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Lean Production and Industry 4.0 integration: how Lean Automation is emerging in manufacturing industry

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ABSTRACT
Despite its potentialities, Lean Automation (LA) has not attracted attention for over two decades. However, due to the new opportunities offered by Industry 4.0 technologies, LA revives expectations and enthusiasm. This paper aims to test empirically the association of LA, in the form of integration of Lean practices and Industry 4.0 technologies, and operational performance. The paper used a rigorous, multi-stage empirical method and data from a set of more than 200 manufacturing firms; one representative from each of the studied companies filled in a survey on Lean practices and Industry 4.0 technology bundles, with productivity, delivery, inventory, quality as performance indicators. The extensive survey results helped in identifying underlying components of LA: one focuses on operational stability and includes practices and technologies supporting efficiency along the supply chain; the other focuses on streamlining the flow, on fastening the process to reach the customer. Moreover, it demonstrates the positive correlation between LA and operational performance. Besides its contribution to the body of knowledge on LA, this research paves the base of improving academics and practitioners understanding of the integration of new technologies with Lean Production systems.

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Lean Automation; Industry 4.0; Lean Production; digitalisation; operational performance; survey

1. Introduction

Since the 1990s, Lean Production (LP) was presented as a solution for the increasing market competition as its implementation led to important benefits in term of cost reduction, productivity and customer satisfaction (Knol et al. 2019; Thürer et al. 2019). LP has been widely adopted in the manufacturing industries, and in recent years, its adoption spread throughout different industries (Borges et al. 2019; Rossini et al. 2019; Torri et al. 2021).

Already in the early years of the Lean, first attempts of integrating automation and digital technologies with LP were carried out under the name of 'Lean Automation' (LA). The original aim of LA was to improve the changeability of production system and to fasten the information flows to meet future market demand (Kolberg and Zühlke 2015). However, LP systems seemed to struggle in successfully adopting automation and digital technologies and the opportunities that follow (Powell 2013). Therefore, the interest in the interplay between LP and digital technologies started vanishing after few years (Tortorella, Giglio, and van Dun 2019). Meanwhile, the advent of Industry 4.0 (I4.0) started to shape a new era of manufacturing and industry in general, promoting a new ecosystem for value creation (Benitez, Ayala, and Frank 2020; Buer et al. 2020). The vision of I4.0 is a smart production system capable of meeting the new challenging market requirements thanks to the introduction of new technologies such as modern information and communication technologies (ICT), cyber-physical systems (CPS), Internet of Things (IoT), virtual simulations, additive manufacturing and cloud computing (Kagermann, Wahlster, and Helbig 2013; Ghobakhloo 2018). The integration of smart components and machines through a digital network, governed by proven internet standards, allows the manufacturing system to be modular and flexible in order to massively manufacture customised products (Cimino, Negri, and Fumagalli 2019; Ghobakhloo 2020).

Then, the new opportunities generated by I4.0 technologies have revived expectations and enthusiasm about LA as a turning point for the current market situation (Buer, Strandhagen, and Chan 2018; Tortorella et al. 2019), sometimes presented under the name of Lean 4.0 (Mayr et al. 2018; Valamede and Akkari 2020).

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Evidences of implementations of LA are still scarce, despite academics and practitioners argued the necessity to implement LA (Kamble, Gunasekaran, and Dhone 2020). In practical terms, few studies approach LA (or the integration of novel technologies into LP) investigating with an overall picture the integration of practices and technologies (Buer et al. 2020). In fact, there is no framework for LA implementation that leads a widespread uncertainty on how companies could integrate LP practices and I4.0 technologies (Buer, Strandhagen, and Chan 2018).

A framework that defines bundles of LA and that guides and supports the implementation strategy of practices, technologies, and tools of the two paradigms is still missing. This is the reason why we think it is imperative to achieve that consensus in order to expand the knowledge on LA.

On these premises, this paper aims at testing empirically the relation between LA implementation and company operational performance, since many authors argue that there is little empirical evidence about the consequences of a systemic implementation of LA and its effect on operational performance (Buer et al. 2020; Kamble, Gunasekaran, and Dhone 2020).

Besides its theoretical contribution, our research provides practical implications that may support leaders and managers to better comprehend the advantages of sustaining LA implementation.

Having defined the topic and research problem, the next section of the paper provides relevant background information and understanding regarding LP, I4.0 technologies and LA. In Section 3, we present the methodology that has been used in order to fulfil the objective of the paper, and in Section 4, we discuss the results that detail how LP practices and I4.0 technologies are integrated to form LA and how it affects operational performances. Discussion is drawn in Section 5 and conclusions are presented in Section 6.

2. Literature review

In this section, we provide the relevant background of the present research. Section 2.1 reviews LP's most recognised frameworks in the literature, Section 2.2 reviews I4.0 technologies literature and Section 2.3 reviews LA literature.

2.1. Lean Production

LP aims at creating a continuous flow of value by systematically eliminating wastes and focusing on value-adding activities (Womack and Jones 1996; Portioli-Staudacher, Costa, and Thürer 2020) and reducing the variability of suppliers, customers and internal resources and processes (Anvari et al. 2011; Shah, Chandrasekaran, and Linderman 2008). Employees have a crucial role in Lean systems, they are considered as active problem-solver for the continuous improvement process (Kaizen) (Costa et al. 2019; Knol et al. 2019). Numerous literatures have reviewed the lean benefits, applications, and implementation initiatives (Bhamu and Sangwan 2016). The initiatives could be grouped into five categories: conceptual frameworks, implementation frameworks, roadmaps, descriptive and assessment checklist (Mostafa, Dumrak, and Soltan 2013). For example, Jina, Bhattacharya, and Walton (1997) suggested a descriptive diagram in applying lean principles to suit the high variety low volume situation; Womack and Jones (2003) described a time framework for a lean leap and Shah and Ward (2003) defined the success of lean implementation considering the plant age, plant size and unionisation. Åhlström (1998) developed a framework for sequencing the LP principles in the implementation process, Rivera and Chen (2007) developed a logical and easy to understand framework for lean implementation. Mostafa (2011) constructed an implementation framework for lean manufacturing in 15 stages. Mostafa, Dumrak, and Soltan (2013) proposed a project-based framework structured to fit lean implementation and divided in four phases, where the first phase mainly involves human factor while the remaining three phases are mainly technical.

Rafique et al. (2017) proposed a Lean implementation framework divided into four phases in order to deploy the technology concept in combination with lean operations, which was considered a big gap from the authors.

Shah and Ward (2007) determined a framework for LP, composed of 41 LP practices that they reduced to ten operational constructs – called bundles - that identify the most salient dimensions of LP. Most of these bundles such as pull, flow, setup time reduction, total productive maintenance and statistical process control allow companies to create and maintain a stable manufacturing system and to improve its efficiency (Hopp and Spearman 2004). With the aim of enhancing the integration and the collaboration along the supply chain, the four bundles considered to be Lean identifiers are Supplier feedback, Just-in-time delivery, Supplier development and Costumer involvement (Shah and Ward 2007). Finally, Employee involvement bundle is of paramount importance in the development and improvement of the entire production system.

2.2. Industry 4.0 technologies

The incorporation of novel ICT into organisations and manufacturers has been claimed as a significant feature of the fourth industrial revolution era (Liao et al. 2017; Love, Matthews, and Zhou 2020). The integration between the physical and the digital world is a feature that justified the term 'Industry 4.0', which is characterised by industries where digital technologies facilitate higher levels of mass customised processes, products and services, allowing companies to achieve improved performance levels (Zuehlke 2010; Zawadzki and Zywicki 2016). This is the reason why CPS is highlighted to play a central role in this revolution (Hermann, Pentek, and Otto 2016; Sanders, Elangeswaran, and Wulfsberg 2016). Along with CPS, IoT is expected to enable promising innovative solutions and to revolutionise the existing manufacturing system (Xu, Xu, and Li 2018) together with Industrial Analytics and Big Data for data elaboration (Santos et al. 2017) as well as for Cloud Computing and Cloud Manufacturing (Shou, Zhao, and Chen 2019; Gupta et al. 2020). Then, additive manufacturing, advanced automation and human machine interface technologies are included as a set of technologies for the change to the new industrial paradigm (Weyer et al. 2015; Negri, Fumagalli, and Macchi 2017).

Although I4.0 has gained significant attention from both researchers and practitioners in the past few years, they have not yet univocally defined which technologies build up I4.0 and how these technologies relate together (Buer, Strandhagen, and Chan 2018).

