

Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement

Guilherme Luz Tortorella

*Department of Systems and Production Engineering,
Federal University of Santa Catarina, Florianopolis, Brazil*

Ricardo Giglio

Federal University of Santa Catarina, Florianopolis, Brazil, and

Desirée H. van Dun

University of Twente, Enschede, The Netherlands

Abstract

Purpose – The purpose of this paper is to examine the moderating role of Industry 4.0 technologies on the relationship between lean production (LP) and operational performance improvement within Brazil, a developing economy context.

Design/methodology/approach – One representative from each of the 147 studied manufacturing companies filled in a survey on three internally related lean practice bundles and two Industry 4.0 technology bundles, with safety, delivery, quality, productivity and inventory as performance indicators. As this study was grounded on the contingency theory, multivariate data analyses were performed, controlling for four contingencies.

Findings – Industry 4.0 moderates the effect of LP practices on operational performance improvement, but in different directions. Process-related technologies negatively moderate the effect of low setup practices on performance, whereas product/service-related technologies positively moderate the effect of flow practices on performance.

Originality/value – With the advent of Industry 4.0, companies have been channelling their efforts to achieve superior performance by advancing levels of automation and interconnectivity. Eventually, widespread and proven manufacturing approaches, like LP, will integrate such technologies which may, in turn, impair or favour operational performance. Contrary to previous studies, the contingencies appeared to have a less extensive effect. The authors point to various options for further study across different socio-economic contexts. This study evidenced that purely technological adoption will not lead to distinguished results. LP practices help in the installation of organisational habits and mindsets that favour systemic process improvements, supporting the design and control of manufacturers' operations management towards the fourth industrial revolution era.

Keywords Emerging economies, Lean production, Industry 4.0, Operational performance improvement

Paper type Research paper

1. Introduction

The fourth industrial revolution is increasingly in the spotlight of researchers, economic policymakers and manufacturers (Liao *et al.*, 2017; Quezada *et al.*, 2017). This new production era was labelled during the German 2011 Hannover Fair as “Industry 4.0” (Liao *et al.*, 2017); it represents an industry characterised by interconnected machines, intelligent systems and products, and inter-related solutions (Tortorella and Fettermann, 2018). Industry 4.0 steers the establishment of smart and dynamic production systems and the mass production of highly customised products (Shrouf *et al.*, 2014). This involves implementing integrated digital elements which monitor and control the physical devices, sensors, information and communication technologies (ICT) and Internet of Things (IoT)



applications (Lasi *et al.*, 2014). Despite its growing notoriety, many companies are still struggling with how Industry 4.0's high-tech practices should be implemented into their operations (Sanders *et al.*, 2016, 2017; Erol *et al.*, 2016). The feasibility and effectiveness of Industry 4.0 integration into existing manufacturing management systems is still understudied (Kolberg *et al.*, 2017).

Specific aspects may undermine Industry 4.0 adoption, especially in manufacturing companies within developing economies, including overall lower technological intensity, restricted investment capital and human resources (Anderl, 2014). Developing economies encounter different challenges when investing in Industry 4.0. For instance, the Brazilian National Confederation of Industry (2016) identified the existing hurdles for Industry 4.0 implementation; the Mexican Ministry of Economy (2016) presented a roadmap for Industry 4.0 adoption in Mexico; and the Indian Government introduced an initiative aimed at positioning the country as one of the main hubs of manufacturing (Forbes India, 2016). Despite these initiatives, little is known about the effects of Industry 4.0 technologies adoption.

Lean production (LP), however, is common practice among several industries and countries, it entails a constant focus on reducing wasteful activities while also improving productivity and quality as seen from the customers' perspective (Womack and Jones, 2003; Junior and Godinho Filho, 2010; Kroes *et al.*, 2018; Narayanamurthy *et al.*, 2018; Soliman *et al.*, 2018). Implementing LP successfully requires a human-centred, low-tech organisational change approach which involves the adoption of various LP practices (Bortolotti *et al.*, 2015; Soliman *et al.*, 2018), a consistent, shared strategic vision with an aligned HR policy, and highly involved employees who have enough resources for continuous process improvement (Van Dun and Wilderom, 2012). Many lean initiatives start on the shop floor (Shah and Ward, 2007), and are then gradually introduced into other units including the corporate level (Hines *et al.*, 2004; Mann, 2005).

