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Assessing to what extent smart manufacturing builds on lean principles

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ABSTRACT

This study explores to what extent the adoption and performance of smart manufacturing technologies builds on the adoption of lean principles. Primary explorative survey data on the level of adoption of smart manufacturing technologies and lean principles and various operational performance outcomes were collected from a set of Dutch manufacturers and analysed using Cluster Analysis, ANOVA, and Necessary Condition Analysis (NCA). The Cluster Analysis shows that while lean is also applied without smart ("lean-only" companies), smart technologies are mostly applied in conjunction with lean ("lean and smart" companies), suggesting that the presence of lean principles is necessary for smart implementation. A third group of companies shows a low use of lean and smart ("non-adopters"). The NCAs further specify the extent of this necessity by showing that all individual smart manufacturing technologies used in our construct require presence of lean principles, with MES systems having the strongest dependency. Performance wise, lean-only and lean and smart companies have comparable superior performance compared to non-adopters when considering an aggregate operational performance measure using the dimensions of quality, delivery, flexibility and cost. When analysed separately, the aggregate level results remain true for quality and delivery performance. However, for flexibility, the superiority of lean-only companies is more apparent, while for cost, lean and smart companies are superior. This shows that implementing smart requires lean, but lean may suffice depending on the specific performance objectives strived for.

1. Introduction

To remain competitive, companies are constantly searching for new concepts that can improve the performance that is important in their industry. In recent decades, the application of principles of lean thinking has steadily progressed and been extended to various industry and service sectors (Hines et al., 2004; Jasti and Kodali, 2014). This has been shown to positively affect operational performance (e.g. Cua et al., 2001; Fullerton et al., 2014; Shah and Ward, 2003). Currently, Industry 4.0 technologies are rapidly changing production environments in many industries (Kang et al., 2016; Porter and Heppelmann, 2015) and provide further opportunities to improve operational performance (Brettel et al., 2014; Dalenogare et al., 2018; Szász et al., 2021).

The aim of this study is to explore to what extent the adoption and performance of smart manufacturing technologies builds on the adoption of lean principles. To address this aim, we specifically determine (1) the extent to which specific smart technologies require the presence of lean principles, and (2) the detailed operational performance contribution (quality, delivery, flexibility and cost) of applying smart manufacturing technologies in combination with lean principles, compared to applying lean principles only.

Only few studies have reported on the necessity of lean for smart. By analysing different clusters of companies based on different levels of lean and smart implementation, some studies concluded that companies that widely implement lean are more likely to adopt smart (Tortorella and Fettermann, 2018), thereby suggesting lean implementation to be a facilitating condition for smart implementation (Rossini et al., 2019). But it is yet unclear to what extent lean implementation is required to become smart, which justifies a more detailed analysis based on necessary conditions (Dul, 2016). A necessity relationship is quite different from a mediating or a moderating one. If a construct mediates the relationship between two other constructs, it is part of the causal pathway between these two constructs. If a construct moderates the relationship between two other constructs, it can alter the direction or the strength of this relationship. In contrast, a necessary condition indicates that in the absence of the condition, the outcome will not occur, while the outcome is not guaranteed if the condition is in place (Dul, 2016).

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Applied to the relation between lean and smart, we focus on whether applying lean is required (necessary) for implementing smart manufacturing technologies. This does not exclude that smart technologies can mediate or moderate the relationship between lean and performance at the same time. In essence, necessity in this context means that a certain level of smart technology implementation cannot exist without a certain level of lean implementation.

Studies reporting on the performance effects of the interaction between smart and lean are more numerous. Several recent studies have studied this based on empirical data (Buer et al., 2021; Kamble et al., 2020; Tortorella et al., 2019). The majority of the studies report complementary performance effects of applying lean and smart (e.g. Buer et al., 2021; Chiarini and Kumar, 2021a; Dombrowski et al., 2017; Khanchanapong et al., 2014; Rossini et al., 2019; Tortorella and Fettermann, 2018). Other studies have further explored the type of interaction, which was shown to be a moderating effect of smart on the relation between lean and performance by several authors (Tortorella et al., 2018, 2019), while Kamble et al. (2020) found a mediating effect of lean on the relation between smart and performance. However, all these studies based their findings on aggregated performance measures. Therefore, possible differences in effects between individual operational performance measures, such as quality, delivery, flexibility and cost, could not be observed.

Our study addresses the aforementioned gaps by exploring to what extent the adoption of smart manufacturing technologies requires the foundation provided by lean and by determining whether smart is able to build on that foundation to contribute to the individual operational performance measures of quality, delivery, flexibility and cost. To address these questions, we use explorative survey data collected from a set of Dutch manufacturers. The data contains the level of adoption of smart manufacturing technologies and lean principles and a wide set of operational performance outcomes.

This study contributes to the literature by showing the extent to which a number of key individual smart manufacturing technologies require presence of lean principles based on empirical data. High implementation levels of product tracking, MES, and flexible automation are shown to require a high implementation level of application of lean principles. Only work-on-screen requires a lower implementation level of lean principles. While low implementation levels of work-on-screen, product tracking, and flexible automation can be realized without the implementation of lean principles, low implementation of MES already requires some presence of lean principles. Furthermore, our study provides insights into the specific performance contribution of applying smart manufacturing technologies compared to lean principles. The results show a superior cost performance when implementing lean and smart, compared to only implementing lean.

The remainder of this paper is structured as follows. Section 2 provides background on smart manufacturing and reviews the recent literature on the relation between smart and lean and its (combined) impact on operational performance. Section 3 motivates the use of Confirmatory factor analysis (CFA), a two-step Cluster Analysis, Analysis of Variance (ANOVA) and Necessary Condition Analysis (NCA) to analyse the empirical data. Furthermore, it specifies and motivates the measures used in this study for indicating the use of smart manufacturing technologies and the use of lean. In addition, it provides the resulting findings on implementation patterns and corresponding performance and on dependencies of smart on lean. Section 4 provides a discussion of the findings and a conclusion.

2. Literature review

Section 2.1 provides background on the concept of smart manufacturing. Next, section 2.2 reviews the recent literature that investigated the relations between smart and lean and its impact on operational performance and shows the gaps in this literature that are addressed within this research.

2.1. Smart manufacturing

There is still quite some ambiguity in the literature and in practice around the concept of Industry 4.0 and its underlying smart manufacturing technologies (Buer et al., 2018; Moeuf et al., 2018). The initial vision of Industry 4.0 already appeared in 1991. Weiser (1991) introduced the notion of 'ubiquitous computing', where computers are integrated with each other and with the world, including production. More recent advances in ICT have now enabled integrated and collaborative manufacturing systems that combine the strengths of information, technology, and humans to be able to respond to changing circumstances in real time. This allows the physical world to get merged with the virtual world, resulting in cyber-physical systems (Lee et al., 2015; Xu et al., 2018). These cyber-physical systems enable flexible and adaptive manufacturing processes by acquiring and processing data, self-controlling certain tasks, and interacting with humans via interfaces (Brettel et al., 2014).

To realize the vision of Industry 4.0, many (new) specific Industry 4.0 technologies are associated with it, such as sensors, wireless communication, visual computing, autonomous robots, augmented reality, artificial intelligence, additive manufacturing, and more. This diversity of technologies does not contribute to the clarity of the concept. Therefore, several authors proposed 'key technologies' (Alcácer and Cruz-Machado, 2019; Kang et al., 2016; Zhong et al., 2017) and/or categorized technologies based on for instance product lifecycle stages, application areas (Frank et al., 2019), or functions within a data-driven paradigm (Klingenberg et al., 2021).