In this direction, Tortorella et al. (2018) presented a framework of I4.0 that reduces ten I4.0 technologies into two constructs. The first construct, named 'Process', includes technologies such as Digital automation with sensors and Remote monitoring that 'aim at supporting and facilitating the management of manufacturing process'. The second construct, named 'Product/Service', includes technologies that improve the flexibility and the reactiveness of the product and service development process, such as IoT, Cloud computing, Big data and Additive manufacturing (Tortorella et al. 2018).

2.3. Lean Automation

LA has regained its importance nowadays, due to the new opportunities offered by I4.0 technologies. Indeed, LA represents the application of I4.0 technologies to LP (Kolberg, Knobloch, and Zühlke 2017) and it has been increasingly discussed in operation management literature over the past few years (Mourtzis, Fotia, and Vlachou 2017; Sartal et al. 2017). From one hand, I4.0 is perceived as a necessary strategy to remain competitive in the future (Mrugalska and Wyrwicka 2017), while on the other, LP has become in the last decades the major approach to ensure high efficiency of the production processes (Kolberg and Zühlke 2015). In essence, while there are authors advocating that I4.0 can conflict with the ground principles of simplicity (Maguire 2015), continuous and small improvements of LP, others might claim that LP and I4.0 may be positively related (Buer et al. 2020) and their integration is essential in defining company's operations strategy (Rossini et al. 2021).

Bittencourt, Alves, and Leão (2020) performed a systematic literature review identifying several research that discussed lean as an enabling effect for I4.0. Kolberg and Zühlke (2015) highlighted lean's role in the implementation process of I4.0, using the 'Lean Automation' to describe such integration. The interdependencies of I4.0 and Lean were studied by Dombrowski, Richter, and Krenkel (2017) where they discussed the need to have efficient processes, waste-free before starting automating them, while Agostini and Filippini (2019) recognised the importance of a deep knowledge of processes to be aware of not digitalising waste. Chiarini and Kumar (2020) investigated and demonstrated how Industry 4.0 technologies and Lean Six Sigma tools and Techniques can be integrated to provide advantages to organisations. Ciano et al. (2020) through multiple case study research explained the one-to-one relationships between LP techniques and I4.0 technologies, examining the enabling effect of LP on I4.0 and the empowering effect of I4.0 on LP. Rosin et al. (2020) highlighted the links between I4.0 and Lean, focussing on how some I4.0 technologies are improving the implementation of lean principles, depending on the technologies' capability levels.

Kolberg, Knobloch, and Zühlke (2017) comment that the existing LA approaches, that aim at integrating I4.0 technologies into LP (i.e. eKanban, digitised Heijunka-Box), are usually proprietary solutions tailored to individual and specific company needs that might conflict with the usual high-tech and capital-intensive efforts of I4.0. They proposed a common, unified communication interface to digitise LP methods with the aim to integrate them into that interface. Other studies tried to integrate I4.0 technologies with LP (Ghobakhloo and Hong 2014; 2020), for example, focused on robotic technology used in a workcell (Polden et al. 2012) or the use of RFID in a value chain (Rafique et al. 2017). The same need for integration was claimed also by Sony (2018) who proposed an end-to-end engineering framework, showing how I4.0 technologies are integrated from the beginning with the identification of the value for the customers until the seek for perfection. Tortorella et al. (2019) and Rossini et al. (2019) studied the differences for companies in LA adoption– intended as the application of both I4.0 and LP – in relation to contextual variables such as the socio-economic context, and they found that those factors – where companies are located, for example – influence the integration between I4.0 and LP. Buer et al. (2020)

investigated the relationships between the use of lean, factory digitalisation, and operational performance and they showed that both lean and factory digitalisation individually contribute to improved operational performance.

From the above studies, it is quite evident that the little research that focused on LA did not aim to provide a holistic investigation on how I4.0 technologies as a whole could be integrated into the LP bundles. In other words, no research investigated how and which I4.0 technologies are associated with LP bundles in order to define LA; this research sheds light on the need, advocated by recent studies (Sony 2018), to provide integration between I4.0 technologies and LP. For that, resource-based view (RBV) is used as a theoretical lens (Barney 1991); and, in particular, the concept of complementarity proposed in the realm of RBV (Teece 1986). RBV is a managerial framework used to determine the strategic resources a firm can exploit to achieve sustainable competitive advantage (Ulrich et al. 1995). Resources can be defined as tangible and intangible assets possessed and controlled by organisations including processes, information systems, knowledge, and technologies, among others, to devise and implement strategies that improve its efficiency and effectiveness (Barney 1991). The concept of complementarity proposed by Teece (1986) can be used to explicate how one resource might influence and impact another, and how this relationship affects the performance of an organisation. Further, a key insight arising from the RBV is that not all resources are of equal importance, nor do they possess the potential to become a source of sustainable competitive advantage (Fahy and Smithee 1999). The sustainability of any competitive advantage depends on the extent to which resources can be imitated or substituted (Lowson 2003). However, the understanding of the causal relationship between the sources of advantage and successful strategies can be very difficult in practice (Barney 1991). Thus, a great deal of managerial effort must be invested in identifying, understanding and classifying core competencies. In addition, management must invest in organisational learning to develop, nurture and maintain key resources and competencies. Individually, LP or I4.0 can be considered as homogeneous and imitable resources and organisation need to find innovative ways of bundling resources that may be difficult for competitors to imitate; and, therefore, resulting in the creation of competitive advantage.

3. Methods

In line with the objective of the paper, we adopted a comprehensive, multi-step approach (as shown in Figure 1), during the development and validation process, following several studies in operations management (Shah and Ward 2007; Tortorella, Miorando, and Marodin 2017; Nielsen, Kristensen, and Grasso 2018). Each step is described briefly below.

3.1. Instrument development

This research is a survey-based research and in line with the aim of the paper, the survey comprised four main parts (see Supplementary material: Annex-A): operational performance indicators (i), information on the respondents and their respective companies (ii), LP implementation (iii) and adoption level of I4.0 technologies (iv).

(i) Since companies often protect financial results carefully, we used operational performance indicators as a proxy for financial performance. We assessed the improvement level of the companies' performance on productivity, delivery service level, inventory level, quality performances during the last three years. Those four indicators have been used and validated by previous survey-based LP studies (Bhasin 2012; Tortorella and Fettermann 2018a, 2018b). Each indicator was measured on a Likert scale (1 – worsened significantly; to 5 – improved significantly).

(ii) Two control variables are considered in this study: Company size and Lean implementation time since they have been demonstrated to be relevant in similar studies (Netland and Ferdows 2016).

(iii) The implementation level of LP was assessed via Shah and Ward's (2007) 41 practices. Each LP practice was measured on a Likert scale (1 – fully disagree; to 5 – fully agree).

(iv) I4.0 sphere includes a huge set of data-driven technologies (Klingenberg, Borges, and Antunes 2019). Some authors argue that I4.0 involves a set of digital technologies as embedded systems, wireless sensor network, 3D printing, cloud computing and big data (Fatorachian and Kazemi 2018; Moeuf et al. 2018). We investigated the adoption of I4.0 through a query of ten digital technologies already defined in similar survey-based research (Tortorella, Giglio, and van Dun 2019). These technologies are: Digital automation without sensors; Digital automation with process control sensors; Remote monitoring and control of production through systems such as MES and Supervisory Control and Data Acquisition; Digital automation with sensors for product and operating conditions identification, flexible lines; Integrated engineering systems for product development and product manufacturing; Additive manufacturing, rapid