Due to Industry 4.0 and LP's convergent and divergent characteristics, it remains unclear whether their concurrent implementation in manufacturing companies will lead to improved performance. On the one hand, lean entails an underlying organisational culture in which problems and abnormalities become opportunities for everyone (Hoseus and Liker, 2008; Spear, 2009; Bortolotti *et al.*, 2015; Narayanamurthy *et al.*, 2018). This psychologically safe shop-floor culture enables the clear identification of process status quos and information sharing (Van Dun and Wilderom, 2012, 2016), which may be further reinforced by the interconnectivity, data acquisition and analysis inherent to Industry 4.0 technologies (Sibatrova and Vishnevskiy, 2016). Furthermore, both LP and Industry 4.0 favour simple decentralised frameworks (Zühlke, 2010). On the other hand, LP entails socio-cultural changes that are stimulated daily through fast and simple work-floor experimentations (Baudin, 2007; Dora *et al.*, 2016), which may conflict with the high levels of capital expenditure and technological expertise demanded by Industry 4.0 (Lasi *et al.*, 2014). These conflicts may occur when both LP and Industry 4.0 practices are implemented in a developing economy context but empirical evidence for this assumption is still generally lacking (Gjeldum *et al.*, 2016; Landscheidt and Kans, 2016; Kolberg *et al.*, 2017) and what is available is contradictory (e.g. Erol *et al.*, 2016; Schumacher *et al.*, 2016; Sanders *et al.*, 2016). The intention of this study, therefore, is to answer the following research question:

RQ1. How does Industry 4.0 adoption moderate the relationship between LP practices and operational performance improvement in a developing economy context?

We surveyed 147 Brazilian manufacturers that had implemented LP practices as well as Industry 4.0 technologies. This research, therefore, contributes to the theoretical fields of advanced manufacturing technology and operational performance improvement. The adoption and management of novel technologies have "gradually become an important task for manufacturing companies across the globe" (Cheng *et al.*, 2018, p. 239). Our study provides a

better understanding of the interactions between the installed LP practices and Industry 4.0 technologies, and their effects on operational performance improvement. Moreover, we initialise the validation of a measure of Industry 4.0 technology adoption. The study may also enable managers to comprehend and anticipate better the advantages and difficulties of incorporating Industry 4.0 technologies into their LP systems. Since managers' financial resources are often scarce, especially in developing economies, it is crucial that their new technology investments are well-informed by studies like ours. Finally, it is also noteworthy that this research expands upon Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher (2018), Tortorella, Giglio and Van Dun (2018) and Tortorella and Fettermann's (2018) research.

This study was grounded on assumptions derived from the contingency theory (Sousa and Voss, 2008; Van de Ven *et al.*, 2013; Romero-Silva *et al.*, 2018). Contextual factors can influence the concurrent implementation of LP and Industry 4.0 (Tortorella and Fettermann, 2018; Rossini *et al.*, 2019). The effect of operations management practices on performance was claimed to differ according to the contextual variables of each company (Sousa and Voss, 2008). Hence, the validity of "one-size fits all" or "best practice" concepts is probably reduced in operations management (Boer *et al.*, 2017). Our study thus includes four contingencies (i.e. technological intensity, tier level, company size, and duration of LP implementation) and considers a specific Brazilian socioeconomic sample because national culture can significantly affect the results of LP (Kull *et al.*, 2014; Erthal and Marques, 2018). We contribute to a better comprehension of the contingencies required to implement LP and Industry 4.0 concomitantly, by describing how their interaction impacts operational performance improvement in the manufacturing industry.

2. Literature review and hypotheses

2.1 LP practices

According to the conceptual definition proposed by Shah and Ward (2007, p. 799), LP covers six core internally related operational elements: pull, flow, low setup, controlled processes, productive maintenance and involved employees. Womack and Jones (2003) also listed: pull, flow and striving for perfection, e.g. low setup (or changeover) times. The aim of those key LP elements (Garcia-Alcaraz *et al.*, 2015) is to achieve smooth material and information flow throughout the value stream (Abdulmalek and Rajgopal, 2007). Yet, LP implementation by manufacturers in emerging economies has been argued to be less extensive than in companies located in developed economies (Saurin and Ferreira, 2009). Saurin *et al.* (2010) demonstrated an unbalanced knowledge and implementation level of LP practices in this industrial context. LP practices associated with just-in-time (JIT) production systems are more widely implemented and understood by manufacturers in emerging economies compared to more advanced statistical process control or total productive/preventive maintenance. Therefore, we assumed that narrowing our study to practices embraced by the Pull, Flow and Set up constructs, which tend to be closely related to JIT, would lead to more reliable and insightful results.

2.2 Industry 4.0 technologies

A wide variety of technologies fall within the fourth industrial revolution. Many researchers have tried to consolidate them into sets and implementation frameworks (e.g. Fettermann *et al.*, 2018; Fatorachian and Kazemi, 2018; Xu *et al.*, 2018). However, regardless of the differences in those frameworks and the categorisation of Industry 4.0 technologies, the latter's overall aims are to enable improvements in companies' value streams by addressing both process- and product/service-related issues (Liao *et al.*, 2017; Buer *et al.*, 2018). Examples of process-related issues that may be solved with technology are time-intensive, manual quality controls. Technologies may also help to reduce product/service-related issues such as inefficiencies that lead to a higher time to market. Since there is still a lack of

consensus on which technologies compose Industry 4.0, we consulted the Brazilian National Confederation of Industry (2016) outcomes of the cross-sector Industry 4.0 survey of 2,225 manufacturers. This survey uncovered the ten most likely digital technologies to be adopted within the Brazilian industrial sector.

