations and Supply Chain Management (OSCM) (Flynn et al., 2010; Huo et al., 2017, 2019; Zhao et al., 2004) as well as other adjacent disciplines such Strategy, Economics, and Human Resource Management (Miller, 2018).

Bokrantz et al. (2020c) specified the Smart Maintenance concept as an organizational configuration: "a tight composition of four interrelated and mutually supportive elements" (p. 11). This implies the need for a holistic perspective where the ideal Smart Maintenance strategy consists of coordinated and joint implementation of all four dimensions. However, in practice, manufacturing plants are likely to place different emphases on the individual dimensions of Smart Maintenance due to e.g., environmental contingencies, strategic directions, resource constraints, or employment modes. A configural lens suggests that differences in the emphasis that manufacturing plants place on the individual dimensions of Smart Maintenance will result in a thematic grouping. This grouping will empirically generate a small set of configurations that help to distinguish between different types of maintenance organizations, according to their patterns of the four dimensions of Smart Maintenance.

When the relationships between the configural elements are important, it is most useful to empirically develop an emergent taxonomy that is based on clear differences between groups (Miller, 2018). Within OSCM, one common approach to developing taxonomies that operationalize the difference in the degree of emphasis of sets of dimensions is to describe the patterns in terms of strength and balance (Flynn et al., 2010). Whereas strength reflects the extent to which the different dimensions are achieved, balance reflects the extent to which equal attention is paid to all dimensions (Huo et al., 2019). For example, while some maintenance organizations may have a skilled workforce that is well integrated internally and externally, they may lack analytics capability. Others may have achieved a complementarity between humans and data but are weaker in their organizational integration. The emergence of an empirical taxonomy from the four dimensions of Smart Maintenance can provide novel and parsimonious insights into the complexities of Smart Maintenance adoption as well as serve as a tool for classifying plants into strategic groups. Therefore, we hypothesize that:

H1. A taxonomy of Smart Maintenance emerges among manufacturing plants, and plants can be classified into groups based on their levels of the four underlying dimensions.

2.3. Environmental contingencies

Configurations are often related to the characteristics of the environment (Brynjolfsson and Milgrom, 2013). That is, different configurations should be more or less common in certain contexts. Several empirical studies have examined the relationships between the operating context and the adoption of maintenance practices. For example, Swanson (2003) studied the effect of production system complexity on the adoption of advanced maintenance practices (e.g., technological variety and mass output orientation); Aboelmaged (2014) assessed how a set of technological, organizational, and environmental factors affect adoption readiness of E-maintenance; Jonsson (2000) examined how contextual factors (e.g., production process, number of employees, breakdown consequences) influence an empirical taxonomy of maintenance prevention and integration; and Tortorella et al. (2022) explored the influence of firms' technological intensity on the joint adoption of Total Productive Maintenance and Industry 4.0 technologies. In this study, we focus on three contingencies that reflect the operating context of the manufacturing plant: mass output orientation, automation, and digitalization. While there exists a myriad of plausible contingencies, we chose these three because they are theoretically relevant for Smart Maintenance and empirically established in the maintenance literature as well as OSCM more broadly.

Firstly, mass output orientation is widely known to impact the overall structure of support processes within manufacturing plants, including maintenance (Jonsson, 2000; Swanson, 2003). Specifically, plants with continuous flow processes are characterized by high-volume production and capital-intensive equipment that strongly emphasizes efficiency. Downtime consequences are immediately visible, costly, and impose environmental and safety risks, which makes high equipment utilization and rapid responses from maintenance more critical. In contrast, plants with discrete-part processes are characterized by intermittent stages with buffers that can more easily absorb variations in downtime, which makes the consequences of equipment failures less obvious (Salonen and Tabikh, 2016). Job shops have even more built-in redundancy and flexibility with large variations in working hours and machine idle times, which allows breakdowns to be sufficiently managed without advanced maintenance practices (Jonsson, 2000). Thus, plants with higher output orientation should favor the adoption of Smart Maintenance. This would be reflected in a positive relationship between the degree of output orientation and more advanced Smart Maintenance patterns.

Secondly, a related but distinct characteristic is the level of automation. Plants with a higher level of automation rely more on production equipment with built-in instrumentation and sensors. This data is often digitized, voluminous, and can be directly transmitted to other processing equipment (Brynjolfsson et al., 2021). In addition, highly automated machinery often requires unique skills to maintain, thus increasing the dependency on the maintenance function's ability to execute rapid and effective maintenance actions. More advanced manufacturing technologies have indeed been empirically linked to more advanced maintenance practices (Swanson, 2003). It is also widely held in the maintenance literature that more advanced maintenance practices are needed to effectively manage the significantly higher levels of automation associated with smart factories (Bokrantz et al., 2017; Roy et al., 2016; Silvestri et al., 2020). Thus, plants with higher levels of automation should favor the adoption of Smart Maintenance. This would be reflected in a positive relationship between the level of automation and more advanced Smart Maintenance patterns.

Thirdly, adopting data-driven management practices within a manufacturing context requires tangible investments in Information and Communication Technology (ICT) to collect, store, and analyze equipment data (e.g., computing hardware and software) (Brynjolfsson et al., 2021). Thus, plants with higher intensity of digital technologies have been posited to possess an advantage in adopting modernized maintenance practices, and recent empirical explorations have indeed pointed in this direction (Tortorella et al., 2022). Earlier studies have also shown that plants with well-designed technological infrastructure are better prepared to adopt E-maintenance (Aboelmaged, 2014). Further, as given by its definition, the core contextual prediction regarding Smart Maintenance is that it would be natural for manufacturing plants to adopt Smart Maintenance if they operate in an environment with pervasive digital technologies (Bokrantz et al., 2020c). Thus, plants with existing digital infrastructure would have an advantage in adopting Smart Maintenance. This would be reflected in a positive relationship between the level of digitalization and more advanced Smart Maintenance patterns.

Overall, we expect that certain operating contexts would favor the adoption of different Smart Maintenance patterns. Further, if certain contingencies differ across the patterns, they may be useful in predicting group membership. Therefore, we hypothesize that:

H2a. Mass output orientation is positively related to more advanced Smart Maintenance patterns.

H2b. Automation is positively related to more advanced Smart Maintenance patterns.

H2c. Digitalization is positively related to more advanced Smart Maintenance patterns.

2.4. Performance implications

Configuration theory suggests that emergent patterns will differ in their relationship with performance (Flynn et al., 2010), specifically that configurations with more 'ideal' patterns are likely to have higher performance (Huo et al., 2019). This view is also consistent with the extensive body of literature on complementarities (Brynjolfsson and Milgrom, 2013), which suggests that organizations that possess mutually reinforcing combinations of tangible and intangible assets will outperform those who do not (Brynjolfsson et al., 2021). Consequently, Bokrantz et al. (2020b) theorize that an ideal Smart Maintenance implementation should focus on a careful, coordinated, and joint implementation of all four dimensions (p. 13). A configuration approach is indeed useful for helping managers in making decisions about Smart Maintenance implementation because it provides information about when and to what extent the four dimensions should be pursued.

To provide a fuller understanding of the performance implications of Smart Maintenance, we combine two distinct yet complementary configurational approaches. The first configurational approach focuses on the overall configurations, i.e., how the different Smart Maintenance patterns differ in their levels of performance. This approach is useful for understanding what the ideal pattern is and how the patterns as a whole are related to performance (Huo et al., 2019), and it has been widely used in OSCM research (Flynn et al., 2010; Huo et al., 2017). Following on from H1, this approach posits that manufacturing plants with strong and balanced Smart Maintenance patterns should have higher levels of performance. The second approach focuses on the four dimensions of Smart Maintenance as single necessary conditions for performance (Dul, 2016). That is, if any of the four dimensions are absent (or below a certain level), performance will not occur, and this cannot be compensated by other determinants. Still, if the four dimensions are present (or above a certain level), performance is not guaranteed, because also other determinants play a role. This approach is useful for understanding how manufacturing plants can prevent guaranteed failure and avoid wasting time, money, and other resources that could benefit the necessary condition(s) (Dul, 2020). Together, the two approaches are complementary because all single necessary conditions must be part of all overall configurations, and if any necessary condition is not satisfied first, performance will not improve by changing the value of any other determinant (Vis and Dul, 2018).