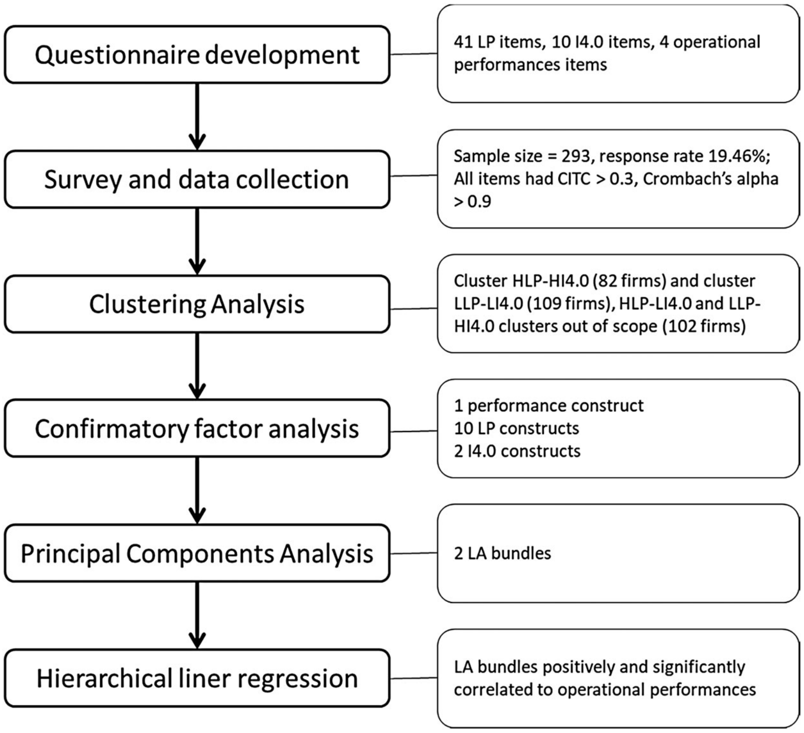

Figure 1. Multi-step approach.

prototyping or 3D printing; Simulation/analysis of virtual models (finite elements, computational fluid dynamics, etc.) for design and commissioning; Collection, processing and analysis of large quantities of data (big data); Use of cloud services associated with the product; Incorporation of digital services into products (Internet of Things or Product Service Systems). Like Tortorella and Fettermann (2018a, 2018b), we explicitly did not mention that these ten technologies are part of I4.0, thereby mitigating any blurred perceptions. Each I4.0 technology adoption was measured on a Likert scale (1 – not used; to 5 – fully adopted).

3.2. Sample characteristics

We targeted respondents from manufacturing companies and, as necessary selection criteria, we consider respondents with experience in both LP and I4.0 (Tortorella et al. 2019). The pervasiveness of both approaches across the industrial spectrum is still scattered (Tyagi et al. 2015; Koh, Orzes, and Jia 2019; Rajput and Singh 2019). Therefore, to avoid excluding respondents who might meet the established selection criteria, thereby reducing sample size and impairing the application of a robust statistical analysis, we did not restrict our data collection to a specific industrial sector. We sent the survey to more than 1000 leaders of a diverse range of Brazilian and European manufacturing companies.

For the Brazilian investigation, leaders of manufacturers that were former students of executive education courses on lean offered by a large Brazilian University were previously contacted to check their compliance with selection criteria. The ones that met these criteria were then contacted by another email containing the questionnaire and a few statements that clarified the purpose of the research and ensured confidentiality and anonymity of the information provided. A final valid sample of 147 respondents from different companies was obtained. In the European survey, 750 leaders from companies that have already collaborated with previous research of one of the largest Italian Industrial Engineering programmes were contacted. Questionnaires were either sent by email or answered during visits to some of these companies. In total, 146 different companies provided valid responses, resulting in a response rate of 19.46%. Finally, in order to check for non-response bias, differences between early and late respondents of both Brazilian and European samples were tested based upon equality of variances (Levene's test) and equality of means (t-test) (Armstrong and Overton 1977). As results were not significant, any issue related to non-response bias from both samples was disregarded.

We received responses from 293 individuals, representing different facilities, yielding a response rate in line with other research papers on lean manufacturing (Nielsen, Kristensen, and Grasso 2018). While large-sized ($\geq$500employees) companies were the majority (55.1%) in the Brazilian dataset, companies with less than 500 employees corresponded to 61.8% of the European sample. On the respondents, we had operations manager or director (82%), supervisor or coordinator (14%) or analyst/technician (4%). They mainly worked for large-sized companies (59.1%); most of the companies belonged to the metal-mechanical sector (49.2%). Examples of the 'other' 5.2% sectors were: civil construction, leather-footwear and graphical industry. Most companies (73%) had begun their formal LP implementation more than two years previously and respondents' personal experience with LP was more than two years in the 80% of respondents. Most of companies (70%) had begun I4.0 technologies implementation less than two years previously as well as respondents' personal experience with Industry 4.0 technologies was less than two years in the 70% of respondents. For what concern the property type, 60% of manufacturing are multinational while the remaining 40% is family owned property type.

3.3. Clustering analysis

According to Ward's hierarchical method, we identified the number of clusters to consider for LP and I4.0 implementation. The results showed that the number of clusters was equal to two for both LP and I4.0 (refer to Rossini et al. 2019 for cluster analysis methodology executed).

Analysis of Variance (Anova) showed that for all LP and I4.0 measures there were significant differences in means (p-values < 0.05 for each measure). Cluster one for LP is composed of 135 observations with an average implementation level of 3.69 – called 'High LP' (HLP) – higher than cluster two that has 148 companies whose average implementation level of LP resulted to be 2.63 – 'Low LP' (LLP).

For what concerns I4.0 adoption, cluster one (118 observations) presents a higher average adoption level equal to 3.10 – called 'High I4.0' (HI4.0) – than cluster two (165 observations) that has a value of 4.0 technologies of 1.76 – called 'Low I4.0' (LI4.0).

In order to understand integration between LP practices and I4.0 technologies, we take into account companies that presented HLP and HI4.0 (82 firms) or LLP and LI4.0 (109 firms). All the other firms, which were characterised by an unbalance between LP and I4.0 adoption (HLP-LI4.0 and LLP-HI4.0 clusters), have been discarded, in order to avoid that interrelation factors between those two dimension would prevent to uncover the underlying measures of LA, as integration between LP and I4.0.

Table 1. PCA results of operational performance indicators. Extraction method: principal component analysis: Rotation method: varimax with Kaiser normalisation.

Manifest variables	Factor loading	Mean	SD
Delivery service level	0.822	3.692	0.88
Quality (scrap and rework)	0.837	3.627	0.93
Productivity	0.842	3.655	0.95
Inventory level	0.680	3.245	1.03
Eigenvalue	2.547		
Cronbach Alpha	0.896		
Percent of variance explained	63.69%		
Kaiser-Meyer-Olkin measure of sampling adequacy	0.759		
Barlett's test for sphericity (p-value)	0.000		

Therefore, in order to investigate LA in the view of integration of LP practices and I4.0 technologies, we focused the analysis on cluster with homogenous implementation of the two paradigms. Hence, all the following steps consider the sample size equal to 191 companies.

3.4. Operational performances, LP and Industry 4.0

In this section, we show the results of principal components analysis (PCA) on the operational performance indicators (3.4.1) and the validity of the theoretical model for LP (3.4.2) and for I4.0 (3.4.3) empirically tested through a Confirmatory Factor Analysis (CFA).

3.4.1. Operational performance improvement

We performed an exploratory factor analysis (EFA) through PCA with varimax rotation on operational performance indicators. Table 1 shows that all the performance indicators load on one factor, with an eigenvalue of 2.547 explaining 63.7% of the variation. Cronbach's α of this factor is 0.896.

3.4.2. Lean practices

As LP practices had been previously validated (Shah and Ward 2007), we performed in R-Studio a CFA using as input data the covariance matrix of the 41 LP measures and maximum likelihood method to estimate the model of the ten LP bundles. First, convergent validity and unidimensionality of the model is conducted (see Supplementary material: Annex-B) to assess how a LP measure behaves within the block of items intended to measure a bundle. Each of the measures of LP loads significantly on its respective bundles. We use both the approaches of factor loading higher than 0.45 (Tabachnick and Fidell 2007) and we consider the factor loadings being significantly higher than their standard errors (Anderson and Gerbing 1988). The proportion of the variance explained (R^2) in the manifest variable that is accounted for by the latent variable influencing it can used to estimate the reliability of a particular item (Shah and Ward 2007).

Table 2. Absolute, incremental and parsimonious measure of fit for LP model.

Measures of fit	Statistic measure	Measured values	Recommended value for acceptable fit
	χ2-Test statistic (d.f.)	1006.265 (707)	N/A
	Root mean square error of approximation (RMSEA)	0.047	$\leq$ 0.08
Absolute	90% confidence interval for RMSEA	(0.040; 0.054)	(0.00; 0.08)
	P-value for test of close fit (RMSEA $<$ 0.05)	0.765	$\geq$ 0.05
	Standardised root mean square residual (RMR)	0.060	$\leq$ 0.10
Incremental	Non-normed fit index (NNFI)	0.914	$\geq$ 0.90
	Comparative fit index (CFI)	0.926	$\geq$ 0.90
	Incremental fit index (IFI)	0.928	$\geq$ 0.90
Parsimonious	Normed χ2 (χ2/d.f.)	1.42	$\leq$ 3.0
	Parsimony normed fit index (PNFI)	0.68	$\geq$ 0.70

Table 3. Absolute, incremental and parsimonious measure of fit for I4.0 model.