Industry 4.0 technologies may not only have a positive impact on the way manufacturing shop floors are managed and organised but also influence organisations' business models, products and services. While the adoption of certain technologies (e.g. digital automation and sensors for remote monitoring and control) may predominantly influence the manufacturing processes (Kolberg *et al.*, 2017), other Industry 4.0 technologies (e.g. big data, cloud services and rapid prototyping) could help the accomplishment of significant improvements in product development and service innovation (Zühlke, 2010; Wan *et al.*, 2015).

2.3 Contingency effects on LP and Industry 4.0

The contingency theory indicates that different environments/contexts often have different needs, thus requiring distinguished approaches to operations management (Sousa and Voss, 2008; Van de Ven *et al.*, 2013; Romero-Silva *et al.*, 2018). The contingency theory is a popular angle (Walker *et al.*, 2015; Danese *et al.*, 2018) and various studies have corroborated to our understanding of the effects of contingencies on LP implementation. Shah and Ward (2003), for instance, indicated a positive influence of plant size on the likelihood of LP implementation, whereas the influence of unionisation and plant age was less pervasive than expected. Kull *et al.* (2014) focussed on comprehending how different dimensions of national culture moderate LP effectiveness. Later, Netland (2016) investigated how four contingency variables (corporation, factory size, stage of LP implementation and national culture) influence what practitioners see as success factors for LP implementation. Complementarily, Tortorella *et al.* (2017) studied the impact of plant size, supply chain level, level of onshore suppliers and age of the LP initiative on LP implementation in supply chains. Overall, most studies reinforce the necessity of primarily comprehending the context in which the organisation is embedded so that LP implementation can be properly tailored. Romero-Silva *et al.* (2018) further advised the examination of both organisational environment and organisational structure type, contingencies that together form the organisational system in which the LP practices are implemented.

Since Industry 4.0 is a more recent research topic, evidence on the effect of contingencies is much scarcer. The few existing studies have vaguely assessed the effect of certain contingencies, such as company size (Brettel *et al.*, 2014) and technological intensity (Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher, 2018), on the adoption level of Industry 4.0. In fact, most studies have only conceptually envisioned some contingencies that might affect Industry 4.0 adoption level, such as socioeconomic aspects (Vacek, 2016) and industry sector (Hofmann and Rüsçh, 2017), but without any empirical validation. This research gap highlights the importance of our study because we assess the results from four organisational environment and organisational structure type contingencies (i.e. technological intensity, tier level, company size and duration of LP implementation). Hereby, we complement previous research and provide empirical evidence of the associations.

2.4 Pull practices and Industry 4.0

According to Rother and Shook (1999), a value stream comprises the sum of all the value provided through the required activities and steps in a company or supply chain from the raw state to its customers, linking both material and information flows (Duggan, 2012). Material flow represents the physical aspects encompassed in the manufacturing of an item; i.e., the processes, steps and activities that either enhance or transform the product according to customers' expectations (Lummus *et al.*, 2006). Information flow corresponds to the procedures, analyses, decisions and orders necessary to support the process in a sequenced way according to

customers' expectations (Seth and Gupta, 2005; Lu *et al.*, 2011), such as product and service development. A lot of the waste identified in manufacturing processes originates from problems that occur in product/service development (Hines *et al.*, 1998; Sim and Rogers, 2009). Hence, to address improvement initiatives properly from a system-wide perspective, all elements of a value stream must be considered in the analysis (Hines *et al.*, 2004; Karim and Arif-Uz-Zaman, 2013). However, their interaction effects on the achievement of higher operational performance are usually neglected (Hines and Rich, 1997; Seth *et al.*, 2017; Hines *et al.*, 2018).

The aim of pull practices is to facilitate manufacturing so that companies produce the required units on time and in the required quantities (Ohno, 1988). This includes *kanban* cards, the signals to trigger production. The successful implementation of pull is highly dependent on accurate and timely product and service information related to internal and/or external customers' demands, thus avoiding overproduction due to misinterpretations or erroneous production triggers (Netland *et al.*, 2015). The incorporation of Industry 4.0 technologies can enhance pull systems in terms of both product/service-related information and manufacturing processes.

First, regarding product/service development, the integration of such technologies as "IoT", "cloud services" and "big data", into *kanban* systems, has been denoted as *e-kanban*, i.e. digitalisation of the conventional *kanban* cards (Takeda, 2006; Junior and Godinho Filho, 2010). *E-kanban* allows the immediate detection of missing or empty bins, triggering automatic replenishment. Physical *kanban* systems are usually undermined due to card losses during their loops between workstations or facilities, leading to mistakes in production control or scheduling and, hence, reduced operational performance (Abdulmalek and Rajgopal, 2007; Marodin *et al.*, 2015). Conversely, adjustments to inventory policies due to changes in batch sizes, market demands, work plans or cycle times tend to be much easier when technologies like *e-kanban* are incorporated into the pull system.