A configural notion of Smart Maintenance is broadly supported in the maintenance literature, which highlights that advanced maintenance practices that effectively leverage a combination of data-centric technologies, human capabilities, and organizational integration, are important to the performance of industrial assets along the lifecycle (Roda and Macchi, 2021; Silvestri et al., 2020). Specifically for manufacturing plants, the four dimensions of Smart Maintenance are proposed to be important for improving maintenance performance (e.g., reduced repair lead time, increased time between failures, and higher conformance quality of maintenance work) as well as improving productivity (e.g., smooth production flows from reduced downtime) (Bokrantz et al., 2020b). Thus, by combining two configurational approaches to understand the relationship between Smart Maintenance and performance, we hypothesize that:

H3a. Manufacturing plants with strong and balanced Smart Maintenance patterns have higher levels of maintenance performance.

H3b. High levels of the four dimensions of Smart Maintenance are necessary for a high level of maintenance performance.

H4a. Manufacturing plants with strong and balanced Smart Maintenance patterns have higher levels of productivity.

H4b. High levels of the four dimensions of Smart Maintenance are necessary for a high level of productivity.

In summary, our hypotheses specify relationships between configurations of Smart Maintenance (H1), environmental contingencies (H2), and key performance outcomes (H3 and H4). Thus, our theoretical framework substantiates how adoption patterns of Smart Maintenance are related to the performance of the manufacturing plant. Consistent with the conceptualization of Smart Maintenance (Bokrantz et al., 2020c), the theoretical domain where the hypotheses are expected to hold is broad and includes all manufacturing plants with a maintenance function. Fig. 1 visualizes the theoretical model and empirical scope of the study.

3. Research design and methods

3.1. Sampling and data collection

A survey instrument was used to collect data from manufacturing plants in Sweden. The focal unit was the manufacturing plant. The sampling frame consisted of a list of 1243 plants with more than 50 employees from the 12 largest sectors within the Swedish manufacturing industry, obtained from Statistics Sweden (food; wood; paper; coke and refined petroleum; chemicals; pharmaceutical; rubber and plastic; basic metals; fabricated metal; electric equipment; machinery and equipment; motor vehicles, trailers, and semi-trailers). These plants were selected because they represent a broad selection of the most important sectors, covering approximately 80% of the number of employees and value-added within the Swedish manufacturing industry. All plants received two physical cover letters. Both letters highlighted the objectives of the research, were respectively addressed to the maintenance manager and production manager at the plant, and included a request to participate in the study by filling out a questionnaire. Phone calls were deployed to stimulate participation. A total of 160 plants agreed to participate in the study. In the end, 145 plants filled out the questionnaire, broadly representing all sectors in the sampling frame. Thus, the overall response rate was 12% whilst the effective response rate was 91% (145 out of 160 identified plants). Early and late responses (i.e., first and last 25% of obtained responses) were compared on the number of employees, industrial sector, sales, and five randomly chosen construct variables (Armstrong and Overton, 1977). T-tests with large p-values (>0.05) suggested that non-response bias may not be a major concern.

The questionnaire was filled out by key informants who are knowledgeable about the variables, so as to reduce respondent bias. Key informants are the maintenance manager or engineer, or the production manager or engineer. In small companies, a single informant answered all questions (Kull et al., 2018). In larger companies, we attempted to have the maintenance questions answered by the maintenance manager or engineer, and the production questions by the production manager or engineer (Flynn et al., 2018). To ensure that the key informants were able to provide valid data, we stated in the cover letter that the

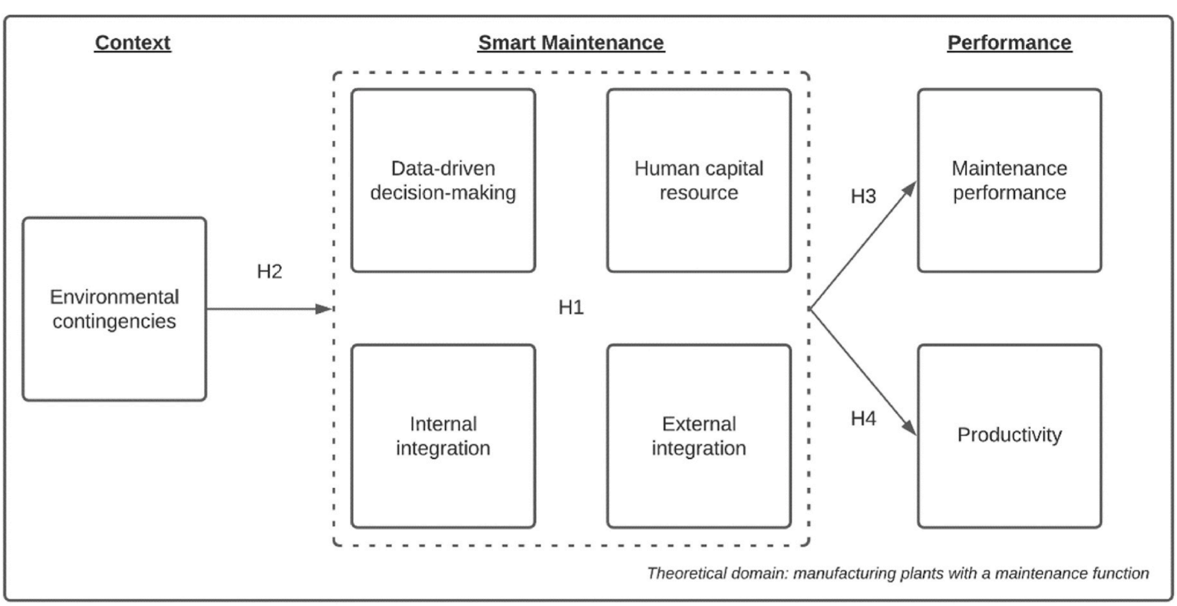

Fig. 1. Theoretical model and empirical scope of the study.

respondent to the questionnaire should have an overall understanding of maintenance and production management as well as an in-depth understanding of the plant's operations. We also clarified that the best persons to answer the question are the maintenance manager and production manager, followed by stating that if you are not the best person to answer the questions, please ask the most knowledgeable person in your plant to answer them. Further, demographic data showed that the average work experience was 11 and 8 years for the maintenance and production informants, respectively. This provided confidence that the respondents were capable of answering the questions in the survey. Further, we deployed a wide range of procedural remedies to reduce the risk of common method bias (Flynn et al., 2018). Specifically, we designed the survey so that independent and dependent variable responses were provided to some extent by different informants; provided explicit verbal and written instructions prior to administration; separated the predictor and criterion variables using buffer items and different response formats; and promised each plant an individual report as a reward for participation (MacKenzie and Podsakoff, 2012). Missing data were minimal: 3.44% and 1.65% construct-level missingness (Newman, 2014) for the single or maintenance informants and the production informants, respectively.

3.2. Measurement

This study focuses on six focal variables: data-driven decision-making (DDD), human capital resource (HCR), internal integration (INI), external integration (EXI), maintenance performance (MAIN), and productivity (PROD) (see Appendix A). Measures for DDD, HCR, INI, and EXI were drawn from Bokrantz et al. (2020a) and used 5-point Likert scales (1 = Not at all, 5 = Completely). Measures for MAIN and PROD were developed for this study. A pool of indicators was first drawn from literature as well as interviews with maintenance and production managers, reflecting sources of variability in quality, quantity, and timing of the corresponding performance dimensions (Holweg et al., 2018). For example, technical availability and mean time between failures reflect maintenance performance, and throughput time and throughput rate reflect productivity. Content validity was assessed by having pairs of academic and industrial raters assigning each indicator to its corresponding dimension. One round with adjustments followed by three rounds of replication provided acceptable results. The final scales consisted of 8 quasi-perceptional indicators per construct and used 7-point Likert scales that assessed performance compared to other plants in their industry (1 = Poor, low end of the industry, 7 = Superior in our industry).