Measures of fit	Statistic measure	Measured values	Recommended value for acceptable fit
	χ2-Test statistic (d.f.)	40.544 (31)	N/A
	Root mean square error of approximation (RMSEA)	0.040	$\leq$ 0.08
Absolute	90% confidence interval for RMSEA	(0.000; 0.071)	(0.00; 0.08)
	P-value for test of close fit (RMSEA $<$ 0.05)	0.66	$\geq$ 0.05
	Standardised root mean square residual (RMR)	0.039	$\leq$ 0.10
Incremental	Non-normed fit index (NNFI)	0.98	$\geq$ 0.90
	Comparative fit index (CFI)	0.99	$\geq$ 0.90
	Incremental fit index (IFI)	0.99	$\geq$ 0.90
Parsimonious	Normed χ2 (χ2/d.f.)	1.31	$\leq$ 3.0
	Parsimony normed fit index (PNFI)	0.66	$\geq$ 0.70

Second, model fit was evaluated using multiple absolute, incremental, and parsimonious measures of fit (Table 2) which provide insights on how the relationships of the model fit the observed data (Shah and Ward 2007). The Root mean square error of approximation (RMSEA), 90% confidence interval for RMSEA and the standardised root mean square residual (RMR) indicate a good to excellent fit. Furthermore, the *p*-value for the test of close fit is higher than the threshold of 0.05; hence, the null hypothesis of close fit could not be rejected. All the other incremental and parsimonious measures of fit reflect an adequate fit and robustness of the theoretical LP model, considering that PNFI commonly agreed-upon cut-off value is accepted even with values higher than 0.6 (Awang 2012; Shadfar and Malekmohammadi 2013). Cronbach Alpha, composite reliability (CR), and average variance extracted (AVE) are used to assess internal consistency.

Values in Table 2 reflect an adequate fit and robustness of the theoretical LP model.

3.4.3. I4.0 technologies

As I4.0 technologies had been previously validated (Tortorella et al. 2018; Rossini et al. 2019), we performed in R-Studio a CFA using as input data the covariance matrix of the 10 I4.0 technologies and maximum likelihood method to estimate the model of the 2 I4.0 constructs – Product/Service and Process. As for CFA of the LP bundles, first convergent validity and unidimensionality of the model is conducted (see Supplementary material: Annex-C) to check that each I4.0 measure loads significantly on its respective construct. Second, model fit was evaluated using multiple absolute, incremental, and parsimonious measures of fit (Table 3) which provide insights on how the relationships of the model fit the observed data, considering that PNFI commonly agreed-upon cut-off value is accepted even with values higher than 0.6 (Awang 2012; Shadfar and Malekmohammadi 2013). Cronbach Alpha, CR, and AVE are used to assess internal consistency. Values in Table 3 reflect an adequate fit and robustness of the theoretical I4.0 model.

3.5. Bias countermeasures

When submitting the questionnaire, we clarified that there were no right or wrong answers and the respondents' responses would be treated anonymously. Also, the respondents had to be key lean implementers in their organisations and were thus appropriate informants.

Non-response bias was analysed for each of the three sections of the survey – LP, I4.0 and operational performance – using Levene's test for equality of variances and a t-test for the equality of means (Armstrong and Overton 1977). Both tests indicated that the three groups' means and variations were not significantly different. Each item has a significance value (*p*-value) of the Levene's test higher than 0.05, thus implying homogeneity of variances. Each *p*-value related to the T-test is higher than 0.05, then the means of the two populations are also equal. Moreover, each item presents a CITC score higher than 0.3 and the Cronbach's alpha of all the three groups of items is higher than 0.8, hence verifying the reliability of the items (Shah and Ward 2007). Results of Cronbach's alpha, CITC, Levene's Test, t-test are reported in Supplementary material: Annex-D. Finally, the Harman's single-factor test, including all the independent and dependent variables (Tortorella, Giglio, and van Dun 2019), displayed a first factor that explained only 43% of the variance. Since no single factor accounted for most of the variance, common method variance was deemed minimal.

4. Calculation and results

In this section, we describe the calculation steps we used in order to define the LA model that integrates LP measures and I4.0 technologies. We conduct a PCA on the 12 constructs identified previously in order to define LA bundles and then we assessed validation of LA model through a CFA. Lastly, we performed regressions in order to assess the impact of LA model on operational performance.

4.1. LA bundles

The 12 constructs (ten LP constructs and two I4.0 constructs) turned in items and they have been submitted to a PCA with varimax rotation to extract the second-order components of LA in line with the objective of the paper.

At this point, the number of items of the analysis changed from 51 (41 LP measures and 10 I4.0 technologies) to 12 items. Since the factor loadings represent the correlation and the relative weight between the manifest variables and corresponding construct, the response value of each of the 12 constructs is obtained through the average of the corresponding practices or technologies included in the construct weighted by their respective factor loadings (Shah and Ward 2007; Tortorella and Fettermann 2018a, 2018b).

In the PCA, in order to define the principal components, two thresholds have been set: according to Kaiser's method, constructs with eigenvalues communalities greater than 1 and all the factor loadings higher than 0.45 were retained (Tabachnick and Fidell 2007).

The PCA with varimax rotation extracted the orthogonal components, resulting in two components (see Table 4).

The Kaiser-Meyer-Olkin resulted higher than 0.6 (KMO = 0.923) and verified adequacy of the sample (Netemeyer, Subhash, and Bearden 2003). The Barlett's test of Sphericity indicated the suitability for a data reduction analysis of the initial dataset (p-value < 0.05) (Tabachnick and Fidell 2007).

Table 4. PCA results for LA model. Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalisation.

First-order latent variables (LP and Industry 4.0)	Bundle-1	Bundle-2
Supplier feedback	0.821	
Supplier JIT delivery	0.762	
Supplier development	0.589	
Involved employees	0.653	
Statistical process control	0.607	
Productive maintenance	0.720	
Process	0.660	
Pull		0.787
Flow		0.787
Low setup		0.652
Involved customers		0.489
Product		0.557
Eigenvalue	3.96	3.18
Cronbach Alpha	0.886	0.795
Initial % of variance explained	51.1%	8.4%
Percent of variance explained	33.0%	26.5%
Kaiser-Meyer-Olkin factor adequacy	0.923	
Bartlett's test for sphericity (p-value)	< 0.05	

Each factor loading resulted to be higher than 0.45 (Tabachnick and Fidell 2007) and each component's Cronbach alpha is higher than 0.70 (Bundle 1 = 0.886, Bundle 2 = 0.795), then they are internally consistent since (Tabachnick and Fidell 2007). Convergent validity is tested which resulted in both eigenvalues higher than 2.0. The same results were obtained through the oblique rotation, as a check for orthogonality (Tortorella et al. 2018).

Furthermore, the LA model was tested through a CFA with the observed covariance matrix of the 12 first-order constructs as input data as shown in Table 5 (Schreiber et al. 2006).

The CFA positively validated the LA components and provided a more rigorous test of convergent and discriminant validity of the LA model. As the LA model has been defined adopting at least three variables, the model is identified (Long 1983). The model fit has been evaluated with maximum likelihood method, adopting absolute, incremental and parsimonious measures of fit (Table 6) which demonstrates how well the model fits the observed data (Schreiber et al. 2006).

A comparison of the measures of fit with recommended thresholds confirmed that the model is satisfactory.

Cronbach's alpha, CR and AVE have been computed to assess construct reliability (Table 7). Both CR and Cronbach alpha values are above 0.7 for the two constructs, thus indicating adequate reliability. Results for convergent validity indicate that each item's coefficient is significantly higher than its standard error and all the factor loadings are highly significant ($p < 0.01$) (Shah and Ward 2007; Farrell and Rudd 2009). HTMT analysis

Table 5. Covariance matrix of the 12 constructs.