From a manufacturing process perspective, implementing technologies such as "production remote monitoring and control" and "sensors for the identification and control of product and operating conditions" can enable rapid identification of potential issues that may disturb the original production schedule and negatively impact the pace of production (Sanders *et al.*, 2017; Buer *et al.*, 2018). The application of ICT within manufacturing processes thus contributes to a quicker problem-solving timeframe as actions move from reactive to preventive (Lasi *et al.*, 2014; Zawadzki and Żywicki, 2016). In turn, process stability increases and potential issues that jeopardise delivering according to internal/external customers' needs ("pull") can be anticipated.

However, the sole adoption of ICT (without effective pull systems) may facilitate the usual pushed systems and their underlying processes but might not benefit operational performance. To test how Industry 4.0 technologies, that support manufacturing processes and product/service development, interact with pull practices to enhance operational performance, we formulated the following hypotheses:

- H1a.* The adoption of Industry 4.0 technologies, that support manufacturing processes, positively moderates the effect of pull practices on operational performance improvement.
- H1b.* The adoption of Industry 4.0 technologies, that support product/service development, positively moderates the effect of pull practices on operational performance improvement.

2.5 Flow practices and Industry 4.0

Lean's principle of creating flow focuses on establishing mechanisms that enable and ease the achievement of a continuous production stream (Rother and Harris, 2001).

Flow practices encompass improvements such as the definition of products families according to similar routines, layout arrangements planned according to these product families and balancing workstation cycle times (Doolen and Hacker, 2005). While providing inventory levels and lead time reductions, flow ensures that production and quality issues are visible to all employees. Thus, its implementation is beneficial to a company's operational performance (Duggan, 2012). However, if high levels of process stability are not achieved, continuous flow can cause unwanted side-effects, such as loss of deliveries and increased costs (Dora *et al.*, 2016).

Industry 4.0 technologies like sensors, Manufacturing Execution System and Supervisory Control and Data Acquisition, can increase process and product connectivity and interaction, thereby enabling more efficient manufacturing processes (Hermann *et al.*, 2016; Ganzarain and Errasti, 2016; Xu *et al.*, 2018). Enhanced interconnection and communication between cells and workstations can facilitate a flexible, fast and high-quality material flow (Erol *et al.*, 2016; Thoben *et al.*, 2017), and, in turn, the feasibility of continuous flow implementation. However, the isolated adoption of technologies, like IoT, cloud services and additive manufacturing, can lead to marginal gains in product/service development, thus frustrating managers in terms of their high investments and expectations (Cheng *et al.*, 2018). Adopting a novel ICT before implementing a reasonable level of "flow" practices leads to high capital expenditure on wasteful and ill-designed processes (Buer *et al.*, 2018).

Flow practices continuously address low-tech improvement opportunities (Womack and Jones, 2003) but Industry 4.0 technologies may catalyse the outcomes of well-established manufacturing processes and product/service development activities (Kamble *et al.*, 2018). Thoben *et al.*'s (2017) case of a German company that had organised its shop floor according to LP principles, illustrates how the introduction of a cyber-physical logistics system can enhance flexibility through autonomous decisions and reduce inventories by solving errors in real time. Although there is an indication of a positive relationship between these approaches, limited empirical evidence confirms such an association. So, we hypothesise that:

H2a. The adoption of Industry 4.0 technologies, that support manufacturing processes, positively moderates the effect of flow practices on operational performance improvement.

H2b. The adoption of Industry 4.0 technologies, that support product/service development, positively moderates the effect of flow practices on operational performance improvement.

2.6 Low setup practices and Industry 4.0

As customers' needs diversify, the product assortment also increases, with a consequent reduction in batch sizes. Hence, high changeover times (and, thus, process downtime) become an obstacle to high performance (Doolen and Hacker, 2005; Stone, 2012). Toyota overcame this by adopting the "single-minute exchange of die" (SMED) concept which enables smaller batches and shorter lead times by drastically reducing changeover times (Shingo, 1988). The full adoption of "low setup practices" improves the flexibility and agility in production delivery, since shorter setup times may lead to reductions in batch sizes (Furlan *et al.*, 2011). Inventory levels are also likely to be reduced, which directly affects the organisation's cash flow (Maskell *et al.*, 2011).

Industry 4.0 technologies can enhance the impact of low setup practices on operational performance. Companies that adopt "rapid prototyping and 3D printing" and "product development and manufacturing integrated engineering systems" may observe lower changeover times due to a reduction in complexity by strict modularisation

(Fatorachian and Kazemi, 2018). System modularity facilitates capacity adjustments in situations such as seasonal fluctuations, contributing to more flexible manufacturing processes. Manufacturing processes can become individual processes through modularity; yet, these can be closely interconnected, offering interchangeability (Lasi *et al.*, 2014; Qin *et al.*, 2016; Kamble *et al.*, 2018). The concurrent implementation of such technologies with low setup practices could thus enhance the flexibility and productivity of manufacturing processes.