Variable scores were estimated using Confirmatory Factor Analysis (CFA) using the WLSMV estimator in Mplus 7 (Muthén et al., 1997). Five indicators were dropped because of weak loadings (<0.5) (see Appendix A). Model fit indices were χ^2 (1875) = 2450.587, RMSEA = 0.046 [0.041–0.051], CFI = 0.92, WRMR = 1.20. The measurement model can therefore be considered acceptable (Hu and Bentler, 1999; MacKenzie et al., 2011; Yu, 2002). Convergent validity was supported by estimates of AVE ranging between 0.47 and 0.67 for all constructs. Although three constructs fall just below the 0.50 cut-off, all indicators had large loadings (>0.5) and small p-values ($p < 0.001$). Reliability was supported by bootstrapped estimates of construct reliability (>0.7, 1000 iterations) (MacKenzie et al., 2011). Discriminant validity was supported by AVE being greater than the squared correlations between constructs, as well as $\Delta\chi^2$ tests between constrained and unconstrained models for all pairs of constructs (Shaffer et al., 2016).

This study also included three complementary variables (see Appendix A): mass output orientation (MASS), automation (AUTO), and digitalization (DIGI). Measures for MASS were adopted from Swanson (2003) and consisted of the extent of use of four types of production processes. Measures for AUTO were adopted from the Productivity Potential Assessment Method (Almström and Kinnander, 2011) and consisted of the extent of use of four types of automation. Measures for DIGI consisted of the extent of use of six types of ICT capital based on the definition by the Organization for Economic Co-operation and Development (OECD) (Peña-López, 2002). All variables used 5-point Likert scales (1 = Not at all, 5 = Very high extent). MASS and AUTO were scored as weighted averages (the lowest type received a weight of one and the highest type received a weight of four, the weighted ratings were then divided by the sum of the weights to produce an index). DIGI was scored as an average.

3.3. Data analysis

To achieve theory-method fit (i.e., that the nature of the theory fits the method for generating meaningful results), we adopted the standardized methodological procedures by Hair et al. (2014) to develop the empirical taxonomy (H1), consisting of a two-step cluster analysis approach coupled with ANOVA and canonical discriminant analysis. This approach has been extensively applied within OSCM (Bokhorst et al., 2022; Flynn et al., 2010; Huo et al., 2017, 2019). Cluster analysis was used to classify plants into Smart Maintenance patterns. Hierarchical clustering was used first to determine the appropriate number of clusters, and non-hierarchical clustering was thereafter used to produce the final cluster solution (Hair et al., 2014). To profile the clusters, ANOVA was used to confirm the distinctiveness of the cluster variable differences (Flynn et al., 2010), and discriminant analysis was used to identify the underlying functions of strength and balance that differentiated the clusters as well as to assess the taxonomy's predictive ability (Huo et al., 2017, 2019). To test the influence of environmental contingencies (H2), discriminant analysis was used to assess if the contingency variables could distinguish whether a plant will belong to a particular Smart Maintenance pattern (Hair et al., 2014).

To test the relationships between Smart Maintenance and performance (H3–H4), we used a multi-method approach based on ANOVA and Necessary Condition Analysis (NCA) that is analytically similar to Bokhorst et al. (2022). Specifically, whereas H3a and H4a focus on the overall Smart Maintenance patterns, H3b and H4b focus on the four Smart Maintenance dimensions as single necessary conditions. Since the two types of hypotheses are complementary yet fundamentally different, different methods are needed. Specifically, we used ANOVA to test whether the Smart Maintenance patterns differ (on average) in their level performance, complemented with the Scheffe post hoc analysis to identify differences between specific patterns (Flynn et al., 2010). We used NCA (Dul, 2016) to test the necessity of the individual Smart Maintenance dimensions for performance. NCA is specifically capable of testing necessary conditions "in degree", i.e., that a certain level of the condition is needed for a certain level of the outcome. For the NCA, the CR-FDH ceiling line for continuous data is most suitable as we used standardized factor scores. We also computed the results with the CE-DFH ceiling line to compare the results between the two methods as a robustness check. The necessary condition hypotheses were evaluated using the effect size and the p-value. The substantive significance of the effect size was assessed by using the benchmarks suggested by Dul (2016) (p. 30): "$0 < d < 0.1$ as a small effect, $0.1 = d < 0.3$ as a medium effect, $0.3 = d < 0.5$ as a large effect, and $d \geq 0.5$ as a very large effect". In addition, $d = 0.1$ was used as the minimum level for considering the effect size as meaningful in theory and practice. To reduce the risk of false positives, we used NCA's statistical test to evaluate the evidence of the observed effect being due to random chance of unrelated variables. We performed 10.000 permutations and used 0.05 as the p-value threshold (Dul et al., 2020). To enhance the interpretation of NCA, we used the NCA bottleneck table, which is a tabular representation of the ceiling lines of the necessary conditions and shows which levels of the necessary conditions are needed for a certain level of performance.

Table 1
Cluster centroids.

	DDD	HCR	INI	EXI	n
Medium - Human Lagging (cluster 1)	0.26 (2,3,4)	−0.48 (2,3)	0.06 (2,4)	0.13 (2,4)	39
High Uniform (cluster 2)	0.73 (1,3,4)	0.64 (1,4)	0.62 (1,3,4)	0.47 (1,3,4)	30
Medium - Human Leaning (cluster 3)	−0.28 (1,2)	0.67 (1,4)	0.29 (2,4)	0.01 (2,4)	32
Low Uniform (cluster 4)	−0.55 (1,2)	−0.47 (2,3)	−0.70 (1,2,3)	−0.46 (1,2,3)	43
F	67.192[a]	93.189[a]	74.834[a]	27.845[a]	

Numbers in parentheses indicate the cluster(s) from which that cluster different with a p-value <0.05, yielded from Scheffe post hoc analysis.
[a] $p < 0.001$.

4. Results

4.1. Emergent taxonomy

H1 postulates that a taxonomy of Smart Maintenance emerges based on the levels of the four underlying dimensions: DDD, HCR, INI, and EXI. Hierarchical clustering was used first to determine the appropriate number of clusters, specifically in the form of an agglomerative approach using Euclidean distance and the complete-linkage method. To decide on the number of clusters, we analyzed the percentage change in the agglomeration coefficient together with scree plots, ensured that no clusters contained less than 10% of the observations, and confirmed that there were clear differences between the cluster variables. One outlier observation was deleted due to appearing in cluster solutions as a single-member and having high average dissimilarity between other observations. A classification using four clusters represented the best solution. We then applied non-hierarchical clustering using the K-means algorithm to produce the final four-cluster solution. The cluster variable differences were tested with ANOVA and Scheffe post hoc analysis (Table 1). Table 1 indicates that there were clear differences in all four dimensions between the clusters, and each cluster was assigned a label based on its patterns of cluster centroids (Fig. 2). The four clusters are labeled 'High Uniform', 'Medium Human Leaning', 'Medium Human Lagging', and 'Low Uniform'.

The High Uniform (cluster 2) comprised 30 manufacturing plants (21% of the sample) and had high levels of all dimensions across the board. The cluster reflected a pattern with high strength and balance, where the efforts to pursue data-driven practices (DDD) and organizational integration (INI, EXI) are distinctively higher than all the other clusters. While the level of HCR is not statistically higher than plants in Medium Human Leaning, it seems that the High Uniform cluster pursues a joint and coordinated implementation of all four dimensions. Plants in this cluster thus represent the leaders in Smart Maintenance adoption.

The Medium Human Leaning (cluster 3) and Medium Human Lagging (cluster 1) included 32 (22%) and 39 (27%) plants, respectively. These two clusters had similar, medium levels of INI and EXI, but they had opposite trends with respect to DDD and HCR. The clusters had small differences in the levels of DDD and large differences in the levels of HCR. Thus, the strongest differentiator between these two clusters

Table 2
Discriminant analysis.

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	4.594	78.2	78.2	0.906[a]
2	1.210	20.6	98.8	0.740[a]
3	0.070	1.20	100	0.256[a]

[a] $p < 0.001$.