	SuppFeed	SuppJIT	SuppDevt	StatPC	EmplInv	TPM	Process	CustInv	Pull	Flow	LowSetup	Product
SuppFeed	0.818											
SuppJIT	0.542	0.977										
SuppDevt	0.365	0.439	0.558									
StatPC	0.429	0.554	0.348	1.122								
EmplInv	0.438	0.517	0.355	0.729	1.112							
TPM	0.406	0.481	0.277	0.626	0.614	0.953						
Process	0.480	0.590	0.374	0.765	0.650	0.610	1.144					
CustInv	0.323	0.400	0.354	0.418	0.410	0.322	0.487	0.828				
Pull	0.259	0.426	0.343	0.488	0.437	0.271	0.467	0.396	1.178			
Flow	0.246	0.363	0.307	0.542	0.407	0.382	0.501	0.357	0.528	0.954		
LowSetup	0.281	0.340	0.318	0.531	0.503	0.367	0.478	0.309	0.388	0.453	0.807	
Product	0.340	0.425	0.311	0.452	0.484	0.385	0.597	0.376	0.464	0.377	0.381	0.841

Table 6. Absolute, incremental and parsimonious measure of fit for LA model.

Measures of fit	Statistic measure	Measured values	Recommended value for acceptable fit
	χ2-Test statistic (d.f.)	91.092 (50)	N/A
	Root mean square error of approximation (RMSEA)	0.066	$\leq$ 0.08
Absolute	90% confidence interval for RMSEA	(0.044; 0.087)	(0.00; 0.08)
	P-value for test of close fit (RMSEA $<$ 0.05)	0.113	$\geq$ 0.05
	Standardised root mean square residual (RMR)	0.047	$\leq$ 0.10
Incremental	Non-normed fit index (NNFI)	0.950	$\geq$ 0.90
	Comparative fit index (CFI)	0.962	$\geq$ 0.90
	Incremental fit index (IFI)	0.963	$\geq$ 0.90
Parsimonious	Normed χ2 (χ2/d.f.)	1.82	$\leq$ 3.0
	Parsimony normed fit index (PNFI)	0.70	$\geq$ 0.70

Table 7. LA constructs, measures and CFA factor loadings model.

	Factor 1	Factor 2	Standard Error	R^2	*p*
Supplier feedback	0.517		0.0623	0.340	***
Supplier JIT delivery	0.661		0.0654	0.462	***
Supplier development	0.455		0.0488	0.421	***
Involved employees	0.801		0.0664	0.598	***
Statistical process control	0.889		0.0666	0.693	***
Productive maintenance	0.689		0.0656	0.491	***
Process	0.789		0.0653	0.600	***
Pull		0.662	0.0757	0.385	***
Flow		0.650	0.0689	0.434	***
Low Setup		0.619	0.0620	0.474	***
Involved customers		0.561	0.0652	0.376	***
Product		0.615	0.0621	0.468	***
CR	0.892	0.820			
Cronbach's α	0.860	0.793			
AVE	0.542	0.477			
HTMT	0.827				

***Significant at 1%.

validated the discriminant validity of the construct with a coefficient lower than 0.9 (Henseler, Hubona, and Ray 2016). The reliability of each item is confirmed from the R^2 that represents the proportion of variance explained in the manifest variable that is accounted for by the respective latent variable.

4.2. LA bundles and operational performances

Finally, we performed a set of Ordinary Least Square (OLS) hierarchical linear regression models in order to assess the influence of the LA components on the improvements in operational performance (Shah and Ward 2003; Andersson, Eriksson, and Torstensson 2006; Tortorella, Miorando, and Marodin 2017).

Two models were examined:

1) Model 1 assesses the effect of the control variables (company size and lean implementation time) on the dependent variable (operational performances improvement).
2) Model 2 assesses the effect of the control variables together and of the two LA bundles on the dependent variable.

The regression results are presented in Table 8.

Table 8. OLS regression for Model 1 and Model 2 with standardised β coefficient for hierarchical regression analysis for Model 1 and Model 2.

	Operational performances improvements	
Variables	Model 1	Model 2
Company size	−0.14	0.015
LP implementation time	0.254***	0.074
Bundle-1		0.501***
Bundle-2		0.114**
F-value	6.235***	28.206***
R^2	0.062	0.378
Adjusted R^2	0.052	0.364
Change in R^2		0.312
P-value of the overall model	0.002	0.000

**Significant at 5%; ***Significant at 1%.

The unstandardised coefficients are reported here since each construct's scales had already been standardised (Goldsby et al. 2013). Furthermore, multicollinearity was not a concern since the variance inflation factors in the regression models were all lower than 3.0. The regression resulted in significant models ($p < 0.01$), all independent and control variables were correlated positively with Operational Performances improvement. As suggested by Hair et al. (2014), we checked for assumptions of normality, linearity, and homoscedasticity between independent and dependent variables (Hair et al. 2012). Residuals were verified to confirm normality of the error term distribution. We tested linearity by plotting partial regression for each model. None of the models rejected the hypothesis of adherence to the normal distribution of residuals (Kolmogorov–Smirnov test). Homoscedasticity was assessed by plotting standardised residuals against predicted value and a visual examination of those plots. Overall, our tests supported the necessary assumptions for an OLS regression analysis.

Control variables (Model 1) account for a small but significant amount of variance (adjusted $R^2 = 0.052$ and *p*-value significant at 5%). The control variable company size showed a negative but not-significant correlation on Operational Performance improvements while the more the lean implementation time the higher the Operational Performance improvements. The inclusions of the LA bundles (Model 2), leads to a change in R^2 of 0.312 which is highly significant (*p*-value = 0.000). Overall the model explains 37.8% of the variance in Operational Performance improvements and it is significant at 1% (*p*-value = 0.000). The analysis indicates that LA components are associated with higher operational performances (Shah and Ward 2003).

5. Discussion

After having assessed the statistical significance of the relationship between the different dimensions of the paradigms, it is necessary to judge the rationality at the basis of the logic that bundles together the specific dimensions into the LA constructs because '*logic provides the theoretical glue that holds a model together*' (Whetten 1989). In the next section, the explanation of the results of second-order PCA will be presented while in Section 5.2 the impact of bundles on performances will be described.

5.1. LA bundles

The 12 first-order constructs were combined by the second-order PCA into two LA bundles as resumed in Figure 2.

One LA bundle combines six first-order constructs of LP (Statistical Process Control, Total Productive Maintenance, Supplier Just-in-time Delivery, Supplier Feedback, Supplier Development, Involved Employees) and one of I4.0 (Process). All the mentioned constructs focus mainly on improving stability, levelling and coordination of processes upstream the supply chain, so the bundle has been named Operational Stability (OS) bundle.

OS bundle confirms examples of successful interplay of LP and I4.0 are already diffused in industry such as the use technology of process control sensors combined with Total Productive Maintenance and Statistical Process Control practices (Ma, Wang, and Zhao 2017), or the practices of involving Supplier in the loop of product development combined with the use of I4.0 Integrated engineering systems for product development (Ciano et al. 2020).

The underlying rationale is that OS plays a key role in the achievement of a healthy relationship and integration of operations along the supply chain, both internal and external to the organisation. In fact, OS sponsors a more efficient process with reduced 'unpredictable stoppages', as defects and failures, recalling constructs that aim at supporting and facilitating management against variability created by internal processes (e.g. Statistical Process Control, Total Productive Maintenance and Process). Similarly, OS sponsors efficiency along the supply chain with reduced variability transmitted to (and coming from) upstream, recalling constructs that aim at smoothing and stabilising the relationship with supply chain partners (e.g. Supplier Just-in-time Delivery, Supplier Feedback, Supplier Development and Process).