Both Frank et al. (2019) and Klingenberg et al. (2021) distinguish between the more fundamental enabling technologies or base technologies that generate, transmit, and store data and the more specific technologies or front-end technologies that apply this data in an industrial setting. Frank et al. (2019) described front-end technologies as defined subsets of technologies related to smart manufacturing, smart products, smart supply chain, and smart working. Base technologies such as the Internet of Things, cloud services, big data, and analytics support the front-end technologies by providing connectivity and intelligence, which are characteristics that distinguish smart manufacturing from earlier manufacturing systems. Next to connectivity and intelligence, the literature mentions other smart manufacturing characteristics, such as information transparency, decentralised decisions, and technical assistance (Hermann et al., 2016), and horizontal, vertical, and end-to-end engineering integration (Brettel et al., 2014; Wang et al., 2016).

These smart manufacturing characteristics enable companies to realize operational performance benefits (Brettel et al., 2014; Dalenogare et al., 2018; Szász et al., 2021). Within smart manufacturing systems, the connected production resources (technical and human) and their outputs (i.e. products) generate data that can be shared with other resources, transformed into information, clearly visualized, and used for intelligent decentralised human or autonomous decision making processes. Szász et al. (2021) empirically show that the implementation of smart manufacturing technologies positively impacts cost, quality, delivery and flexibility.

Meanwhile, lean thinking has become a common manufacturing philosophy in industry, focusing at a strategic level on specifying value from the customers' perspective, lining up value-creating actions in the best sequence, preventing interruptions and striving for perfection (Womack and Jones, 1996). Since the 1990s, lean has spread beyond the automotive sector and academic output related to lean has steadily increased (Bhamu and Singh Sangwan, 2014; Marodin and Saurin, 2013; Samuel et al., 2015). Lean thinking has evolved over the years, starting from a simple set of operational practices and tools with a shop floor focus on waste and cost reduction and growing toward more complex lean business systems aimed at enhancing value in companies and their supply chains (Arlbjørn and Freytag, 2013; Hines et al., 2004).

Since both lean and smart can be used to improve operational performance, it becomes relevant to look at the relationship between these two concepts. The literature in this area will be reviewed in the next subsection.

2.2. Relation between smart and lean and its impact on operational performance

In recent years, more and more attention has been paid in the academic literature to the relationship between smart and lean. Buer et al. (2018) provided a first overview of this relationship through a systematic literature review of 21 articles within the then emerging research area, which they structured by considering: (1) how smart influences lean, (2) how lean influences smart, (3) the performance implications when integrating smart and lean, and (4) how environmental factors (e.g. repetitive versus non-repetitive environment) affect an integration of smart and lean. Their review showed that most of the early literature studied the relation between smart and lean conceptually. Furthermore, most studies took the point of view of how smart influences lean. Within this research stream, smart technologies are shown to tackle some of the shortcomings of traditional lean systems and to support basic lean methods and specific tools such as just-in-time, Heijunka, Kanban, value stream mapping, total productive maintenance, single-minute exchange of dies, visual management, and poka-yoke (Mayr et al., 2018; Sanders et al., 2016; Wagner et al., 2017). More recently, Rosin et al. (2020) considered the impact of smart technologies on lean principles using a bibliographic research methodology and including the technologies' capability levels of monitoring, control, optimisation, and autonomy as proposed by Porter and Heppelmann (2014). Using empirical data based on qualitative focus group sessions with industry experts, Cifone et al. (2021) identified underlying mechanisms explaining how digital technologies can support lean practices.

Buer et al. (2018) showed that much less attention had been paid to how lean can be used as a foundation for smart implementations. However, it appears logical to first apply lean to streamline and simplify processes before automating the remaining value-adding activities (Bortolotti and Romano, 2012). In light of our research aim to explore the extent to which lean implementation is required to become smart, the distinction between how smart influences lean, or how lean influences smart, is not relevant. In both cases, smart may require presence of lean principles.

Several recent studies have empirically confirmed the early results reported in Buer et al. (2018) concerning the complementary performance effects of combining lean and smart (Buer et al., 2021; Chiarini and Kumar, 2021a; Rossini et al., 2019; Tortorella and Fettermann, 2018; Yilmaz et al., 2022). This implies that lean should not be substituted by smart, since there is additional value in the combination. Whereas Chiarini and Kumar (2021a) used qualitative interview and observation data and Yilmaz et al. (2022) analysed case studies identified from the literature to show how the integration of smart and lean can provide performance benefits, the other studies mentioned used a survey approach to determine the complementary performance effects. While these survey-based studies all incorporated a set of individual operational performance measures (e.g. productivity, delivery service level, inventory level, quality, flexibility, etc.), these were aggregated into a single operational performance construct that was subsequently used in the analyses. As a result, no findings were reported on the complementarity of smart and lean at the individual performance level.

Other recent studies have shown moderating effects of implementing smart on the relation between lean and performance. Tortorella et al. (2018) focused on the external process components of lean, relating to the supplier and customer, within the Brazilian industry. They specifically found a moderating effect for customer-related lean practices. In addition, Tortorella et al. (2019) focused on three internally related lean practice bundles of Shah and Ward (2007) within the Brazilian industry and they included four contingency factors. Their findings show that technologies related to products or services positively moderate the effect of flow practices on operational performance. Both studies analysed performance impacts using a single aggregated performance construct.

Few studies relating smart and lean looked at implementation patterns and the necessity of lean for smart. Yilmaz et al. (2022) reviewed 42 case studies mentioned in the literature to explore the economic, social, and environmental benefits, barriers, and success factors of integrated smart and lean implementations. A part of their study considered the sequence of applying smart and lean in these cases. They showed that lean principles were applied before smart in 50% of the cases, there was a simultaneous application in 40% of the cases and smart was applied first in only 10% of the cases. Tortorella and Fettermann (2018) used cluster analyses to distinguish groups of companies differing in two levels (low & high) of lean implementation level, smart implementation level, and performance improvement over the last 3 years. One of their findings was that high smart implementation was rarely found in low lean implementation settings. Also Rossini et al. (2019) found in a similar study setup with European manufacturers, that the adoption of smart was significantly linked to lean implementation, while lean implementation was independent from smart implementation. While they stated that higher lean implementation 'appears as a necessary condition' for smart implementation, they did not analyse the conditions using necessity logic, nor did they consider this for specific smart technologies.

A recent literature stream focuses particularly at the combination or integration of lean and smart, which is considered a next level of lean automation (e.g. Kolberg et al., 2017; Tortorella et al., 2021b, 2021a, 2021c, 2020). In this research stream a lean automation framework is proposed (Tortorella et al., 2021c), the differences between lean automation implementation levels in emerging and developed economies are assessed (Tortorella et al., 2021a), the implementation sequence in which lean and smart practices lead to high-performing lean automation implementation is studied (Tortorella et al., 2020), and the main bundles of lean automation practices and principles and their impact on operational performance are provided (Tortorella et al., 2021b). However, the underlying assumption of this research stream is that lean automation, as the integration of lean and smart, is preferred over lean-only or smart-only for all individual operational performance measures. This has not been explored yet. The two studies that actually included operational performance (Tortorella et al., 2020, 2021b) used it as an aggregate measure, consisting of the indicators safety (work accidents), quality (scrap and rework), delivery service, productivity and inventory. An analysis of the impact of lean automation on the individual indicators lacks, while also the operational performance indicators of flexibility and cost are not completely covered by their performance indicators.