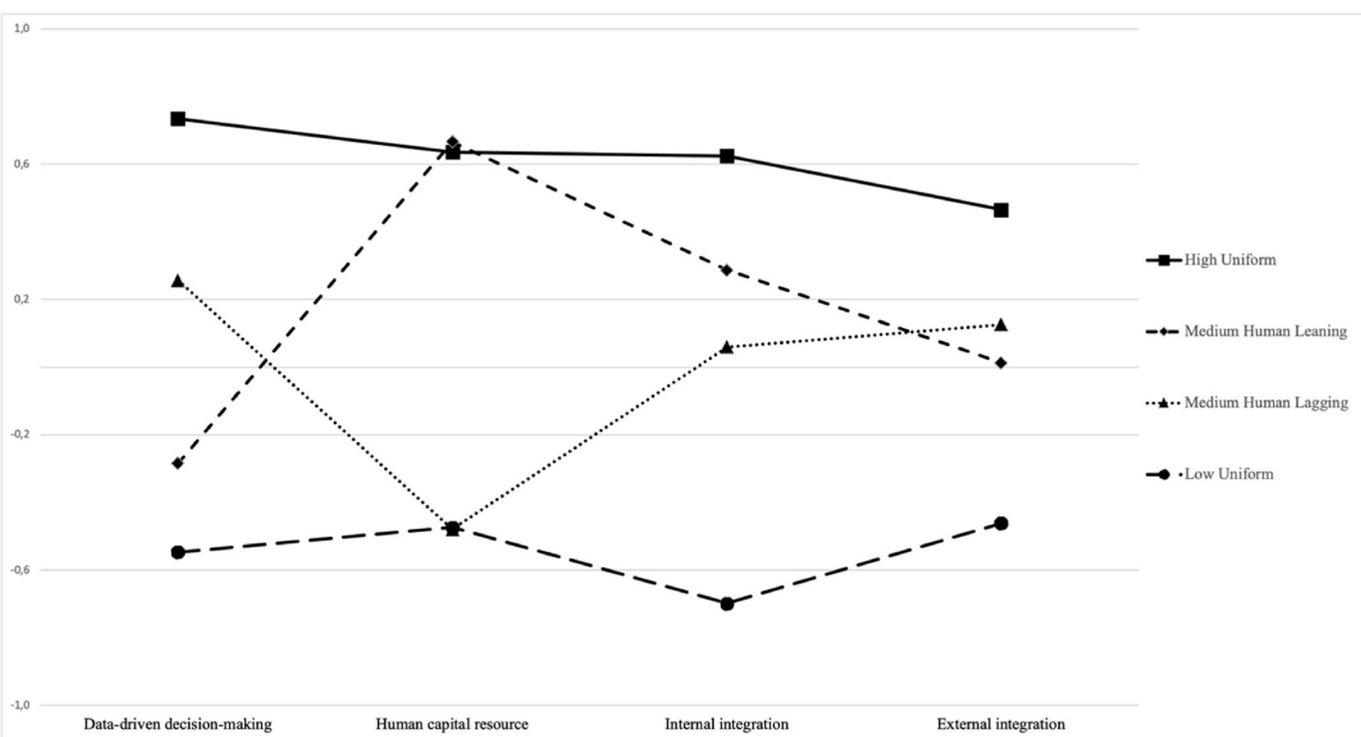

Fig. 2. Taxonomy of Smart Maintenance.

Table 3
Standardized canonical discriminant function coefficients.

	Function 1	Function 2
DDD	0.560	0.613
HCR	0.506	−0.772
INI	0.569	0.030
EXI	0.399	0.284

was the level of HCR, hence the label Human Leaning/Lagging. In essence, the Leaning cluster emphasizes the role of humans (HCR) and aims to leverage this capability within and across organizational borders (INI, EXI), whereas the Lagging cluster puts comparably more effort into developing technological decision-support (DDD). Since the two clusters vary in strength and balance, they are also characterized by plants that have put some effort into Smart Maintenance implementation but are still in the process of adjusting and improving the coordinated adoption of all four dimensions.

The Low Uniform comprised 43 plants (30%) and had low levels of all dimensions across the board. The cluster reflected a pattern with low strength but high balance and is thus characterized by plants that do not specifically emphasize any of the principles of Smart Maintenance. The levels suggest that these plants have underdeveloped technological infrastructures (DDD), low human resource focus (HCR), and maintenance functions that operate in organizational silos (INI, EXI). In essence, these plants lag behind in Smart Maintenance adoption.

To provide additional insights into the differentiation of the patterns, canonical discriminant analysis identified the functions that defined the clusters (Table 2). Table 3 reveals that the first two discriminant functions had eigenvalues larger than 1 and jointly explained 98.8% of the variance. The third function was discarded due to having a small eigenvalue (0.07) and low explained variance (1.2%). Function 1 was important in differentiating between High Uniform and Low uniform, whilst Function 2 was important in differentiating between Medium Human Lagging and Medium Human Leaning. Function 1 thus represents strength and Function 2 represents balance, which is illustrated in Fig. 3. Since Function 1 explained substantially more variance (78.2%) compared to Function 2 (20.6%), strength represents the strongest differentiator between the patterns.

Finally, a total of 97.2% of the cross-validated plants were correctly classified, indicating that the Smart Maintenance taxonomy has high predictive validity and is not prone to misclassification. Taken together, this evidence suggests that manufacturing plants can be clustered into groups with different levels of Smart Maintenance strength and balance, based on the four dimensions of DDD, HCR, INI, and EXI. This provides support for H1.

4.2. Environmental contingencies

H2 postulates that three different environmental contingencies are related to the Smart Maintenance patterns. Discriminant analysis with all three variables (MASS, AUTO, and DIGI) showed that the cluster mean differences had a smaller p-value for DIGI ($p = 0.018$) compared to MASS ($p = 0.891$) and AUTO ($p = 0.054$). AUTO and MASS also did not have a substantively meaningful portion of explained variance or canonical correlation. Thus, there was no evidence that supported H2a or H2b. A discriminant analysis using only DIGI yielded a function with substantively meaningful canonical correlation ($r = 0.268$, $p = 0.016$). However, the eigenvalue was just below 1 and the function could only correctly classify 46.5% of the plants. Thus, the level of digitalization did not have strong validity for predicting cluster membership. Still, the positive loadings for High Uniform (0.398) and Medium Human Leaning (0.138) and the negative loadings for Medium Human Lagging (−0.04) and Low Uniform (−0.353) indicate that more advanced Smart Maintenance patterns are related to environments characterized by a higher level of digitalization. This is illustrated in Fig. 4. The evidence thereby provides partial support for H2c.

4.3. Performance implications

H3 and H4 postulate that Smart Maintenance is related to the maintenance performance and the productivity of the manufacturing plant. The ANOVA results (Table 4) show that there were differences in

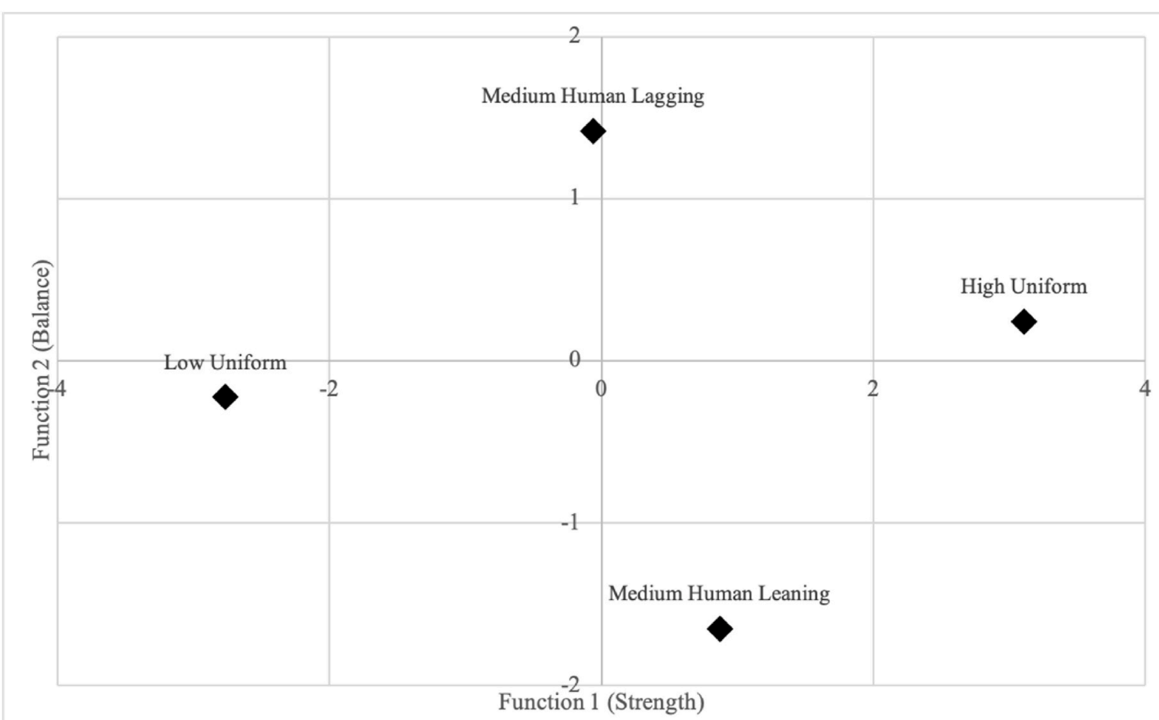

Fig. 3. Cluster centroids.