In turn, the other LA bundle combines four constructs of LP (Flow, Pull, Involved Customer, Low setup) and one of I4.0 (Product). All the mentioned constructs focus mainly on streamlining the flow downstream of supply chain, on fastening the process to reach customer as soon as possible, so the bundle has been named Fast-to-Market (FtM) bundle. FtM bundle confirms trends of companies of combining I4.0 technologies such as 3D

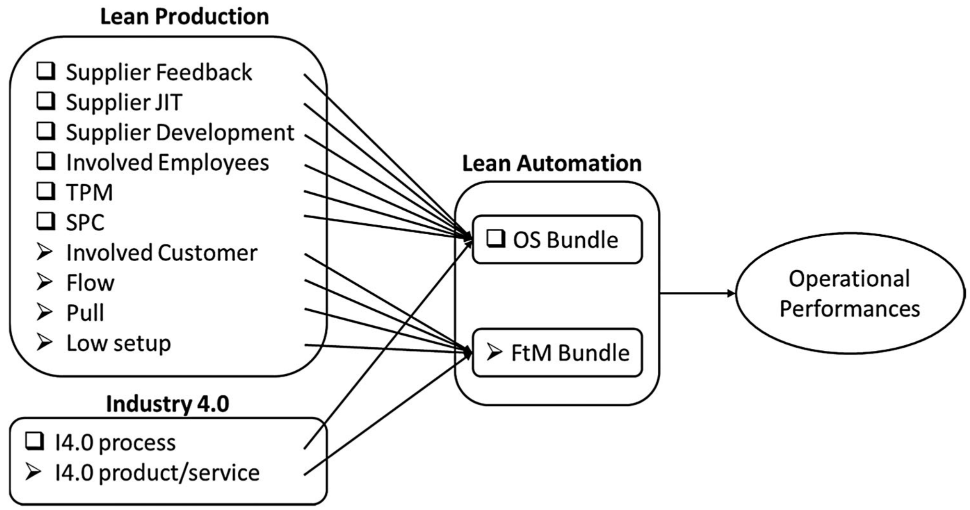

Figure 2. Sum-up of LA bundles and their composition.

and setup times reduction to result more flexible at the customer requests (Ciano et al. 2020) and of combining the use of cloud technology and Customer Involvement Practices for enhancing product development capabilities (Núñez-Merino et al. 2020).

The underlying rationale is that FtM concerns constructs that contribute to more flexible and faster product and service development, which make the organisation closer to market requests and more capable to follow customer requests. In fact, FtM sponsors improvement of the reactiveness to the variability generated by the market recalling constructs that speed up the delivery to the customer (e.g. Flow, Low setup and Product) and constructs that enable to answer specific customer requirements in a timely way and to deliver high-quality products (Involved Customer, Pull and Product). All the 12 first-order constructs load positively and significantly on the corresponding LA bundle (validated even by the CFA analysis): it seems reasonable as both LP and I4.0 are directed towards similar goals of productivity and flexibility (Buer, Strandhagen, and Chan 2018).

These results advance the body of knowledge of interplay between I4.0 and LP significantly. First, they reinforce the literature of the relationship between I4.0 and LP (Buer et al. 2020; Ciano et al. 2020) given another empirical prove of its existence. Moreover, the research explores a new part of literature that focuses on how this interplay has been built up by the companies in the medium term (Tortorella, Narayanamurthy, and Thurer 2021), showing a strategy of integration for LP and I4.0 that LA bundles lead. It is possible to simplify that OS bundle combines constructs that focus on efficiency impact and towards upstream direction of the supply chain, while FtM bundle combines constructs that focus on effectiveness and towards downstream direction of the supply chain (concept of arriving as fast as possible to the market).

5.2. *LA bundles and operational performances*

Each LA bundle contributes positively and significantly to operational performances, which suggests the synergic effect of implementing LA bundles together. While the contextual variable result in a small positive but not-significant impact on operational performances improvement.

The findings from the hierarchical regression model suggest that the implementation of LA has a significant positive impact on operational performance improvements, validating what Dombrowski, Richter, and Krenkel (2017) and Buer, Strandhagen, and Chan (2018) hypothesised in their analysis. Indeed, OS and FtM together positively explain 31.2% of the variation in operational performance improvements. The fact that OS bundle has a higher impact on operational performances than FtM bundle is reasonable because of the performance measure considered in this research. According to the logic that FtM bundles focuses on reaching customer rapidly, hence other different performances should be more impacted as lead-time for launching a new product or flexibility in planning.

The regression analysis demonstrates that LA enables companies to compete successfully designing operations system where high-tech applications and human-based simplicity are integrated. Buer et al. (2020) presented LP system and I4.0 technologies as complementary element for creating competitive advantages in operations system. The regression model presented in this paper reinforces their research: it shows that LA implementation generates a competitive advantage, probably because it integrates simultaneously so many elements of LP and I4.0 that comes difficult to imitate by competitors. Moreover, the results pave the base for additional insight into the interplay between LP and I4.0. Many authors defined a clear position of the two paradigms, where one paradigm plays the role of enabler for the success in the implementation of the other paradigm. Some research works argued that LP is the enabler for the successful implementation of I4.0 technologies (Tortorella et al. 2019; Buer et al. 2020), other authors presented I4.0 empowering adoption of LP systems in a broadly way (Kolberg and Zühlke 2015; Núñez-Merino et al. 2020). This work reinforces the perspective where the benefit of the interplay works in both direction (Ciano et al. 2020), and the interaction and integration is intertwined at different levels.

Examining the results from the perspective of the RBT, they clarify some general credence related to the difficulty of integrating LP and technologies (Maguire 2015).

They show that organisations, implementing LA, create complex operations system through integration of processes, practices and technologies that promotes innovation and provide competitive advantages over their competitors. The value of LA implementation as competitive advantage is guaranteed by the difficulty in replicating such integration that includes many elements and by the time necessary to implement such integration. LA is the opportunity for companies to exploit the combination of novel technologies and human-centered operating practices. Therefore, technology adoption with LP practices could create value for people and processes when included in a clear pattern.

5.3. Limitations of the study

Some limitations of this study must be highlighted. For what concerns the sample, all the respondents were European or Brazilian manufacturers, a characteristic that limits the generalisation of the analysis. Future studies could take into consideration a wider set of countries to improve the robustness of the findings. Moreover, as the pace in which new technologies are invading the market is very high, the interest and appetite for integrating brand new technologies in manufacturing systems will increase. Nevertheless, manufacturers may consider, for future implementation, technologies that are not comprehended in this study. Thereby, future studies may tackle the LA topic with a more holistic representation of Industry 4.0 technologies. It should also be interesting to analyse LA dimensions for companies comprehended in the intermediate clusters (companies with High LP implementation and low Industry 4.0 adoption and companies with high Industry 4.0 adoption and low LP implementation). This analysis could present a different distribution of practices and technologies within LA clusters, as one approach could support the other or vice-versa. Finally, LA has been analysed with a focus on operational performances. Further research should be promoted in order to include other operational performances or the impact of LA on indicators that do not have a direct link with operational/economic performances, such as environmental sustainability and social impact, which are even more relevant in the long-term point of view.

6. Conclusion

The research investigated LA, in the form of the integration of LP practices and I4.0 technologies, within the manufacturing sector.

Although several studies have proven that a concurrent implementation of LP and I4.0 is positively linked with a firm's performances, this study addresses the lack of a comprehensive view on how those two paradigms consolidate in LA framework.

In theoretical terms, this study develops our knowledge on LA by developing and empirically validating a multi-dimensional framework and paves the base toward a clarification about the relation between LP and I4.0.

The research defines the underlying components of LA and explains how integration between LP practices and I4.0 technologies builds up LA components.

A PCA analysis defined and validated empirically two LA bundles: OS bundle and FtM bundle. The former one more supplier oriented and focusing on preventing unexpected process variability, while the latter is more customer-oriented and focuses on shortening and improving the delivery process. Both the bundles combine LP constructs and I4.0 constructs. Furthermore, the analysis showed that the adoption of LA generated a positive significant effect on operational performance improvements for companies.

This study can be considered as one of the pioneers in analysing LA in such a detailed way. In fact, our paper enhances the research done by Tortorella, Narayanamurthy, and Thurer (2021) that showed the temporal sequence of LP and I4.0 technology implementations. The major theoretical contribution our paper adds is the evidence that LA bundles depict clearly that the integration of LP practices and I4.0 technologies is not randomly happening, but certain LP practices are combined with certain I4.0 technologies. Moreover, this research reinforces the body of knowledge of the literature empirically demonstrating the LA (or the integration or LP and I4.0) has significant positive effect on operational performances (Buer et al. 2020).

In terms of managerial implications, this study re-emphasises the importance of building operations process capabilities based on the effective principles of LP practices and I4.0 technologies. Furthermore, the results disclose the positive effect that LA has on operational performance improvements regardless of the contextual factors. Managers should understand that integrating these paradigms is critical for building and improving a firm's competitive performance.

From a practical perspective, a better grasp of the meaning of LA may support proactive initiatives that could converge with previous efforts of adopting LP practices and implementing I4.0 technologies. The insights of this research provide managers a guideline for efficient integration of LP practices and I4.0 technologies, supporting them to prioritise efforts and more objectively focus on the proper set of items. The paper should support practitioners in designing robust strategies to achieve a high level of supply chain integration, giving them more awareness about LA framework and avoiding speculation-based behaviours derived from the short-term governmental incentives for I4.0 adoption.