Plug'n'Produce and distributed systems are equipped with self-optimising and machine-learning behaviours, allowing companies to adapt machines to particular products and to produce small batch sizes (Brettel *et al.*, 2014; Sanders *et al.*, 2016). Low setup practices mainly focus on internal setup activities (Shingo, 1988; Nicholas, 2015), whereby Plug'n'Produce technologies reduce the amount of time required for changing tools and/or computer numerical control programmes, which typically requires the machines to be stopped. Similarly, “process control sensors” and “product and operating conditions identification” enable identifying process problems faster so that potential changeover issues can be anticipated. Hence, these technologies do not only mitigate the need for machine adjustments after setup (Fatorachian and Kazemi, 2018), but also increase the likelihood of correct first-time products (Albers *et al.*, 2016).

Kolberg and Zühlke (2015) anticipated that standardised physical and ICT interfaces could expand SMED concepts from one work unit to whole manufacturing areas, leading to more assertive product/service developments. Likewise, Moëuf *et al.* (2018) identified that one of the main reasons for Industry 4.0 adoption by small-sized companies is the increased flexibility through cloud computing and radio-frequency identification whereby the right moments for machine changeovers can be predicted. The flexibility of both manufacturing processes and product/service development, due to increased levels of automation and changeability probably, reinforces the benefits of implementing low setup practices. Therefore, we propose:

- H3a.* The adoption of Industry 4.0 technologies, that support manufacturing processes, positively moderates the effect of low setup practices on operational performance improvement.
- H3b.* The adoption of Industry 4.0 technologies, that support product/service development, positively moderates the effect of low setup practices on operational performance improvement.

As elaborated below, the hypotheses were tested empirically in a cross-sector survey.

3. Methods

3.1 Sample selection and characteristics

We targeted respondents from Brazilian manufacturing companies with experience in both lean and Industry 4.0 technologies. The pervasiveness of both approaches across the industrial spectrum is still scattered, especially in emerging economies (Tortorella *et al.*, 2015; Marodin *et al.*, 2016; Tortorella and Fettermann, 2018). 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 147 leaders of a diverse range of Brazilian manufacturing companies (see Table I). They were former students of different LP executive education courses offered in February, April, July and September 2017 and had agreed to receive updates about LP-related research. Following the ethical standards, we indicated in the invitation that participation was voluntary and anonymous. The participants mainly worked for large-sized companies

Category	Description	Quantity	%
Tier level	1 and 2	97	65.9
	3 and 4	50	34.1
Company size	Large (≥ 500 employees)	81	55.1
	Small and medium (< 500 employees)	66	44.9
Technological intensity	High and medium-high	79	53.7
	Low and medium-low	68	45.3
Industrial sector	Metal-mechanic	73	49.6
	Chemical	19	12.9
	Food	13	8.8
	Textile	7	4.8
	Others	35	23.8
	Duration of LP implementation	< 2 years	66
Respondents' experience with LP	≥ 2 years	81	55.1
	< 2 years	79	53.7
Respondents' job title	≥ 2 years	68	46.3
	Engineer or analyst	62	42.2
	Supervisor or coordinator	53	36.0
	Manager or director	32	21.8

Note: $n = 147$ companies

Table I.
Sample composition

(55.1 per cent); most of the companies belonged to the metal-mechanical sector (49.6 per cent). Examples of the “other” 23.8 per cent sectors were: civil construction, leather-footwear and graphical industry. A total of 65.9 per cent were involved in the first and second tiers. Regarding the companies' technological intensity, 53.7 per cent were categorised as high or medium high (Brazilian National Confederation of Industry, 2016). Most companies (55.1 per cent) had begun their formal LP implementation more than two years previously, although the majority (53.7 per cent) of respondents' personal experience with LP was less than two years. Regarding the respondents' job positions, 42.2 per cent were either engineers or analysts, 36.0 per cent supervisors or coordinators and 21.8 per cent managers or directors.

3.2 Measures, construct validity and reliability

The survey comprised four main parts (see the Appendix): performance indicators, information on the respondents and their respective companies (see Table I), LP implementation and adoption level of Industry 4.0 technologies.

3.2.1 Operational performance improvement. We assessed the improvement level of the companies' performance during the last three years. Since financial results are often carefully protected by companies and, sometimes, exclusively shared among a company's senior managers, we used a composition of operational performance indicators as a proxy for financial performance. Improvements in operational performance are more likely to be perceived by a wider range of respondents, such as middle managers. Since LP implementation is known to impact a wide variety of performance aspects, we measured five process- and people-related indicators suggested by Bhasin (2012) and validated by survey-based LP studies (e.g. Tortorella and Fettermann, 2018; Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher, 2018; Rossini *et al.*, 2019): productivity, delivery service level, inventory level, quality and safety (i.e. accidents). Each indicator was measured on a five-point scale (1 = worsened significantly; to 5 = improved significantly). We performed an exploratory factor analysis (EFA) through principal components analysis (PCA) with varimax rotation. Table II shows that all the performance indicators loaded on one factor, with an eigenvalue of 3.259 explaining 65.1 per cent of the variation. Cronbach's α of this factor was 0.86.