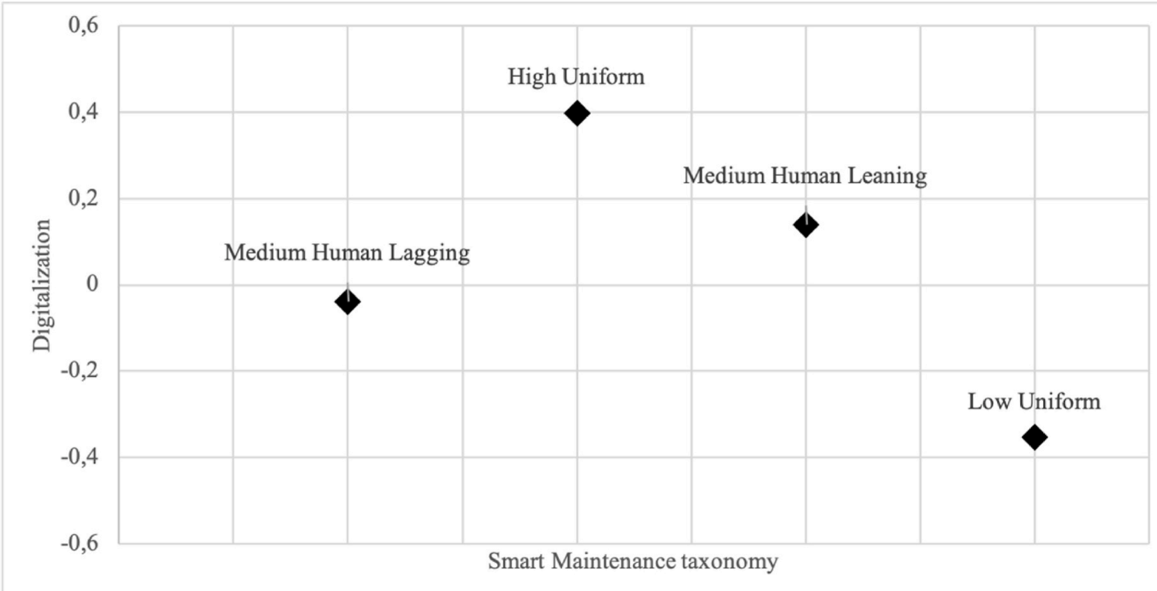

Fig. 4. Cluster centroids at the corresponding level of digitalization.

Table 4
Analysis of variance.

	Medium Human Lagging (cluster 1)	High Uniform (cluster 2)	Medium Human Leaning (cluster 3)	Low Uniform (cluster 4)	F
Maintenance performance	−0.344 (2,3)	0.72 (4)	0.431 (4)	−0.489 (2,3)	11.648[a]
Productivity	−0.181 ()	0.255 ()	0.193 ()	−0.158 ()	14.227[a]

Numbers in parentheses indicate the cluster(s) from which that cluster is different with a p-value <0.05, yielded from Scheffe post hoc analysis.
[a] $p < 0.001$.

Table 5
NCA parameters.

Model	Ceiling line	Effect size	P-value
DDD - MAIN	CE-FDH	0.22	<0.001
	CR-FDH	0.23	<0.001
HCR - MAIN	CE-FDH	0.30	<0.001
	CR-FDH	0.29	<0.001
INI - MAIN	CE-FDH	0.21	0.001
	CR-FDH	0.19	0.010
EXI - MAIN	CE-FDH	0.21	0.003
	CR-FDH	0.19	0.007
DDD - PROD	CE-FDH	0.10	0.314
	CR-FDH	0.10	0.295
HCR - PROD	CE-FDH	0.10	0.399
	CR-FDH	0.09	0.509
INI - PROD	CE-FDH	0.09	0.437
	CR-FDH	0.08	0.493
EXI - PROD	CE-FDH	0.18	0.004
	CR-FDH	0.16	0.012

maintenance performance between the patterns, supporting H3a. The Scheffe post hoc analysis yielded additional insights into the differences between specific patterns. We observed a tendency towards two main groups: high performers and low performers. The high performers were High Uniform and Medium Human Leaning. They had the best maintenance performance (0.720 and 0.431, respectively) and there was no clear difference between them. The low performers were Low Uniform and Medium Human Lagging. They had the worst maintenance performance (−0.344 and −0.489, respectively) and there was no clear difference between them. The two high performers were different from the two low performers. The results in Table 4 also show that there were differences in productivity between the Smart Maintenance patterns, supporting H4a. Similar to the results for maintenance performance, the high performers, i.e., High Uniform and Medium Human Leaning, had the best productivity (0.255 and 0.193, respectively). The low performers, i.e., Low Uniform and Medium Human Lagging, had the worst productivity (−0.181 and −0.158, respectively). However, the Scheffe post hoc analysis showed that there were no clear differences between any specific patterns. In sum, the evidence suggests that manufacturing plants with stronger and more balanced Smart Maintenance patterns have higher maintenance performance and productivity.

The NCA results are shown in Table 5. Medium effect sizes ($0.19 = d < 0.30$) and small p-values (well below 0.05) are observed for the relationships between four Smart Maintenance dimensions (DDD, HCR, INI, EXI) and maintenance performance (MAIN). The largest effect size is observed for HCR-MAIN ($d = 0.30$). The effect sizes are substantively meaningful and the statistical tests indicate a low probability of the evidence of the observed effect being due to random chance of unrelated variables. The presence of necessary conditions is illustrated by fairly large empty spaces in the upper-left corner of the NCA XY-plots (see Appendix B). Thus, the evidence provides support for H3b. In contrast, small effect sizes ($0.08 = d < 0.18$) and large p-values ($0.295 = p < 0.509$) are observed for three of the relationships between Smart Maintenance dimensions (DDD, HCR, INI) and productivity (PROD). That is, the effect sizes are equal to or less the minimum level to be considered meaningful ($d = 0.1$), and the statistical tests imply that the evidence for the effects may be due to unrelated random variables. Thus, H4b is not supported. Still, one of the relationships (EXI – PROD) shows a medium effect size and small p-value, warranting further attention for its potential to be considered a necessity. In sum, the evidence suggests that the four dimensions of Smart Maintenance are single necessary conditions for maintenance performance, but not for productivity.

Table 6 shows the NCA bottleneck table for the supported necessary conditions in H3a. Because the results for CE-FDH and CR-FDH are similar (Table 5), we only show the bottleneck table for the CR-FDH

Table 6
NCA bottleneck table.