The LA dimensional framework represents LA bundles and managers of manufacturing companies have a supporting guideline to combine consciously LP and I4.0 for maximum benefits. LA dimensions will thus work as a reference point for practitioners seeking to improve operational performances.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

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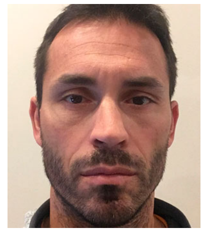

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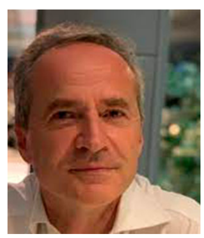

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Disclosure statement

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

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ANNEX-A

Applied Questionnaire

This survey is part of an academic study led by operations management researchers from Politecnico di Milano – Italy and from Univesidade Federal de Santa Catarina. Since this is an exploratory study, therefore, there are no right answers for each of the following questions.

It is noteworthy that all responses will be treated anonymously, and confidentiality of data will be kept. Any publication of this material will require authorization beforehand and will only occur with respondents' agreement.

1 – Please, provide the information below:

Number of employees in your company: ( ) Less than 500 ( ) More or equal to 500

Type of ownership of your company: ( ) Family-owned ( ) Corporate-owned

Business operating model: ( ) B2B (business-to-business)

( ) B2C (business-to-customer)

LP implementation time length: ( ) $\leq$ 5 years ( ) $>$ 5 years

Industrial sector of your company: _______________

2 – Please, indicate below the agreement level with the following statements based upon your company's current status:

3 – Please, indicate below the adoption level of the following digital technologies in your company:

4 – Please, indicate the improvement level of the following operational performance indicators observed in your company during the last three years:

ANNEX-B

Confirmatory Factor Analysis LP - n = 191 observations

ANNEX-C

Confirmatory Factor Analysis I4.0 - n = 191 observations

ANNEX-D

Bias Countermeasures for LP – I4.0 and Operational Performances

LEAN PRODUCTION	Fully disagree		Fully agree		
	1	2	3	4	5
We frequently are in close contact with our suppliers					
We give our suppliers feedback on quality and delivery performance					
We strive to establish long-term relationship with our suppliers					
Suppliers are directly involved in the new product development process					
Our key suppliers deliver to plant on JIT basis					
We have a formal supplier certification program					
Our suppliers are contractually committed to annual cost reductions					
Our key suppliers are located in close proximity to our plants					
We have corporate level communication on important issues with key suppliers					
We take active steps to reduce the number of suppliers in each category					
Our key suppliers manage our inventory					
We evaluate suppliers on the basis of total cost and not per unit price					
We frequently are in close contact with our customers					
Our customers give us feedback on quality and delivery performance					
Our customers are actively involved in current and future product offerings					
Our customers are directly involved in current and future product offerings					
Our customers frequently share current and future demand information with marketing department					
Production is pulled by the shipment of finished goods					
Production at stations is pulled by the current demand of the next station					
We use a pull production system					
We use *kanban*, squares, or containers of signals for production control					
Products are classified into groups with similar processing requirements					
Products are classified into groups with similar routing requirements					
Equipment is grouped to produce a continuous flow of families of products					
Families of products determine our factory layout					
Our employees practice setups to reduce the time required					
We are working to lower setup times in our plant					
We have low set up times of equipment in our plant					
Large number of equipment/processes on shop floor are currently under SPC					
Extensive use of statistical techniques to reduce process variance					
Charts showing defect rates are used as tools on the shop floor					
We use fishbone type diagrams to identify causes of quality problems					
We conduct process capability studies before product launch					
Shop floor employees are key to problem solving teams					
Shop floor employees drive suggestion programs					
Shop floor employees lead product/process improvement efforts					
Shop floor employees undergo cross functional training					
We dedicate a portion of everyday to planned equipment maintenance related activities					
We maintain all our equipment regularly					
We maintain excellent records of all equipment maintenance related activities					
We post equipment maintenance records on shop floor for active sharing with employees					

DIGITAL TECHNOLOGIES	Not used		Fully adopted		
	1	2	3	4	5
Digital automation without sensors					
Digital automation with process control sensors					
Remote monitoring and control of production through systems such as Manufacturing Execution System and Supervisory Control and Data Acquisition					
Digital automation with sensors for product and operating conditions identification, flexible lines					
Integrated engineering systems for product development and product manufacturing					
Additive manufacturing, rapid prototyping or 3D printing					
Simulation/analysis of virtual models (finite elements, computational fluid dynamics, etc.) for design and commissioning					
Collection, processing and analysis of large quantities of data (big data)					
Use of cloud services associated with the product					
Incorporation of digital services into products (Internet-of-Things or Product Service Systems)					

OPERATIONAL PERFORMANCE INDICATORS	Worsened significantly				Improved significantly
	1	2	3	4	5
Productivity					
Delivery service level					
Inventory level					
Quality (scrap and rework)					

	Estimate	Std.Err	z-value	$P(>\|z\|)$	Std.lv	Std.al	R^2	T-test
Supplier FeedBack								
SF1	1.00				0.76	0.76	0.581	11.57
SF2	1.09	0.10	10.64	0.00	0.83	0.83	0.687	12.96
SF3	0.92	0.10	9.19	0.00	0.70	0.70	0.489	10.33
JIT Delivery								
J1	1.00				0.66	0.66	0.439	9.49
J2	1.07	0.13	8.19	0.00	0.71	0.71	0.504	10.32
J3	0.90	0.13	7.12	0.00	0.60	0.60	0.359	8.40
Developing Supplier								
DS1	1.00				0.55	0.55	0.303	7.54
DS2	0.64	0.16	4.10	0.00	0.35	0.35	0.124	4.60
DS3	1.16	0.18	6.38	0.00	0.64	0.64	0.410	9.04
DS4	1.08	0.18	6.10	0.00	0.59	0.60	0.355	8.29
DS5	0.75	0.16	4.68	0.00	0.41	0.42	0.172	5.48
DS6	1.03	0.17	5.88	0.00	0.56	0.56	0.318	7.77
Involved Customers								
IC1	1.00				0.64	0.64	0.410	9.38
IC2	1.15	0.14	8.41	0.00	0.73	0.74	0.540	11.25
IC3	1.29	0.14	9.15	0.00	0.83	0.83	0.687	13.36
IC4	1.25	0.14	8.92	0.00	0.80	0.80	0.636	12.62
IC5	1.05	0.13	7.85	0.00	0.67	0.67	0.454	10.01
Pull								
P1	1.00				0.76	0.76	0.585	11.77
P2	0.97	0.10	9.97	0.00	0.74	0.74	0.548	11.26
P3	1.11	0.10	11.26	0.00	0.85	0.85	0.721	13.63
P4	0.86	0.10	8.78	0.00	0.66	0.66	0.431	9.28
Flow								
F1	1.00				0.73	0.73	0.532	10.99
F2	1.02	0.11	9.47	0.00	0.74	0.74	0.554	11.30
F3	1.06	0.11	9.83	0.00	0.77	0.78	0.603	11.97
F4	1.01	0.11	9.39	0.00	0.74	0.74	0.544	11.16
Low Setup								
LS1	1.00				0.81	0.82	0.665	12.21
LS2	0.75	0.09	7.99	0.00	0.61	0.61	0.377	8.60
LS3	0.80	0.09	8.54	0.00	0.65	0.66	0.430	9.32
Controlled Process								
CP1	1.00				0.82	0.82	0.667	13.32
CP2	1.06	0.08	13.78	0.00	0.87	0.87	0.751	14.61
CP3	0.96	0.08	11.99	0.00	0.78	0.78	0.608	12.44
CP4	0.78	0.08	9.19	0.00	0.63	0.63	0.400	9.38
CP5	0.76	0.09	8.96	0.00	0.62	0.62	0.384	9.14
Involved Employees								
IE1	1.00				0.85	0.85	0.728	14.32
IE2	0.97	0.07	13.95	0.00	0.82	0.83	0.681	13.60
IE3	1.04	0.07	15.49	0.00	0.88	0.88	0.781	15.14
IE4	0.84	0.07	11.30	0.00	0.72	0.72	0.514	11.10
Productive Maintenance								
PM1	1.00				0.72	0.72	0.514	10.78
PM2	1.13	0.11	10.09	0.00	0.81	0.81	0.654	12.75
PM3	1.06	0.11	9.57	0.00	0.76	0.76	0.578	11.69
PM4	1.00	0.11	9054.00	0.00	0.71	0.72	0.51	10.76