3. Methodology and results

This section describes and motivates all main steps performed in the research. If applicable, the results are integrated with (or reported immediately after) the description of a step.

3.1. Questionnaire development and measures

To answer our research question, primary data was collected through survey research. To ensure the validity of the questionnaire, the scales were tested in two steps. We first asked ten experts in the field of lean and smart technologies to assess the survey questions. Based on their feedback, small revisions have been made, mostly in relation with the questions on smart technologies (wording and additional examples). Secondly, we conducted a pilot survey by contacting 24 manufacturing companies. The aim of the pilot survey was to ensure that the questions were meaningful in a variety of different industries. After filling the questionnaire, we interviewed the respondents and all agreed that the survey captured their understanding of both lean principles and smart industry technologies. Descriptive statistics of the data gathered during the pilot survey do not differ significantly from the final dataset. The small percentage of missing values in the final dataset provides further evidence of the clarity of the survey questions. The final survey questions used to collect data are provided in the Appendix.

The respondents of the final questionnaire were asked to refer to their own local company situation in order to make sure that they could provide knowledgeable answers based on first-hand experience. The questions related to (1) generics (founding year, size in FTE, company industry, and respondent function), (2) the use of five components of smart manufacturing technologies as described below, (3) the use of four lean rules/principles, and (4) the operational performance of the company relative to industry peers.

The use of subjective and self-reporting measures raises concerns about potential common method bias. Podsakoff et al. (2003) proposed a set of techniques for controlling and reducing such potential negative effects. In terms of the study design, to avoid undesirable artefactual covariance between different variables, questions were separated from each other in the questionnaire. To further reduce the likelihood of method bias in the study design, the research project was presented to potential respondents as a study aiming at understanding the level of implementation of smart technologies and lean principles. The aim of assessing to what extent smart manufacturing builds on lean principles and their effects on operational performance was not mentioned, so that respondents' attention was not drawn to the main objectives of this study. In terms of respondents, we targeted the potentially most knowledgeable respondents based on the managerial position (e.g., CEO, production manager, project manager) and asked them to answer questions as honestly as possible, and allowed them anonymity. In this way, we aimed to minimize potential biases related to unfamiliar terms and at the same time reduce any apprehension that the respondents might have that could lead to them providing socially desirable answers. Finally, we employed different scale anchors and formats to measure practices' adoption and performance.

3.2. Measures

We identified five broad and generic components of smart manufacturing technologies in order to be able to measure the use of smart manufacturing in any industry context. Including specific technologies such as 'additive manufacturing' or 'augmented reality' would distort the measurement, since these specific technologies are not likely to be useful in all contexts. Furthermore, we also aimed to include components that reflect readily useable smart technologies, excluding very advanced and still rarely used technologies in practise (e.g. artificial intelligence).

Our smart manufacturing technologies construct is operationalized as a first-order 5-item reflective variable. The five items are 'Work-on-screen solutions', 'Product tracking', 'Information systems', 'MES systems', and 'Flexible automation', which can be related to the components of a smart factory's reference architecture, as developed by Yoon et al. (2012). They identified the following ubiquitous components of a u-Factory (smart factory): u-Human, u-Resource, u-Product, u-MES (manufacturing execution system), data acquisition and transmission on the shop floor as device to the ubiquitous system (D2U), and an information exchange infrastructure (UPLI: ubiquitous product lifecycle information highway) where information is transmitted, exchanged, and retrieved by various stakeholders in various stages of the product lifecycle. Table 1 provides an overview of the components included in our smart manufacturing technologies construct, with a description and examples.

The lean principles construct is operationalized as a first-order 4-item reflective variable. The four items related to the four rules derived from the Toyota Production System by Spear and Bowen (1999): (1) a direct customer-supplier connection, (2) standardization of products and processes, (3) flow production and reduced throughput times,

Table 1
Smart manufacturing technologies.

Component	Description	Examples
Work-on-screen solutions [u-Human]	'Interface devices to provide operators with information anywhere, anytime for a comfortable and safe working environment' (Yoon et al., 2012, p. 2180).	Use of digital assistance systems to present information (e.g. digital work instructions, drawings, part lists, real-time status information, etc.), on desktop computers, laptop, tablets, smart glasses and/or smartphones.
Product tracking [u-Product]	Products can be identified and are accessible to manage information on status or location in real time (Yoon et al., 2012).	Digital tracking of location or status of products through technologies such as RFID, Bluetooth Low Energy or Ultra-Wideband beacon technology, or barcodes.
Information systems [UPLI]	Current information systems, such as enterprise resource planning and customer relationship management, are essential to ensuring horizontal and vertical integration (Wang et al., 2016).	Transaction processing systems that support business processes, such as CRM (supporting required actions towards the customer) and ERP (supporting e.g. order fulfilment and inventory control).
MES systems [u-MES]	'Application systems to manage and control the whole shop floor' (Yoon et al., 2012, p. 2180).	Digital initiation of actions using real-time data from shop floor processes and underlying operations to support, control, and integrate shop floor processes.
Flexible automation [u-Resource]	Digitised and interconnected physical resources (Lee et al., 2015).	Interconnected machining centers, robots, automatic guided vehicles, etc.

and (4) continuous improvement. Compared to the five principles developed by Womack and Jones (1996) and the 14 principles developed by Liker (2004), the four rules by Spear and Bowen focus more on the actual behaviour as it is manifested by employees on the shop floor. Compared to more extensive instruments on lean practices (e.g. Shah and Ward, 2007, 2003), these principles represent a more abstract view on the extent that lean is present in an organization. Given the diverse set of organizations in our sample, this representation is considered more suitable.

Operational performance is operationalized as a 4-item formative variable. A formative measure of operational performance is consistent with the prior literature (e.g. Bozarth et al., 2009). The four items are quality, delivery, flexibility and cost (Slack et al., 2010). The present study focuses on operational performance as an aggregate measure, but also on the single dimensions separately.

All questions (except for the generics) were scored on a 9-point Likert scale to collect interval data (Karlsson, 2009) and, given the single questions per concept, to overcome measurement error (Finstad, 2010). Questions related to categories 2 and 3 were ranked on a scale anchored at 'not' (1), 'somewhat' (5) and 'considerably' (9). An example is: "To what extent do you use the lean principle 'continuous improvement' in your company?" Questions related to category 4 were ranked on a scale anchored at 'worse' (1), 'average' (5) and 'better' (9). An example is: "How does your company score on flexibility compared to your industry peers?" All survey questions were translated into Dutch to ensure that all participants could understand the concepts surveyed.