CR-FDH (percentage range)					CR-FDH (percentiles)				
MAIN	DDD	HCR	INI	EXI	MAIN	DDD	HCR	INI	EXI
0	NN	NN	NN	NN	0	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)
10	NN	NN	NN	NN	10	0.0 (0)	0.0 (0)	0.0 (0)	0.0 (0)
20	NN	NN	NN	NN	20	0.7 (1)	0.0 (0)	0.0 (0)	0.0 (0)
30	NN	NN	NN	NN	30	2.1 (3)	2.1 (3)	0.0 (0)	0.0 (0)
40	8.1	8.1	NN	NN	40	2.8 (4)	2.8 (4)	0.7 (1)	1.4 (2)
50	17.9	21.2	8.7	10.2	50	5.5 (8)	4.8 (7)	2.8 (4)	1.4 (2)
60	27.7	34.3	19.7	20.6	60	11.0 (16)	10.3 (15)	4.1 (6)	2.1 (3)
70	37.5	47.3	30.8	31.0	70	13.8 (20)	18.6 (27)	6.2 (9)	3.4 (5)
80	47.3	60.4	41.9	41.4	80	18.6 (27)	36.6 (53)	15.9 (23)	9.7 (14)
90	57.1	73.5	53.0	51.7	90	38.6 (56)	53.8 (78)	29.7 (43)	25.5 (37)
100	66.9	86.6	64.1	62.1	100	77.9 (113)	93.8 (136)	77.9 (113)	89.7 (130)

ceiling line. The bottleneck table is displayed to the left as the percentage range between min (x,y) and max (x,y), and to the right as percentiles (percentage and between brackets the number of plants that were not able to reach the desired level of maintenance performance). The left side of Table 6 (percentage range) shows that for low levels of maintenance performance (up to 30% MAIN), none of the conditions are necessary ("NN"). This indicates that manufacturing plants do not need to put any of the Smart Maintenance dimensions in place, as long as they satisfy with being low performers. If plants have a desire to become at least medium performers (above 50% MAIN), then at least low levels of the four dimensions are needed (17.9% DDD; 21.2% HCR; 8.7% INI; 10.2% EXI). Finally, plants that aim to become high performers (80% MAIN or higher) need medium to high levels of the four dimensions (47.3–66.9% DDD; 60.4–86.6% HCR; 41.9–64.1% INI; 41.4–62.1% EXI). The right side of Table 6 (percentiles) shows that almost no plants are blocked from becoming medium performers (up to 50% MAIN) due to their current levels of the four dimensions (between 1.4 and 5.5% for the four dimensions, respectively). However, between 14 and 53% of the plants in the sample (27% DDD; 53% HCR; 23% INI; 14% EXI) are blocked from becoming high performers (80% MAIN or higher). The bottleneck table thereby illustrates how the four dimensions of Smart Maintenance are individually necessary for a high level of maintenance performance.

5. Discussion

By applying a configurational approach, we developed an emergent taxonomy of Smart Maintenance and empirically showed that more advanced Smart Maintenance patterns may be more prevalent in operating environments characterized by a high level of digitalization. We also uncovered that manufacturing plants with strong and balanced Smart Maintenance patterns have higher maintenance performance and productivity, as well as that high levels of the four dimensions of Smart Maintenance are individually necessary for a high level of maintenance performance. Our findings have a range of theoretical and managerial implications.

5.1. Theoretical implications

Research on Smart Maintenance is still in its infancy, and unified scholarly development has been constrained by the use of different notions of Smart Maintenance and similar/overlapping concepts (Huang et al., 2019; Roda and Macchi, 2021). This issue of concept proliferation has caused confusion among maintenance scholars and acted as a barrier to consistent operationalizations and reproducibility of theory-testing research. In this study, we remedy this issue by building on the previous conceptualization (Bokrantz et al., 2020c) and operationalization (Bokrantz et al., 2020a) of Smart Maintenance and obtaining large-sample confirmatory evidence of construct validity (Appendix A). By empirically testing the relationships between items and constructs for the four dimensions of Smart Maintenance (DDD, HCR, INI, EXI), we firmly establish a foundation for accumulated knowledge creation. Specifically, the evidence of construct validity facilitates empirical replications and extensions, enables comparability across studies, and serves as a base for interpreting a variety of literature that focuses on maintenance practices within Industry 4.0 more broadly (Sandu et al., 2022; Silvestri et al., 2020; Tortorella et al., 2022).

Owing to the consistent conceptualization and operationalization of Smart Maintenance, this study is the first to empirically investigate adoption patterns and performance implications. By jointly studying the four dimensions of Smart Maintenance, environmental contingencies, and maintenance performance and productivity, the study adds richness to the Smart Maintenance literature. Specifically, the emergent patterns show that manufacturing plants can be classified based on their different levels of Smart Maintenance dimensions. The empirical taxonomy thus reveals insights into the underlying structure of Smart Maintenance and illustrates how managers place different emphases on the four dimensions. The taxonomy thereby substantiates the Smart Maintenance concept and provides a parsimonious classification that is useful for research and pedagogy. Further, finding that more advanced Smart Maintenance patterns may be more prevalent in digitalized operating environments provides evidence for the core predictions made during its original conceptualization (Bokrantz et al., 2020c). By combining two configurational approaches and using multiple methods for testing the relationships between Smart Maintenance and performance, we uncover that the emergent patterns of Smart Maintenance differ in their levels of maintenance performance and productivity. We also show that the four Smart Maintenance dimensions are single necessary conditions for maintenance performance, implying that they must be put and kept in place to enable a high level of maintenance performance. These findings substantially confirm the significant role of Smart Maintenance in maintenance theory and practice (Bokrantz et al., 2020b; Roda and Macchi, 2021). As a whole, this study advances research on Smart Maintenance from theory building to theory testing, which expands and strengthens its theoretical and empirical foundation.

5.2. Managerial implications

The findings provide substantial managerial advice for making strategic decisions about Smart Maintenance implementation. The combined evidence from ANOVA (Table 4) and NCA (Tables 5–6) broadly suggests that managers should pursue better performance by implementing Smart Maintenance as a whole. That is, managers who formulate and execute strategies for Smart Maintenance should focus on coordinated and joint implementation of all four dimensions. Further, our multimethod approach yields granular managerial guidelines that can be used to formulate evidence-based blueprints for successful Smart Maintenance implementation. To this end, we propose managerial guidelines at two levels: (1) generic guidelines for Smart Maintenance as a whole and (2) specific guidelines for each strategic group within the taxonomy.

Managers seeking generic guidelines for Smart Maintenance implementation are advised to pursue the following two-step recommendations. Firstly, maintenance managers need to satisfy the necessary conditions. That is, manufacturing plants with a desire to become high maintenance performance must first ensure that all four dimensions of Smart Maintenance are put and kept in place at the required minimum level. Each plant should make different strategic choices based on its current levels of Smart Maintenance and desired level of performance. We therefore advise maintenance managers to conduct a current state assessment by thoroughly evaluating their existing levels on all of the four dimensions, combined with formulating the desired target level of maintenance performance. Since most manufacturers face limitations in time, money, and other resources, maintenance managers need to focus their attention on investing in the current bottleneck dimension (if any) for achieving the desired maintenance performance level. Secondly, when, and only when, all four dimensions have been put and kept in place at the required minimum level, managers should focus their attention on further progressing toward stronger and more balanced Smart Maintenance patterns. Both strength and balance are important to maintenance performance and productivity, implying that managers should strive for the long-term goal of achieving a strong and balanced (i.e., 'ideal') pattern of Smart Maintenance.

Managers seeking specific guidelines for their manufacturing plant, based on the corresponding group membership in the taxonomy, are advised to pursue the following recommendations. The Low Uniform cluster comprised plants that lag behind in Smart Maintenance adoption. We recommend that these plants first ensure a solid base of maintenance fundamentals (e.g., preventive maintenance planning and skills in mechanical and electrical maintenance). To advance their maintenance operations, it is important for managers to reflect on the role and importance of maintenance for their plant, and if deemed appropriate and desired, start exploring the potential of adopting the principles of Smart Maintenance. The Medium Human Lagging cluster included plants where the human resources represent the most important short-term improvement potential. Therefore, we recommend that these plants conduct a mapping of current and future roles in maintenance, identify competence gaps, and invest in the education and training of the workforce. To reinforce the adoption of Smart Maintenance, we also recommend augmenting workers with new digital technologies. Plants in the Medium Human Leaning cluster have humans as their strongest capability. To further stimulate a transition towards more advanced Smart Maintenance patterns, we recommend identifying shifts from traditional to future competence profiles, investing in digital technologies that augment workers, and creating new organizational processes that leverage new technologies. Finally, the High Uniform cluster represented the leaders in Smart Maintenance adoption. We recommend that these plants continue their improvement journey to further strengthen their position as industry role models; not only to advance themselves but also to help others that lag behind. For example, it is advised to keep exploring and developing more advanced solutions for data analytics (e.g., machine learning for predictive maintenance) and focusing on creating novel synergies between all four dimensions of Smart Maintenance.