3.2.2 *Lean practices.* The implementation level of lean practices related to the pull, flow and low setup constructs was assessed via Shah and Ward's (2007) 11 items which had been translated into Portuguese. Each practice statement was evaluated through a Likert scale from 1 (fully disagree) to 5 (fully agree). As these practices had been previously validated, we performed a confirmatory factor analysis (CFA) of the three constructs (see Table III) using the lavaan R programming language package (Oberski, 2014) to confirm their convergent validity and unidimensionality. Initially, three CFA models (one for each construct) were estimated, with factor loadings above 0.45 (Tabachnik and Fidell, 2007). We then re-assessed each CFA model to check their goodness of fit based upon a χ^2 test (χ^2/df), comparative fit index (CFI) and standardised root mean square residual (SRMR). CFI values greater than 0.90 combined with SRMR values lower than 0.08 were used as thresholds, following Hu and Bentler's (1999) recommendations for smaller sample sizes (< 250 observations). All items loaded satisfactorily on their constructs (> 0.45, $p < 0.01$) and all had good Cronbach's α levels.

Table II.
PCA results for operational performance improvement indicators

Performance indicators	Mean	SD	Factor 1
Productivity	3.795	1.193	0.590
Delivery service level	3.619	0.974	0.792
Inventory level	3.503	1.029	0.858
Quality (scrap and rework)	3.544	1.086	0.802
Safety (accidents)	3.156	1.083	0.707
Eigenvalues			3.259
Initial % of variance explained			0.571
Rotation sum of squared loadings (total)			2.854
% of variance explained			0.651

Notes: $n = 147$. Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalisation

Table III.
LP operational constructs, measures and CFA factor loadings

Construct	Questionnaire item	Coef.	AVE	χ^2/df	CFI	SRMR
Pull	Production is pulled by the shipment of finished goods	0.945	0.657	21.886/2	0.942	0.049
	Production at stations is pulled by the current demand of the next station	1.073				
	We use a pull production system	1.158				
	We use Kanban, squares, or containers of signals for production control	0.845				
Flow	Products are classified into groups with similar processing requirements	0.883	0.588	16.721/2	0.945	0.049
	Products are classified into groups with similar routing requirements	0.953				
	Equipment is grouped to produce a continuous flow of families of products	0.857				
	Families of products determine our factory layout	0.933				
Low setup	Our employees practice setups to reduce the time required	0.669	0.539	10.770/2	0.949	0.050
	We are working to lower setup times in our plant	0.747				
	We have low set up times of equipment in our plant	0.795				

Many possible extenuating situations can influence the χ^2 test (χ^2/df). It is extremely sensitive to sample size and the number of observed variables per construct so it should not be used as a sole acceptance or rejection criterion (Schermelleh-Engel *et al.*, 2003). Moreover, there is no absolute consensus in the literature for acceptable normed χ^2 values, whose indications vary between three and five (Marsh and Hocevar, 1985). According to Hair *et al.* (2014), the acceptability of a model’s goodness-of-fit should not be assessed from a single criterion. We, therefore, checked and reported both absolute (χ^2) and incremental (CFI) goodness-of-fit measures. Many of the construct validity measures met the recommended thresholds, including the CFI and SRMR indices. Additionally, although the χ^2/df values were higher than the recommended thresholds, their respective *p*-values were lower than 0.01. They do not undermine our results and can therefore be accepted.

Finally, we checked the discriminant validity via average variance extracted (AVE). Each construct’s value should be greater than the squared correlation coefficients (Fornell and Larcker, 1981; Bagozzi and Yi, 1988). Our squared correlation coefficients were lower than the AVE of each construct. The only exception was the correlation between “Flow” and “Low setup” with a squared coefficient of 0.616, which was slightly above the AVE of 0.588 and 0.539, respectively. Table III shows that each latent variable’s AVE exceeded the cut-off value.

3.2.3 Industry 4.0 technologies. Industry 4.0 is a recent, shallowly understood approach by companies. Although some authors (e.g. Wan *et al.*, 2015; Rübmann *et al.*, 2015; Fatorachian and Kazemi, 2018; Kamble *et al.*, 2018; Moefuf *et al.*, 2018) argue that Industry 4.0 involves a set of digital technologies (embedded systems, wireless sensor network, 3D printing, cloud computing and big data), most of which were developed prior to 2011. Since many manufacturers might have adopted the technologies before they were deemed part of the fourth industrial revolution era, we investigated the adoption level of ten digital technologies (Brazilian National Confederation of Industry, 2016). Like Tortorella and Fettermann (2018), we explicitly did not mention that they are part of Industry 4.0, thereby mitigating any blurred perceptions.