3.3. Sample and data collection

The survey was distributed to a stratified random sample of small, medium, and large Dutch manufacturing companies via the online survey tool Qualtrics. Manufacturing was defined using the classification of economic activities in the European Community (commonly referred to as NACE) as 'Level 1, Group C: Manufacturers' (European Commission, 2010). 120 respondents filled in the questionnaire, this is considered sufficient for our Confirmatory factor analysis (CFA) (Fornell and Larcker, 1981), Cluster Analysis and ANOVA (Hair et al., 2014), and NCA (Dul, 2016), and exceeding other exploratory papers on either smart technologies (e.g. Reyes et al., 2012), lean management (e.g. Phan et al., 2011) or operational performance (e.g. Merschmann and Thonemann, 2011). Preliminary tests on our dataset have been carried out to provide evidence on the validity of the questionnaire and the sample. The survey was administered to managers and executives of 1000 companies, indicating a 12% response rate that can be considered acceptable (Dillman, 2011). To rule out a non-response bias, we compared the responses of the first 50 per cent of respondents against the last 50 per cent. All the t-tests were non-significant, therefore we concluded that non-response bias is not an issue. We checked the qualification of the respondents to ensure that their managerial positions were adequate to guarantee a certain level of knowledge regarding operational practices implementation and plant performance compared to competitors. Respondents were most frequently owners/CEOs or production managers. In the sample, 36 of the 120 companies were large (≥250 employees), 57 were medium-sized (50–250 employees) and 27 were small (<50 employees), while two respondents did not mention their company size. The average founding year was 1954, with large companies on average being somewhat older than small companies. Companies came from process and discrete industries (e.g. chemicals, plastics & rubber, food, tobacco, automotive, consumer & household products, metal works, industrial & building material, high-tech, and machinery) for business-to-business and business-to-consumer markets. We compared our number of cases per industry with the sectoral analysis of manufacturing (Eurostat, 2018) and found it to be representative. The characteristics of the companies and respondents in our sample are summarized in Table 2.

Table 2
Overview of generics: founding year, size in FTE, company industry, and respondent function.

	Min.	Avg.	Max.
Founding year	*1812*	*1954*	*2016*
Large companies (30%)	1819	1928	2016
Medium-sized companies (47.5%)	1812	1955	2013
Small companies (22.5%)	1946	1988	2015
Size in FTE	*10*	*2.063*	*112.000*
Large companies (30%)	250	6.118	112.000
Medium-sized companies (47.5%)	50	123	224
Small companies (22.5%)	10	26	45

	Percent		Percent
Company industry (Eurostat)		*Respondent function*	
Machinery and equipment	12.39	Owner/CEO	17.8
Fabricated metal products	11.5	Production Manager	16.95
Food products	9.73	Project Manager	11.86
Electrical equipment	9.73	Consultant	6.78
Motor vehicles, trailers and semi-trailers	7.08	Production Engineer	5.08
Basic metals	6.19	Lean/Six Sigma Manager	5.08
Repair and installation of machinery and equipment	6.19	R&D Manager	4.24
Rubber and plastic products	5.31	Other	4.24
Other manufacturing	5.31	Plant Manager	3.39
Basic pharmaceutical products	3.54	Quality Manager	3.39
Other transport equipment	3.54	Process Engineer	3.39
Furniture	3.54	Sales Engineer	2.54
Other non-metallic mineral products	2.65	Accountant/ Controller	2.54
Beverages	2.65	Team Leader	2.54
Printing and reproduction of recorded media	2.65	Account Manager	1.69
Coke and refined petroleum products	1.77	Service Manager	1.69
Tobacco products	1.77	Supply Chain Manager	1.69
Paper and paper products	0.88	Mechanical Engineer	1.69
Wood and products of wood and cork	0.88	Product Manager	0.85
Textiles	0.88	Manager Engineering	0.85
Wearing apparel	0.88	R&D Engineer	0.85
Leather and related products	0.88	Lean/Six Sigma Engineer	0.85

3.4. Measurement model validity and reliability

Before testing the measurement model validity, we screened our data and verified the normality assumption. Descriptive statistics reported in the Appendix provide evidence of normality of our data. Specifically, all skewness and kurtosis absolute values were below 0.99 and 1.31, respectively, values well below the commonly accepted thresholds (Muthen and Kaplan, 1985). To test the validity and reliability of the construct measuring smart manufacturing technology and lean principles (the measurement model), a CFA was performed using STATA 16.1 (Jöreskog, 1969). Although the results of the CFA indicated that the complete set of items was acceptable to measure our constructs ($\chi 2$ = 54.76; df = 27; $\chi 2$/df = 2.03; CFI = 0.941; SRMR = 0.110; RMSEA = 0.092), the analysis of the modification indices revealed that one item measuring smart manufacturing technology (Information systems) was problematic in terms of cross-loading. A possible explanation of the cross-loading is that Information systems, defined as digital indication of required actions towards the customer (CRM) and towards purchasing and production processes (ERP, shop floor control), are commonly used in many manufacturing companies, not only in companies adopting smart technology, and therefore it is a common technology for lean companies too, independently on their level of smart technology adoption. Following judgemental criteria (Wieland et al., 2017) and considering the content of the remaining items (content validity) (Hair et al., 2014), it was decided to delete this item as the content validity was not compromised, while all the fit indices of the CFA improved significantly, showing strong validity of the measures ($\chi 2$ = 34.03; df = 20; $\chi 2$/df = 1.70; CFI = 0.967; SRMR = 0.073; RMSEA = 0.076). Convergent validity is guaranteed by having all factor loadings and average variance extracted (AVE) higher than 0.50 (Fornell and Larcker, 1981). Discriminant validity is confirmed since both AVE values are above the shared variance of the two constructs (Fornell and Larcker, 1981). Finally, composite reliability measures guarantee internal reliability as both are above the 0.70 cut-off (Hair et al., 2014). These measures are given in Table 3.

3.5. Cluster analysis and one-way ANOVA

A two-step cluster analysis and a series of one-way ANOVA tests were

Table 3
Data quality measures.

Construct	Factor loading	Average variance extracted	Composite reliability
Smart manufacturing technologies		*0.53*	*0.82*
Flexible automation	0.69		
MES	0.85		
Product tracking	0.70		
Information systems	–		
Work-on-screen	0.66		
Lean principles		*0.70*	*0.90*
Supplier and customer link	0.57		
Standardization	0.87		
Flow	0.91		
Continuous improvement	0.85		

adopted to (1) explore what type of implementation patterns of smart manufacturing technologies and lean principles can be found in our sample and to (2) explore whether different implementation patterns lead to differences in operational performance outcomes. Different groups were identified by conducting a two-step cluster analysis. The first step (hierarchical clustering) provides the number of clusters in the data by evaluating the percentage change in the agglomeration coefficient when reducing the number of clusters. The second step (non-hierarchical clustering) provides the clusters themselves (Hair et al., 2014). This method of analysis follows other examples of cluster analysis, such as by Flynn et al. (2010). The change percentage in the agglomeration coefficient of the hierarchical clustering was stable or decreasing until it significantly increased from a three- to a two-cluster solution (31 per cent). This result suggested the presence of three clusters in our sample. A random sampling of dendrograms confirmed that three clusters represented the best solution. The second step (k-means) grouped companies into three groups. Next, we used a series of one-way ANOVA to identify differences in implementation levels of smart manufacturing technologies and lean principles, differences in terms of operational performance outcomes (as aggregate dimension and as single performance dimensions of Quality (Q), Delivery (D), Flexibility (F) and Cost (C)), and differences in size (measured as logarithm of FTE) among the three identified clusters.

3.5.1. Resulting implementation patterns and operational performance outcomes

Table 4 reports the results of the two-step cluster analysis and series of one-way ANOVA tests.