SF1	We frequently are in close contact with our suppliers
SF2	We give our suppliers feedback on quality and delivery performance
SF3	We strive to establish long-term relationship with our suppliers
J1	Suppliers are directly involved in the new product development process
J2	Our key suppliers deliver to plant on JIT basis
J3	We have a formal supplier certification program
DS1	Our suppliers are contractually committed to annual cost reductions
DS2	Our key suppliers are located in close proximity to our plants
DS3	We have corporate level communication on important issues with key suppliers
DS4	We take active steps to reduce the number of suppliers in each category
DS5	Our key suppliers manage our inventory
DS6	We evaluate suppliers on the basis of total cost and not per unit price
IC1	We frequently are in close contact with our customers
IC2	Our customers give us feedback on quality and delivery performance
IC3	Our customers are actively involved in current and future product offerings
IC4	Our customers are directly involved in current and future product offerings
IC5	Our customers frequently share current and future demand information with marketing department
P1	Production is pulled by the shipment of finished goods
P2	Production at stations is pulled by the current demand of the next station
P3	We use a pull production system
P4	We use *kanban*, squares, or containers of signals for production control
F1	Products are classified into groups with similar processing requirements
F2	Products are classified into groups with similar routing requirements
F3	Equipment is grouped to produce a continuous flow of families of products
F4	Families of products determine our factory layout
LS1	Our employees practice setups to reduce the time required
LS2	We are working to lower setup times in our plant
LS3	We have low set up times of equipment in our plant
CP1	Large number of equipment/processes on shop floor are currently under SPC
CP2	Extensive use of statistical techniques to reduce process variance
CP3	Charts showing defect rates are used as tools on the shop floor
CP4	We use fishbone type diagrams to identify causes of quality problems
CP5	We conduct process capability studies before product launch
IE1	Shop floor employees are key to problem solving teams
IE2	Shop floor employees drive suggestion programs
IE3	Shop floor employees lead product/process improvement efforts
IE4	Shop floor employees undergo cross functional training
PM1	We dedicate a portion of everyday to planned equipment maintenance related activities
PM2	We maintain all our equipment regularly
PM3	We maintain excellent records of all equipment maintenance related activities
PM4	We post equipment maintenance records on shop floor for active sharing with employees

	Estimate	Std.Err	z-value	$P(>\|z\|)$	Std.lv	Std.all	R^2	T-test
Process								
PRC1	1.00				0.45	0.36	0.13	4.86
PRC2	2.46	0.51	4.81	0.00	1.10	0.81	0.65	12.88
PRC3	2.46	0.52	4.78	0.00	1.10	0.79	0.62	12.24
PRC4	2.35	0.49	4.79	0.00	1.05	0.79	0.63	12.55
PRC5	2.17	0.46	4.70	0.00	0.97	0.73	0.53	11.16
Product/Service								
PRD1	1.00				0.81	0.62	0.38	8.46
PRD2	0.84	0.15	5.54	0.00	0.68	0.49	0.24	6.54
PRD3	1.13	0.16	7.09	0.00	0.91	0.69	0.48	9.74
PRD4	0.95	0.15	6.53	0.00	0.76	0.61	0.37	8.37
PRD5	0.95	0.14	6.63	0.00	0.77	0.62	0.39	8.59

PRC1	Digital automation without sensors
PRC2	Digital automation with process control sensors
PRC3	Remote monitoring and control of production through systems such as Manufacturing Execution System and Supervisory Control and Data Acquisition
PRC4	Digital automation with sensors for product and operating conditions identification, flexible lines
PRC5	Integrated engineering systems for product development and product manufacturing
PRD1	Additive manufacturing, rapid prototyping or 3D printing
PRD2	Simulation/analysis of virtual models (finite elements, computational fluid dynamics, etc.) for design and commissioning
PRD3	Collection, processing and analysis of large quantities of data (big data)
PRD4	Use of cloud services associated with the product
PRD5	Incorporation of digital services into products (Internet-of-Things or Product Service Systems)

	Measures	Cronbach's α	CITC	Levene's stat (sign)	T-test (sign)
Lean Production	SF1	0.945	0.566	0.308 (0.580)	−0.031 (0.975)
	SF2		0.636	1.503 (0.218)	0.614 (0.540)
	SF3		0.637	0.035 (0.852)	−0.236 (0.814)
	J1		0.490	0.838 (0.362)	−0.887 (0.376)
	J2		0.449	2.103 (0.149)	0.074 (0.941)
	J3		0.533	0.264 (0.608)	−0.070 (0.944)
	DS1		0.407	1.076 (0.301)	1.177 (0.241)
	DS2		0.301	2.244 (0.136)	0.702 (0.484)
	DS3		0.503	0.114 (0.737)	0.946 (0.346)
	DS4		0.423	2.699 (0.103)	−1.144 (0.254)
	DS5		0.340	0.664 (0.416)	1.728 (0.086)
	DS6		0.353	1.234 (0.269)	0.367 (0.714)
	IC1		0.582	0.057 (0.812)	0.872 (0.385)
	IC2		0.617	0.112 (0.738)	0.338 (0.736)
	IC3		0.695	1.117 (0.292)	0.287 (0.775)
	IC4		0.628	0.003 (0.955)	1.978 (0.050)
	IC5		0.544	0.001 (0.975)	1.401 (0.163)
	P1		0.629	0.308 (0.579)	−1.001 (0.319)
	P2		0.604	0.151 (0.698)	0.186 (0.853)
	P3		0.696	2.828 (0.095)	−1.040 (0.300)
	P4		0.581	1.149 (0.286)	2.062 (0.410)
	F1		0.601	2.368 (0.126)	1.467 (0.145)
	F2		0.613	0.344 (0.559)	1.008 (0.315)
	F3		0.612	2.629 (0.107)	−1.491 (0.138)
	F4		0.584	0.090 (0.765)	−1.126 (0.262)
	LS1		0.546	0.033 (0.856)	0.202 (0.841)
	LS2		0.519	0.045 (0.833)	−0.069 (0.945)
	LS3		0.448	0.314 (0.576)	−0.555 (0.580)
	CP1		0.641	0.563 (0.454)	−0.147 (0.884)
	CP2		0.704	0.602 (0.439)	−1.084 (0.280)
	CP3		0.602	1.155 (0.284)	−0.585 (0.560)
	CP4		0.522	0.008 (0.927)	0.334 (0.739)
	CP5		0.447	0.000 (0.986)	−0.632 (0.528)
	IE1		0.682	0.363 (0.548)	0.371 (0.711)
	IE2		0.684	0.336 (0.563)	0.207 (0.836)
	IE3		0.686	0.007 (0.933)	0.372 (0.711)
	IE4		0.530	0.033 (0.856)	0.383 (0.702)
	PM1		0.552	2.377 (0.125)	0.135 (0.893)
	PM2		0.641	0.201 (0.655)	0.114 (0.909)
	PM3		0.592	1.648 (0.201)	0.280 (0.780)
	PM4		0.529	0.019 (0.890)	1.023 (0.308)

	Measures	Cronbach's α	CITC	Levene's stat (sign)	T-test (sign)
Industry 4.0	PRC1	0.847	0.365	0.724 (0.396)	−0.271 (0.786)
	PRC2		0.675	0.029 (0.864)	−1.463 (0.146)
	PRC3		0.618	1.781 (0.184)	−0.258 (0.797)
	PRC4		0.618	0.016 (0.898)	−1.123 (0.263)
	PRC5		0.625	1.705 (0.194)	1.442 (0.152)
	PRD1		0.529	2.907 (0.090)	−1.277 (0.204)
	PRD2		0.364	0.489 (0.486)	−0.146 (0.884)
	PRD3		0.571	0.130 (0.719)	−0.105 (0.917)
	PRD4		0.537	0.006 (0.937)	0.150 (0.881)
	PRD5		0.564	2.934 (0.089)	1.028 (0.306)

	Measures	Cronbach's α	CITC	Levene's stat (sign)	T-test (sign)
Operational performances	Delivery Service Level	0.806	0.631	3.414 (0.067)	1.179 (0.240)
	Quality (scrap and rework)		0.667	0.328 (0.568)	0.568 (0.826)
	Productivity		0.680	1.426 (0.234)	-1.212 (0.227)
	Inventory level		0.523	2.323 (0.130)	0.815 (0.417)