We used a five-point Likert scale where 1 meant “not used” and 5 referred to “fully adopted”. A PCA with varimax rotation was used to extract orthogonal components, resulting in two components (see Table IV). Oblique rotation gave similar results. Thus, as

Industry 4.0 technologies	Principal components				Industry 4.0 technologies focus
	Mean	SD	Factor_1	Factor_2	
<i>i</i> ₁ _non_sens_autom	2.63	1.22	0.483	0.133	Process
<i>i</i> ₂ _sens_autom	2.74	1.28	0.810	0.305	
<i>i</i> ₃ _remote	2.43	1.34	0.781	0.295	
<i>i</i> ₄ _prod_operationID	2.30	1.30	0.748	0.340	
<i>i</i> ₅ _integratedPD&Manuf	2.46	1.27	0.562	0.424	
<i>i</i> ₆ _3Dprinting	2.01	1.18	0.416	0.464	Product/Service
<i>i</i> ₇ _simulation	1.94	1.20	0.268	0.505	
<i>i</i> ₈ _big_data	2.27	1.28	0.268	0.732	
<i>i</i> ₉ _cloud	2.16	1.24	0.178	0.820	
<i>i</i> ₁₀ _services	2.10	1.22	0.383	0.599	
Eigenvalues			2.256	1.085	
Initial % of variance explained			0.509	0.118	
Rotation sum of squared loadings (total)			2.871	2.529	
% of variance explained			0.287	0.253	
Bartlett’s test of sphericity (χ^2)			196.51		
Kaiser-Meyer-Olkin factor adequacy (Overall MSA)			0.74		

Notes: *n* = 147. Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalisation

Table IV.
PCA results
for Industry
4.0 technologies

suggested by Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher (2018), the mainly manufacturing processes-oriented technologies were grouped into the “Process-related” construct, while the ones mainly focusing on supporting more efficient product/service development were combined into the “Product/Service-related” construct. Process-related technologies are mainly focussed on enhancing and facilitating the actual manufacturing processes, such as digital automation, sensors and Manufacturing Execution System. Additionally, these technologies are closely related to material flow improvement as they help to identify and address eventual issues on processes and machines. Such support allows a higher level of process stability through the reduction of variations and disruptions, which entails smoother and more reliable value streams (Rother and Harris, 2001; Duggan, 2012). The second, product/service-related technologies, such as virtual models and IoT, aim to improve and support processes related to product development and service innovation. The technologies included in this construct are likely to enhance information flows or to support management to develop products and services faster and more assertively, such as 3D printing (Tortorella, Giglio and Van Dun, 2018). These links were briefly envisioned by Lee *et al.* (2014) and Anderl (2014), but not empirically validated. We verified unidimensionality by using PCA at each component level (see Table IV)[1]. The α values above 0.80 (see Table V) denoted high reliability.

3.2.4 Control variables. Regarding the effects of contingencies, company size is seen to influence the level of LP implementation (e.g. Shah and Ward, 2003; Tortorella *et al.*, 2015). Tortorella and Fettermann (2018) indicated that company size can also affect the association between Industry 4.0 and LP, although not to the same extent. Second, the Brazilian National Confederation of Industry (2016) and Tortorella, Miorando, Caiado, Nascimento and Portioli Staudacher (2018) assessed the effect of technological intensity on the adoption level of Industry 4.0, suggesting that this variable may have a positive influence on Industry 4.0 adoption. Furthermore, Marodin *et al.* (2016) and Tortorella *et al.* (2017) suggested that tier level has a significant effect on LP implementation, especially in the Brazilian industrial sector whose specific supply chain characteristics are different to most developed economies. Finally, the duration of LP implementation was argued as a critical contextual variable, since it may be used to represent a company’s LP maturity level (Netland, 2016; Netland and Ferdows, 2016). Rossini *et al.* (2019) also considered this in the analysis of Industry 4.0 adoption by European manufacturers. Hence, we included the following four contingencies as control variables in our study: technological intensity, tier level, company size and duration of LP implementation.

Technological intensity was classified into two categories based on their industrial sector suggested by the Organisation for Economic Cooperation and Development (OECD, 2011): high and medium-high, and low and medium-low. Moreover, we divided the companies into tiers 1 and 2, and tiers 3 and 4, as displayed in Table I. Company size was dichotomised as large (> 500 employees) and small and medium (≤ 500 employees) (SEBRAE, 2010). Finally, following Netland and Ferdows’ (2016) categorisations of the duration of LP implementation, the companies were divided into less than two years and more than two years of implementation.

3.3 Bias countermeasures

Non-response bias was analysed for each of the four surveyed executive education classes ($n_1 = 35$, $n_2 = 41$, $n_3 = 37$ and $n_4 = 34$) 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 four groups’ means and variations were not significantly different ($p < 0.05$). So, there was no evidence of differences among these groups compared to the population.