The results of the cluster analysis show that there is a group of companies that do not adopt lean and smart (group 1 named "non-adopters" characterized by companies with a low use of lean and smart technology). Furthermore, we found that lean principles are often applied alone (group 2 named "lean-only" characterized by companies with a high use of lean and a low use of smart technology), this is not the case for the use of smart technologies as they are seen in conjunction with lean (group 3 named "lean and smart" characterized by companies with a high use of both lean and smart technology). Furthermore, a group of smart-only companies is not evident.

In terms of operational performance, when considering the dimensions of quality, delivery, flexibility and cost as an aggregate and formative construct, the results show that lean-only and lean and smart companies have comparable superior performance compared to the non-adopters. However, when analysing performance dimensions separately, the superior and comparable results found at the aggregate level remain true only for quality and delivery performance. Regarding flexibility, lean-only companies are superior to the non-adopters, while lean and smart companies do not differentiate substantially from the non-adopters although not performing significantly worse than lean-only companies. Regarding cost instead, lean and smart companies are superior to the non-adopters, while lean-only companies do not differentiate substantially from the non-adopters and perform worse than lean and smart companies at a 90% confidence level.

When considering the size of the companies within the clusters, results show that there is a significant difference in the size of the companies, computed in the logarithm of FTE. In fact, smart and lean companies are significantly larger than the other groups, while lean-only and non-adopters do not significantly differ. Fig. 1 provides a visual overview showing that the largest companies are predominantly found in the smart and lean group. With SMEs (FTE <250), the variation in use of lean and smart is higher. Fig. 1 also shows that, for all company sizes, the level of activity in the field of smart manufacturing is usually lower than that for lean: the round dots are predominantly lower than the related triangles. Interestingly, a qualitative check of the industry representation in the three groups does not show any evident difference as companies operating within the same or similar industry are distributed

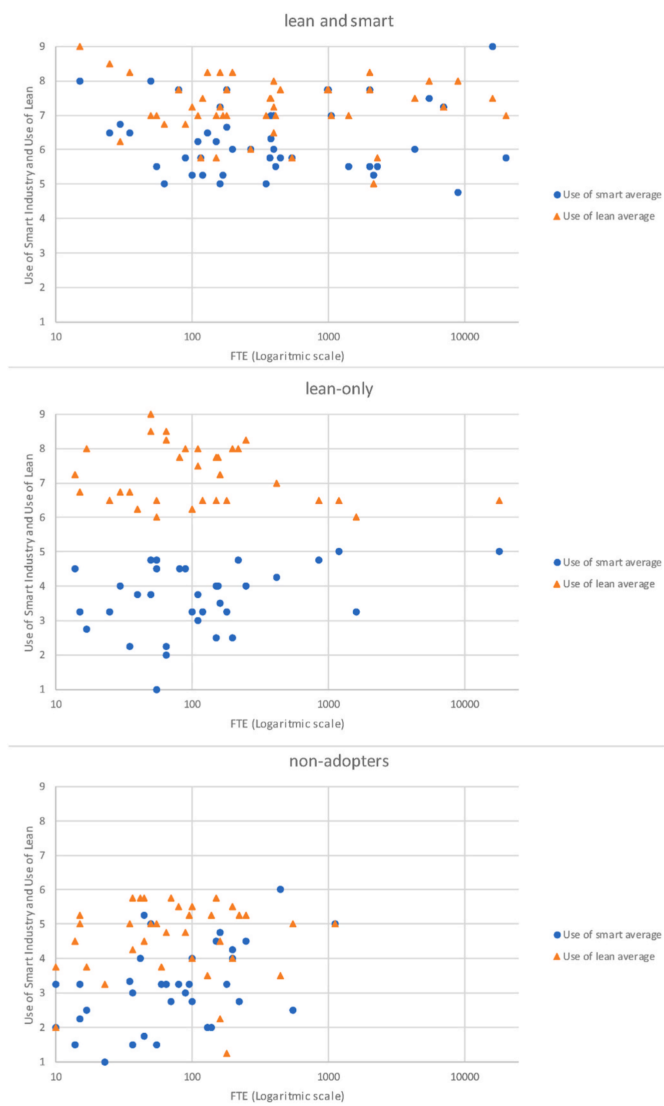

Fig. 1. Company size versus their use of smart and lean per cluster.

Table 4
Comparison of the three groups resulting from the cluster analysis.

	N	Lean	Smart	Size	PERF	Q	D	F	C
Group 1 Non-adopters	37	$4.58^{a,b}$	3.28^{a}	4.47^{a}	$5.67^{a,b}$	$6.36^{a,b}$	$5.03^{a,b}$	6.64^{c}	4.69^{c}
Group 2 Lean-only	34	7.25^{a}	3.64^{b}	4.66^{c}	6.75^{a}	7.38^{a}	7.03^{a}	7.62^{c}	4.94^{d}
Group 3 Lean and smart	49	7.27^{b}	$6.38^{a,b}$	$5.72^{a,c}$	6.82^{b}	7.25^{b}	7.06^{b}	7.04	$5.72^{c,d}$

Sheffe pairwise comparison tests of mean differences.
a,b: p-value < 0.01; c: p-value < 0.05; d: p-value < 0.10.

across the three groups, and within the same group companies operate in a variety of different industries.

3.6. Necessary Condition Analysis

To deepen the results from the cluster and ANOVA analyses and specify the extent to which smart requires lean, we ran a Necessary Condition Analysis (NCA) (Dul, 2016) for each individual item within our construct of smart manufacturing technology. A necessary condition (here: use of lean principles) enables the outcome (here: use of smart technology) when present and constrains the outcome when absent (Dul et al., 2020). In contrast to regular regression analyses that study variables in a probabilistic relationship to each other, an NCA allows the study of variables that are necessary but no guarantee for a certain outcome to occur. The NCAs in this study thus identified the extent to which using lean principles is necessary for using each of the smart manufacturing technologies included in our construct.

An NCA starts with drawing a ceiling line through the upper-left observations of an x-y plot. As the data are continuous, a ceiling regression line (CR-line) is used (Dul, 2016). This line separates the ‘empty space’ and the ‘full space’ of the dataset (Goertz et al., 2013) indicating the degree to which a smart manufacturing technology (y-axis) could be implemented without the presence of lean principles (x-axis). Fig. 2 shows the x-y plots for the use of lean principles and smart manufacturing technologies. The solid orange lines represent CR-lines, which define the empty space. The larger the empty space (relative to the total space with observations), the more X (here: use of lean principles) constraints Y (here: smart manufacturing technology).

To determine the validity and significance of the ceiling lines, the accuracies, effect sizes and p-values were calculated. These measures are given in Table 5. The accuracies (>95%) were found sufficient to use the CR lines in the NCA (Dul, 2016). The effect sizes exceeded the threshold of 0.1 and were found to be moderate (0.1–0.3) to large (>0.3), indicating an enabling effect of the conditions on the outcome. After running the approximate permutation test with 10.000 resamples, the p-values (Dul et al., 2020) were found to be significant (<0.050).

Table 5
NCA validity and significance measures.