These managerial implications complement and extend previous research. Prior empirical studies have focused on two topics: (1) understanding *why* managers choose to implement modernized maintenance practices using the Diffusions of Innovation theory (Lundgren, 2021; Tortorella et al., 2021); and (2) *how* maintenance managers can be supported in their strategy development endeavors by developing practice-oriented methodologies (Lundgren et al., 2021; Polenghi et al., 2021) and maturity models (Macchi and Fumagalli, 2013; Nemeth et al., 2019; Poór et al., 2019) that facilitate the formulation of goals, priorities, and improvement activities. We complement this literature by providing novel empirical insights about *when* and to *what extent* the four dimensions of Smart Maintenance should be pursued to achieve a desired level of performance. We also extend these research streams by providing a validated measurement instrument (Appendix A) that practitioners can use as a self-assessment tool to understand, evaluate, and benchmark Smart Maintenance in their organization.

5.3. Limitations and further research

While our study makes significant contributions to the maintenance literature and has important implications for practice, it also has limitations. Firstly, we used a cross-sectional, partly single-respondent survey design that has limitations concerning common method bias and respondent bias (Flynn et al., 2018). Thus, future research would benefit from further advancing the research design and careful collection of good data (i.e., sampling and measurement), especially studies aiming at replications and extensions. Secondly, we used cluster analysis to identify the Smart Maintenance configurations, which is suitable for large-sample research that aims to investigate thematic patterns (Hair et al., 2014; Hinings, 2018; Short et al., 2008). This approach has two main limitations: (1) the robustness of the empirically derived cluster solutions needs to be cross-validated across more samples, and (2) the causal relationships within specific configurations remain unknown (Miller, 2018). Future research could overcome these limitations by pursuing replication studies and examining more in-depth nuances across configurations through complementary qualitative data and neo-configural methods such as Qualitative Comparative Analysis (QCA) (Ragin, 2008). Thirdly, the scope of our study was limited to testing whether the emergent patterns were more prevalent in certain operating environments, and we were surprised that propositions with clear theoretical backing lacked empirical support. Thus, we call for more research that further investigates the influence of environmental contingencies, which would entail not only further assessing the prevalence of Smart Maintenance in certain environments but also examining the returns on Smart Maintenance in those environments. Fourthly, while our recommendations for successful Smart Maintenance implementation provide clear guidance to practicing managers, they are still limited to Smart Maintenance as a whole and the four emergent patterns. Therefore, future research could focus on upscaling the managerial implications by developing individualized recommendations for specific manufacturing plants. One such avenue would be to use the insights from this study as a foundation for developing a maturity model that is theoretically grounded, methodologically rigorous, and empirically validated (Becker et al., 2010). Specifically, the emergent patterns in this study can be interpreted as representing progression toward maturity through stages of configurations of multiple, complex conditions. In other words, there is no single, linear way of developing Smart Maintenance, rather there exist multiple, equally effective pathways to move between the four configurations (Fig. 2). To empirically develop a maturity model capable of deriving individualized pathways for manufacturing plants, researchers could make use of recent developments in social science research methods such as a combination of NCA and QCA (Lasrado et al., 2016).

6. Conclusions

This study extends and strengthens research on industrial maintenance management by applying a configurational approach to examine adoption patterns and performance implications of Smart Maintenance (i.e., data-driven decision-making, human capital resource, internal integration, and external integration). Firstly, we substantiate the concept of Smart Maintenance by developing an empirical taxonomy consisting of four emergent patterns that reflect the strength and balance of the underlying dimensions (i.e., Low Uniform, Medium Human Lagging, Medium Human Leaning, and High Uniform). Secondly, we show that the Smart Maintenance patterns are related to the operating environment of the manufacturing plants, where more advanced patterns may be more prevalent in plants with higher levels of digitalization. This firmly positions the Smart Maintenance concept within the overall landscape of industrial digitalization. Thirdly, we move from theory building to theory testing by empirically demonstrating that manufacturing plants with stronger and more balanced Smart Maintenance have higher maintenance performance and productivity, as well as that high levels of four dimensions of Smart Maintenance are individually necessary for a high level of maintenance performance. In sum, this study provides both richness and comprehensiveness to the maintenance literature by enhancing our understanding of Smart Maintenance, and it offers practical advice to managers when developing strategies for Smart Maintenance implementation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. Measurement items and factor analysis

Factor model and items for the six focal variables in the study (DDD, HCR, INI, EXI, MAIN, PROD).

Construct and items	Loading	S.E
Data-driven decision-making (DDD)		
Our maintenance decisions are data-driven	0.67	0.04
We direct our maintenance actions based on collected equipment data	0.81	0.03
Our maintenance plans are based on credible data analysis	0.87	0.03
We combine several different data sources in order to make maintenance decisions	0.80	0.04
Our maintenance decisions are based on quality-assured data	0.86	0.03
Our decisions about maintenance actions are based on data from the plant	0.76	0.04
We make improvement decisions based on data analysis	0.79	0.03
Our maintenance plans are determined using all available equipment data	0.85	0.03
We use data analysis to make maintenance decisions	0.92	0.02
We make maintenance decisions based on quality-assured equipment data	0.85	0.04
Human capital resource (HCR)		
Our maintenance employees are well-trained to carry out their work tasks	0.73	0.04
Our maintenance employees have sufficient education to carry out their work tasks	0.79	0.04
Our maintenance employees quickly learn how to carry out new work tasks	*	*
Our maintenance employees easily exchange knowledge with each other	0.51	0.06
Our maintenance employees have insufficient competence**	0.85	0.03
Our maintenance employees are considered the best in our industry sector	0.84	0.04
Our maintenance employees have the right competence to carry out their work tasks	0.84	0.04
Our maintenance employees lack the competence to carry out their work tasks**	0.75	0.04
Our maintenance employees have sufficient experience to carry out their work tasks	0.59	0.05
Our maintenance employees are experts within their respective roles	0.67	0.05
Our maintenance employees continuously develop their skills	0.57	0.05
Our maintenance employees are skilled at solving problems together	0.63	0.06
Our maintenance employees are skilled at carrying out their work tasks	0.73	0.05
We have a lack of maintenance competence in our plant**	0.58	0.06
Internal integration (INI)		
Maintenance collaborate well with Production in our plant	0.67	0.05
Our maintenance actions are coordinated with other functions in our plant	0.67	0.05
Maintenance participate in new acquisition projects in our plant	*	*
Communication between Maintenance and other functions works well in our plant	0.75	0.06
Maintenance regularly share data with other functions in our plant	0.72	0.06
Maintenance is isolated from other functions in our plant**	0.55	0.07
Maintenance and Production achieve common goals together in our plant	0.65	0.05
Maintenance and other functions understand each others' work tasks in our plant	0.73	0.04
Maintenance are well synchronized with Production in our plant	0.85	0.03
Knowledge is shared between Maintenance and other functions in our plant	0.75	0.04
Maintenance easily exchange information with other functions in our plant	0.68	0.05
Maintenance make joint decisions together with other functions in our plant	0.78	0.04
The maintenance system (CMMS) is integrated with other systems in our plant	*	*
Maintenance solves problems together with other functions in our plant	0.64	0.05
There are no barriers between Maintenance and other functions in our plant	0.62	0.05
External integration (EXI)		
We are well-integrated with our suppliers regarding maintenance	0.64	0.05
We share maintenance data within external networks of companies	0.80	0.06
We collaborate with other plants regarding maintenance	0.72	0.06
We easily exchange information with our suppliers regarding maintenance	0.63	0.05
We synchronize our maintenance actions with our suppliers	0.69	0.04
We collaborate with our suppliers to improve their quality regarding maintenance	0.65	0.06
We collaborate closely with our suppliers regarding maintenance	0.82	0.03

(*continued on next page*)

(*continued*)

Construct and items	Loading	S.E
We collaborate within networks of other companies regarding maintenance	0.54	0.07
Our suppliers are actively involved in our maintenance improvement projects	0.70	0.05
We share equipment data with our suppliers regarding maintenance	0.64	0.05
We solve maintenance problems together with our suppliers	0.77	0.04
Our maintenance systems are **not** integrated with those of our suppliers**	*	*
We have strategic partnerships with our suppliers with regard to maintenance	*	*
Maintenance performance (MAIN)		
Technical availability	0.80	0.03
Mean Time Between Failures (MTBF)	0.90	0.03
Mean Time To Repair (MTTR)	0.75	0.04
Mean Time Waiting (MTW)	0.63	0.05
Unplanned downtime	0.77	0.04
Number of unplanned maintenance actions	0.62	0.04
Conformance quality of maintenance work	0.84	0.04
Maintenance work causing downtime	0.50	0.05
Productivity (PROD)		
Throughput time	0.83	0.04
Throughput rate	0.75	0.04
Time from customer order to delivery	0.61	0.06
On time delivery performance	0.61	0.06
Set-up time	0.64	0.06
Production yield	0.74	0.05
Deviation from actual production plan	0.72	0.05
Scrap and rework	0.57	0.06

* Dropped item.