Construct	Accuracy (%)	Effect size	p-value
Lean principles – Work-on-screen	99.2	0.146	0.045
Lean principles - Product tracking	96.9	0.242	0.011
Lean principles - MES systems	95.3	0.375	<0.001
Lean principles - Flexible automation	97.6	0.254	0.003

NCA’s bottleneck table is used to efficiently represent all ceiling lines of the different smart technologies numerically (see Table 6 in Section 3.6.1). The first column represents the outcome level Y (presence of smart technology) and the next columns represent the threshold level of condition X (presence of lean principles) for each of the smart manufacturing technologies. The first row represents the lowest level of Y in the range of observations, the last row the highest level. Per row (particular level of Y), the threshold levels of condition X can be read for each smart manufacturing technology. We provide the levels of X and Y both as percentiles and as percentages, since percentiles say more about the population of companies whereas percentages might be more interesting for individual companies.

When applying percentiles, the levels of Y in the first column are expressed as percentiles, ranging from 0 to 100. Next, for each percentile level of Y, the percentile level of X is provided. This represents the percentage of companies that were *not* able to achieve the necessary level of condition X for the given level of Y (with the actual number of companies provided between brackets). Therefore, the percentile for X is

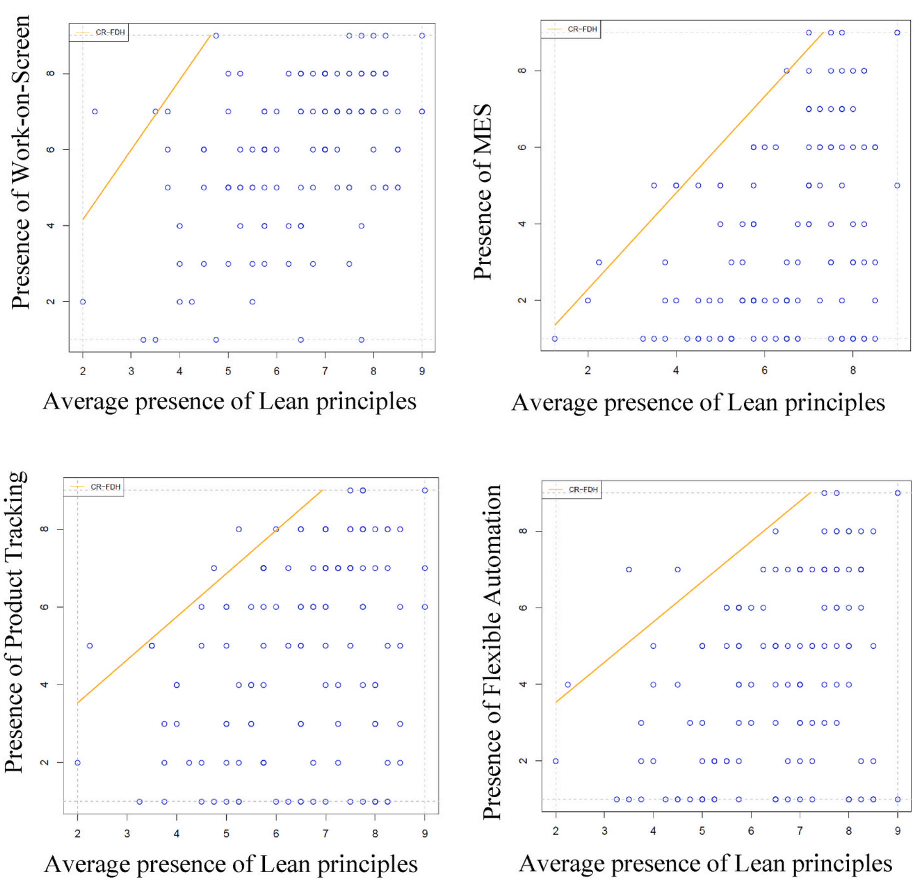

Fig. 2. NCA plots of Lean principles for different Smart Manufacturing Technologies.

an indicator of the importance of the necessary condition. A 0.0 (0) indicates that all companies were able to reach the required level of X for the corresponding level of Y.

When applying percentages, the X and Y values of each of the ceiling lines are translated into percentages of the range of observations. The first column then shows a 0%–100% range of the observed maximum use of the smart technology and the next columns show which percentage of the observed maximum use of lean principles is required to reach the desired level of the particular smart technology. NN denotes that lean principles are not required (Not Necessary) for the desired level.

This method of analysis slightly deviates from other examples of NCA application. Knol, Slomp et al. (2019b) identified the relative importance of improvement routines for developing lean practices, Sousa and da Silveira (2017) found necessary degrees of services in the process of servitisation, and Van der Valk et al. (2016) determined the criticality of contracts and trusts for supplier relations. Such studies consider several conditions as necessary for one outcome. In contrast, this study considers one condition (presence of lean principles) for several outcomes (presence of different smart manufacturing technologies).

3.6.1. Resulting dependencies of smart on lean

Table 6 shows the results of the NCA analyses for each individual item within our construct of smart manufacturing technology in a bottleneck table. The first column shows the outcome level Y, indicating the level of presence of the smart manufacturing technology. The remaining columns show the percentiles and percentages of the levels related to the presence of lean principles for each of the specific smart manufacturing technologies.

The Bottleneck table clearly shows three things. First, when focusing on the highest level of presence of the smart manufacturing technologies in the range of observations (100th percentile), many companies did not have the required levels of lean to achieve this level for product tracking, MES, and flexible automation (68, 85 and 80 companies, respectively). Looking at the percentages, full presence (100%) of implementation of smart manufacturing technologies was accompanied by a high (≥74.3%) degree of application of lean principles for these three smart manufacturing technologies. Only for work-on-screen, all but 16 companies in our dataset had sufficient levels of lean to be able to achieve the highest level (100th percentile) of this smart technology. For work-on-screen a somewhat lower degree of application of lean principles (≥41.2%) was required to achieve the highest level (100%). This indicates that for product tracking, MES and flexible automation, presence of lean principles is necessary and very important for companies. No companies used product tracking, MES, or flexible automation 'considerably' (≥90%) without also using lean principles 'considerably' (≥63.5%).

Second, when focusing on the lower levels of presence of the smart manufacturing technologies in the range of observations, the companies (all but two or three) in our dataset had the required levels of lean to at least partially (up to 50th percentile) implement the smart technology. However, even low levels of MES (≥10%) were only achieved with at least some presence (≥4.6%) of lean principles. For work-on-screen, product tracking and flexible automation, low levels (<30%) of use could be achieved without presence (NN) of lean principles. This means that already for low levels of MES, presence of lean principles is necessary. For low levels of the other smart technologies, presence of lean principles is less important and required levels are achieved already.

Third, when focusing on the presence of the smart manufacturing technologies between the 40th and 70th percentile (mid-range), it can be observed that companies did not always meet the required levels of lean principles. For a desired level of 40% or more, all smart technologies required at least some presence (2.3%–29.2%) of lean principles, indicating that increasingly, implementation of these technologies required presence of lean principles. The presence of lean principles in this mid-range seems most important for product tracking, indicated by the highest percentile levels of lean principles (representing the percentage of companies that were *not* able to achieve the necessary level of presence of lean principles for the given implementation level of the smart manufacturing technology).

4. Discussion and conclusions

The aim of this paper was to explore to what extent the adoption and performance of smart manufacturing technologies builds on the adoption of lean principles. Therefore we considered the extent to which specific smart technologies require the presence of lean principles and the performance contribution of smart in terms of the performance dimensions of quality, delivery, flexibility and cost. Sections 4.1 and 4.2 reflect on the main findings, Section 4.3 explains the theoretical contributions and practical implications, and Section 4.4 offers recommendations for future research.

4.1. The extent that lean is necessary for smart

While some earlier studies have shown that the adoption of smart was linked to lean implementation (Rossini et al., 2019; Tortorella and Fettermann, 2018), our findings provide a more elaborate view on the extent of this dependency for different types of smart manufacturing technologies. The Necessary Condition Analysis (NCA) for each individual item of smart manufacturing technology included in our construct (work-on-screen, product tracking, MES systems, and flexible automation) showed that they all require lean principles to realize high implementation levels, with the strongest effects for product tracking, MES systems, and flexible automation. Lean principles are thus found

Table 6
Bottleneck table with levels of presence of Smart manufacturing technology and levels of presence of Lean principles as percentiles and percentages for different Smart manufacturing technologies.

Smart manufacturing technology [y]	Lean principles [Work-on-screen]		Lean principles [Product tracking]		Lean principles [MES systems]		Lean principles [Flexible automation]	
	Percentile	%	Percentile	%	Percentile	%	Percentile	%
0	0.0 (0)	NN	0.0 (0)	NN	0.0 (0)	NN	0.0 (0)	NN
10	0.0 (0)	NN	0.0 (0)	NN	0.0 (0)	4.6	0.0 (0)	NN
20	0.8 (1)	NN	0.0 (0)	NN	0.0 (0)	12.8	0.0 (0)	NN
30	1.6 (2)	0.4	0.0 (0)	NN	0.0 (0)	21	0.0 (0)	NN
40	1.6 (2)	6.2	1.6 (2)	2.3	0.0 (0)	29.2	0.0 (0)	9.1
50	1.6 (2)	12.1	2.4 (3)	14.9	1.6 (2)	37.4	1.6 (2)	20
60	3.9 (5)	17.9	8.7 (11)	27.6	2.4 (3)	45.6	2.4 (3)	30.9
70	3.9 (5)	23.7	19.7 (25)	40.3	8.7 (11)	53.8	9.5 (12)	41.7
80	8.6 (11)	29.6	19.7 (25)	53	14.2 (18)	62	23.8 (31)	52.6
90	8.6 (11)	35.4	38.6 (50)	65.7	26.8 (35)	70.2	23.8 (31)	63.5
100	12.5 (16)	41.2	52.8 (68)	78.3	66.1 (85)	78.4	61.9 (80)	74.3

necessary for the application of smart technologies. Only low levels of smart technology implementation were achieved without lean implementation (with the lowest level for MES), indicating that the application of lean is a necessary condition to implement smart.

Additional evidence for the general claim that lean is necessary for smart is provided by the clusters found in our data. We found a group of non-adopters, a group of lean-only adopters and a group of lean and smart adopters. This supports the idea that lean does not become obsolete when implementing smart and that lean may facilitate the implementation of smart. The absence of a group of smart-only adopting companies indicates that in practice smart is generally not implemented without lean, which is in line with earlier findings (Rossini et al., 2019; Tortorella and Fettermann, 2018; Yilmaz et al., 2022). Furthermore, it corroborates with outcomes from a recent study on the adoption pathways of lean automation, which showed that a start-up cluster within the lean automation implementation sequence consisted of lean practices only, while smart and lean practices were found in the second (in-transition) and third (advanced) clusters of lean automation implementation (Tortorella et al., 2020). Smart implementations are thus done simultaneously with lean or after lean implementations, as also shown for different smart technologies in our more detailed NCA analyses.

Although our study did not provide any qualitative data to explain the underlying mechanisms that lead to the dependency of smart on lean, other recent literature has provided some possible explanations. From 21 interviewees and 216 respondents, Chiarini and Kumar (2021b) explain that the majority agreed that, for example, smart sensors and RFID technologies were helpful to improve processes. One of their examples shows that such technologies allowed them to identify and trace products and packaging, and even tools and people. This subsequently helped the company to perfectly trace who made which product, with which tools, to reduce errors and defects and improve their processes. Additionally, Chiarini and Kumar (2021b) found that MES systems helped to halt machines in case of nonconformities, preventing further defects and allowing for root cause problem solving. From ten interviews and an in-depth case study, Chiarini and Kumar (2021a) found that it is important to first rethink the production layout and reduce waste, and then automate this process with robots, automated vehicles, and such. In general, they found that there was a common understanding that smart technologies can only be implemented after streamlining and creating flow in processes, thereby also confirming the finding of Bortolotti and Romano (2012) that processes should be streamlined with lean before pursuing automation.

4.2. The specific performance contribution of smart compared to lean

The findings of our study show that when operational performance is considered as an aggregate and formative construct of the dimensions of quality, delivery, flexibility and cost, firms that implement lean-only or lean and smart realize comparable and superior performance compared to firms that do not adopt lean and smart. These findings are in line with earlier literature showing performance improvements when implementing lean (e.g. Cua et al., 2001; Fullerton et al., 2014; Shah and Ward, 2003), but contrast with literature stating that implementing lean and smart results in superior performance compared to implementing lean-only (Buer et al., 2021; Tortorella et al., 2019, 2021a). Only when looking more specifically at the individual dimensions of performance, we found superior cost performance of implementing lean and smart compared to only implementing lean.

This finding could imply that implementing smart manufacturing technologies can be regarded as a next layer in the sand cone of practices (Bortolotti et al., 2015), which starts with a sequence of lean practices and may thus be expanded with smart technology implementations. Prior work on lean had already grouped lean practices in bundles and related these bundles to several operational performance measures (Furlan et al., 2011; Shah and Ward, 2003, 2007). Subsequently, Bortolotti et al. (2015) distinguished an organizational fitness bundle consisting of HRM and TPM practices, which was shown to provide a foundation for the more specific TQM and JIT bundles representing the next layers of the sand cone of practices, respectively. Furthermore, they provided support for the sand cone model of cumulative performance (Ferdows and De Meyer, 1990) through relating the sequence of lean practices to implement to the sand cone sequence of cumulative performance. Where TQM directly related to quality performance only (the base layer of the sand cone of cumulative performance), JIT directly improved quality and delivery performance (second layer of the sand cone). In addition, both bundles related to the higher performance levels of flexibility and cost (the higher layers of the sand cone), but only indirectly through their relationship to quality and delivery performance. Our findings show that by building on the foundation of lean, smart manufacturing technologies seem to be able to specifically contribute to cost, representing the highest level in the sand cone of cumulative performance. When the aim is to address flexibility (third level in the sand cone of cumulative performance), smart technologies are not distinctive compared to lean practices.

Our findings show that smart-only implementations generally do not occur in practice, while lean-only could be just as good an approach as lean and smart when the aim is to improve the lower performance levels of quality and delivery in the sand cone of cumulative performance or even the flexibility level. Only to achieve cost differentiation smart technologies need to be added. This means that lean and smart (lean automation) may not always be the appropriate path for the future, apparently there are also circumstances where it is sufficient to implement lean and where smart technologies are therefore not strictly necessary.