** Reverse item.

Measures for the three complementary variables in the study (MASS, AUTO, and DIGI).

Mass output orientation (MASS), from Swanson (2003).

Type	Definition
Job shop	Machines of the same type placed together
Cellular	Production cells with batch process
Line	Line-oriented manufacturing process
Process	Continuous manufacturing process

Automation (AUTO), from Almström and Kinnander (2011).

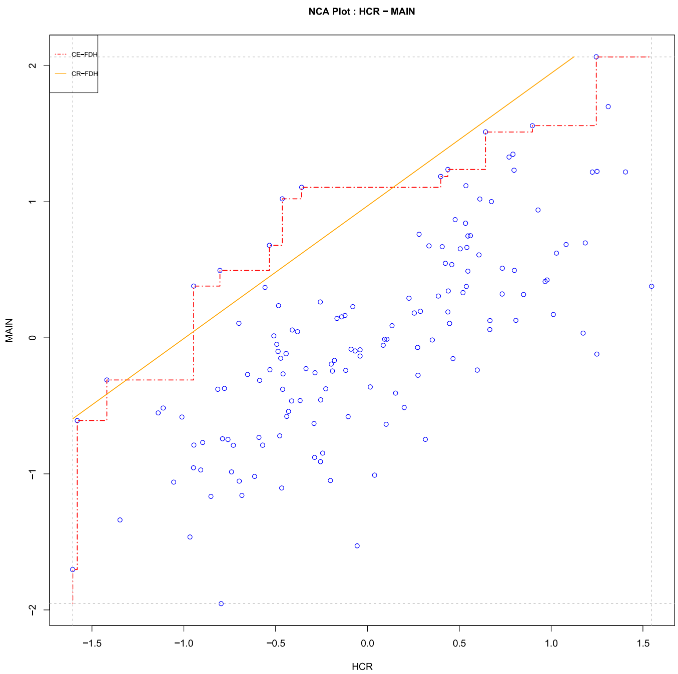
Type	Definition
Manual production	Manual work, e.g., assembly or machining.
Semi-automatic production	Automatic equipment with more manual work, e.g., manual set-up or finishing.
Fully automated production	Automatic equipment with manual material handling. Some manual work during set-up.
Process production	Completely automatic equipment, only manual monitoring and quality control.

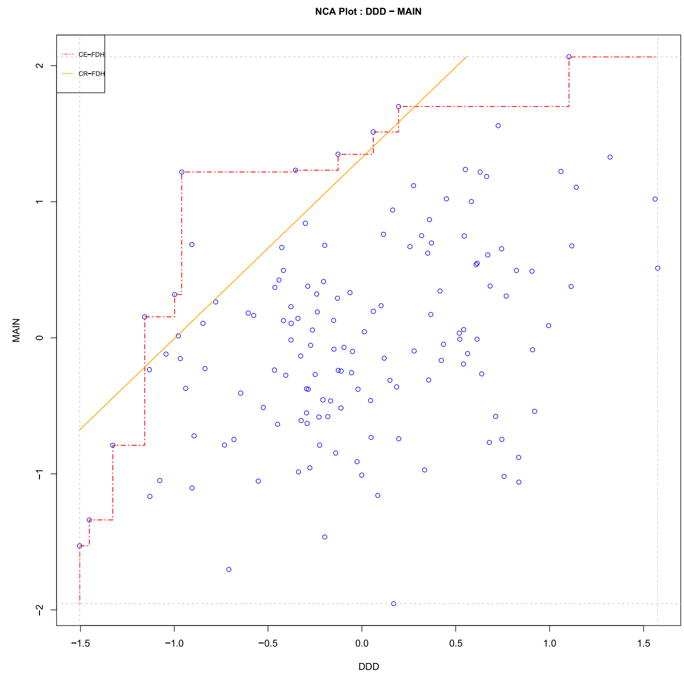
Digitalization (DIGI), from Peña-López (2002).

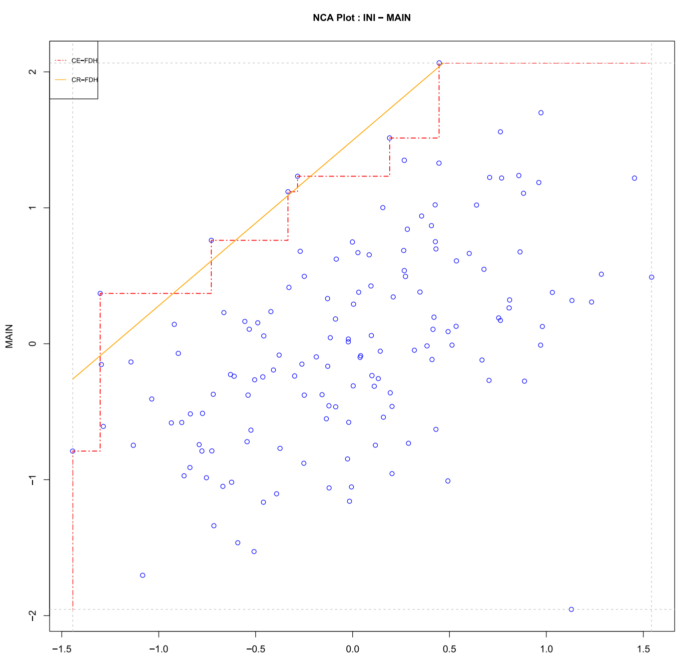
Type	Definition
Hardware, internal	Computation and storage hardware such as computers, servers, programmable controllers, sensors, PLC, etc.
Hardware, external	Computation and storage hardware as a service, e.g., cloud service.
Software, purchased from suppliers	Information systems and tools such as ERP, MES, CMMS, SCADA, IoT platforms, etc.
Software, developed in-house	In-house information systems, including also extension and development of external systems.
Fixed communication equipment	Infrastructure and equipment for digital communication such as routers, switches, networks, firewalls, etc.
Mobile communication equipment	Infrastructure and equipment for wireless communication such as access points for WiFi, radio-based stations for 4G, etc.

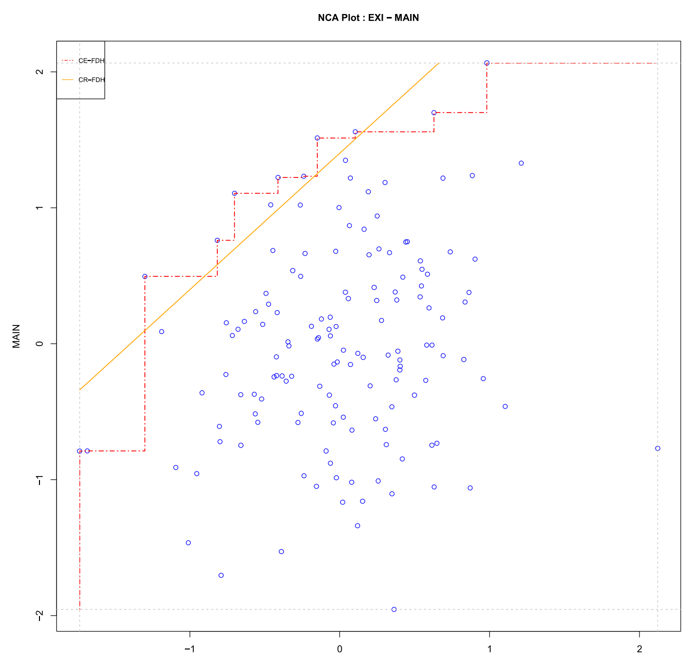
Appendix B. NCA plots

NCA XY-plots (CR-FDH and CE-FDH ceiling lines) for the supported necessary conditions in Table 5.









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