Additional findings related to company size as a contextual factor corroborate with earlier research findings. On average, large companies use smart manufacturing technologies and lean principles more extensively than smaller companies. Apparently, conditions such as the presence of sufficient knowledge, time, and money are more favourable at larger companies. For smart technologies, this observation aligns with the finding of Szász et al. (2021) that larger companies invest more in implementing Industry 4.0 technologies than smaller ones and with the statement of Rüttimann and Stöckli (2016), who claimed that SMEs will not easily benefit from Industry 4.0 due to the large investments required. Furthermore, Rüttimann and Stöckli (2016) stated that Industry 4.0 enables large companies to fulfil smaller customised demands, which were previously usually fulfilled by SMEs. This may endanger the relative competitive position of smaller companies compared to larger companies. However, our study also shows that some SMEs manage to make good use of lean principles and smart technologies. Those companies can be regarded as forerunners from which other SMEs may learn.

4.3. Theoretical contributions and practical implications

With regards to theory, our research showed the extent to which smart manufacturing technologies require presence of lean principles: a high use of smart manufacturing technologies requires a high use of lean principles and even for low levels of smart implementation some lean implementation is required. Smart-only implementations were generally absent. These findings add to the extant literature that describes the mediating and moderating relations between lean, smart, and performance. In this regard, this study adds more nuance to the relation between lean and smart and the importance of the presence of lean when aiming to implement smart manufacturing technologies.

While the compatibility of smart manufacturing and lean thinking was confirmed by their joint presence in practice (a lean and smart cluster), we provided additional insights into the specific performance contribution of applying smart manufacturing technologies combined with lean compared to applying lean-only. In contrast to earlier findings that the integration of lean and smart results in better overall performance than implementing lean-only, our detailed results on the specific performance dimensions of quality, delivery, flexibility and cost show its superiority related to cost only. This suggests that smart technology implementations can be regarded as a next step in a lean sequence of practices, but specifically to address cost benefits as a top level in the sand cone of cumulative performance.

In practical terms, this research has implications for managers, educators, and policymakers. For managers, the dependencies between these concepts can help to decide in what to invest, and in which sequence. To a certain extent, this depends on their aims; if they aim for performance differentiation in the lower layers of the sand cone model of cumulative performance (e.g. quality and delivery), the presence of lean principles seems sufficient. If they aim for performance differentiation in the higher layers of the sand cone model of cumulative performance (e.g. flexibility and cost) and specifically aim to realize low costs, combining lean principles with smart manufacturing technologies is recommended. However, before implementing smart technologies, managers are advised to focus on implementing lean principles. Specifically, if they plan to implement MES systems, presence of lean principles is needed. And if they aim for full presence of smart technologies, then high levels of lean principles are required. Furthermore, practitioners in SMEs need to be aware of the often more difficult conditions they face compared to multinational companies in terms of knowledge, time, and money when implementing smart manufacturing technologies.

Educators for practitioners or academics are advised to incorporate these findings into their curriculum. Educators focusing on smart manufacturing technologies can help their students by also incorporating lean principles in their program. Educators focusing on lean can help their students by explaining the specific performance gains that can be achieved by combining smart manufacturing technologies with lean.

For federal policymakers, the findings in this paper imply that their research and development programmes might be more effective if they not only consider smart manufacturing or its related technologies, but also incorporate their dependence on lean principles and combined effect on operational performance. Over the last decade, much attention has been paid to the concepts of Industry 4.0 and smart manufacturing. While this attention is justified and helpful, this and other studies show that broadening the focus by integrating lean can be very helpful.

4.4. Limitations and recommendations for future research

This study considered generic and broad smart manufacturing technologies, relating to the ubiquitous components of Yoon et al. (2012). Since there is still some ambiguity about which technologies are at the core of smart manufacturing, other choices could be made (see e.g. Alcácer and Cruz-Machado, 2019; Lennon Olsen and Tomlin, 2019; Posada et al., 2015) and future research might include some of the more advanced technologies that are currently sparsely implemented in practice. Furthermore, this study operationalized smart manufacturing and lean as first-order factors. This design strategy implies that we were able to empirically assess construct validity for smart manufacturing and lean, but not for their underlying technologies and principles. Taken together, we call for future studies conceptualizing and measuring smart manufacturing technology as a second-order factor, including a more comprehensive set of technologies. This will allow a more robust assessment of construct validity, a better understanding on which technologies are at the core of smart manufacturing, and ultimately it will facilitate replication studies and comparison of the conclusions across smart manufacturing technology studies (Kaynak and Hartley, 2006).

The extent to which smart manufacturing technologies require presence of lean principles are described from an implementation point of view, but the exact mechanisms that lead to these links were not uncovered in this research. This requires more qualitative longitudinal case studies, which could also clarify the sequential effects of applying lean principles and implementing smart manufacturing technologies. This could then, for example, lead to a technology road map for organizations. Manufacturing SMEs with a high presence of both smart manufacturing technologies and lean principles might be excellent candidates for this research, since SMEs particularly face inherent harsh circumstances.

The intent and focus of this paper were to study the interplay between smart manufacturing technologies and lean principles, which relate to technology and processes. This focus omitted another major component: the role of human agency, relating to people. Future research might examine the interrelationships between smart manufacturing technologies and human agency, as well as the interdependencies of all three components, as each one heavily depends on the others (Knol, Lauche, et al., 2019; Orlikowski, 1992).

Finally, this explorative survey was performed in a single country (the Netherlands), which may not be representative of the situation in other countries. Therefore, future research is needed to replicate this study in other areas of the world.

Declaration of competing interest

None.

Appendix. Survey questions and descriptive statistics

Questions [scales]				
Generics				
In what year was your company founded? [select year]				
What is the size of your company in FTE? [open question]				
In which industry is your business? [select Eurostat category]				
My current function within the company is: [open question]				
Smart manufacturing technologies	**Descriptive statistics**			
To what extent do you use the following smart manufacturing technologies within your company? [All options 9-point Likert scale anchored at 'not' (1), 'somewhat' (5) and 'considerably' (9)]	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
Flexible automation: digitization of machines (investments in robots, machining centers, automatic guided vehicles, etc.)	4.1	2.4	0.16	−1.14
MES: digital initiation of actions by real-time monitoring of production processes	3.7	2.5	0.54	−0.96
Product tracking: digital tracking of where products are located in the production process, which processes have been carried out on the products	4.7	2.5	−0.16	−1.31
Information systems: digital indication of required actions towards the customer (CRM) and towards purchasing and production processes (ERP, shop floor control)	5.9	2.0	−0.62	−0.12
Work-on-screen: replacing paper with digital information on desktop computers, laptop, tablets and/or smartphones	5.9	2.0	−0.73	−0.06
Lean principles				
To what extent do you use the following lean principles within your company? [All options 9-point Likert scale anchored at 'not' (1), 'somewhat' (5) and 'considerably' (9)]				

(*continued on next page*)

(*continued*)

Questions [scales]				
Supplier and customer link	6.6	1.7	−0.99	1.01
Standardization of processes	6.5	1.6	−0.76	0.17
Flow production	6.0	2.1	−0.62	−0.49
Continuous improvement	6.6	1.9	−0.95	0.34
Operational performance				
How does your company score on the performance indicators below compared to your industry peers? [All options 9-point Likert scale anchored at 'worse' (1), 'average' (5) and 'better' (9)]				
Cost	5.1	2.0	−0.81	0.09
Quality	7.2	1.7	−0.96	0.73
Delivery	6.6	2.1	−0.95	0.30
Flexibility	7.0	1.9	−0.73	−0.17

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