Variables	1	2	3	4	5	6	7	8	9
1. Pull	—								
2. Flow	0.667**	—							
3. Low setup	0.635**	0.785**	—						
4. Process-related technologies	0.259**	0.369**	0.401**	—					
5. Product/service-related technologies	0.319**	0.291**	0.349**	0.143*	—				
6. Operational performance improvement	0.356**	0.423**	0.505**	0.381**	0.216**	—			
7. Technological intensity	-0.188**	-0.148	-0.192*	-0.077	-0.164*	-0.182*	—		
8. Tier level	-0.096	-0.016	-0.060	0.050	0.030	0.155*	0.000	—	
9. Company size	-0.026	-0.049	0.050	0.278**	-0.039	0.100	0.049	-0.026	—
10. Duration of LP implementation	0.338**	0.418**	0.422**	0.315**	0.155*	0.259*	-0.177*	-0.008	0.343**
Cronbach's α	0.873	0.853	0.772	0.855	0.827	0.860	0.860	0.860	0.860
Composite reliability	0.881	0.855	0.784	0.842	0.807	0.871	0.871	0.871	0.871

Notes: * $p < 0.1$; ** $p < 0.01$ level (two-tailed)

Table V.
Correlation matrix

Since single respondents answered both the dependent and independent variable questions, we took various countermeasures to avoid common method and source bias, following Podsakoff and Organ (1986) and Podsakoff *et al.* (2003). First, regarding the survey structure, the dependent variable items were far away from the independent variable items. Moreover, we kept the original scale labels: using different scale anchors is argued to curb covariation (Podsakoff *et al.*, 2003). Naturally, 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. Finally, the Harman's single-factor test, with an EFA including all the independent and dependent variables (Malhotra *et al.*, 2006), displayed a first factor that explained only 23.5 per cent of the variance. Since no single factor accounted for most of the variance, common method variance was deemed minimal.

3.4 Data analysis

We performed a set of Ordinary Least Square (OLS) hierarchical linear regression models to test our hypotheses. Three models were examined. Model 1 only included the effect of the control variables (technological intensity, tier level, company size and duration of LP implementation). We also tested all the models with dummy industry sector variables because process considerations and external contingencies inferred by the industrial sector may explain the maturity level of both LP and Industry 4.0. The four industry-type dummies (see Table I) were not significant and the results remained the same on excluding these variables from the regression models. Thus, to increase the degrees of freedom and significance of our tests, we followed Tortorella, Fettermann, Frank and Marodin's (2018) procedure and disregarded industry sector in the regression. Model 2 included the direct effect of the three LP constructs and the two Industry 4.0 technologies constructs. Finally, Model 3 entailed adding the moderating effects of Industry 4.0 technologies.

As suggested by Hair *et al.* (2014), we checked for assumptions of normality, linearity, and homoscedasticity between independent and dependent variables. 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 $p < 0.05$). 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.

4. Results and discussion

Table V shows the correlations of all the variables, Cronbach's α s and composite reliabilities. All the independent variables presented a significant positive correlation with operational performance improvement. Technological intensity was significantly negatively correlated with pull and low setup practices as well as product/service-related technologies. Company size and duration of LP implementation were significantly positively correlated; while duration of LP implementation was significantly negatively correlated with technological intensity.

The regression results, with operational performance improvement as a dependent variable, are shown in Table VI. 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 results suggest that the addition of both the independent variables (Model 2) and the interaction terms (Model 3) led to an incremental improvement of the model (i.e. the Change in Adj. R^2 was significant in both models). Model 3, which explains 33.1 per cent of the

Variables	Operational performance improvement		
	Model 1	Model 2	Model 3
Technological intensity (control)	-0.338**	-0.172	-0.121
Tier level (control)	0.476*	0.567**	0.682***
Company size (control)	-0.071	0.076	0.186
Duration of LP implementation (control)	0.373**	-0.043	-0.067
Pull		0.063	0.073
Flow		0.013	0.088
Low setup		0.382***	0.299**
Process		0.197**	0.194**
Product/Service		0.021	0.005
Pull × Process			-0.072
Flow × Process			0.110
Low setup × Process			-0.296**
Pull × Product/Service			0.022
Flow × Product/Service			0.366**
Low setup × Product/Service			-0.214
<i>F</i> -value	4.111***	7.676***	5.812***
<i>R</i> ²	0.103	0.334	0.400
Adjusted <i>R</i> ²	0.078	0.290	0.331
Change in Adj. <i>R</i> ²	-	0.212***	0.041*

Notes: *n* = 147. Unstandardised regression coefficients are reported. Change in Adj. *R*² reports results compared with the previous model. **p* < 0.1; ***p* < 0.05; ****p* < 0.01

Table VI.
Ordinary least
squares regression
results

variance (*F*-value = 5.812; *p* < 0.01), shows that the addition of the interaction terms significantly enhanced the prediction capacity of operational performance improvement, as indicated by the change in adjusted *R*². None of the contingencies seem to have had an impact on perceived operational performance improvement, with the exception of tier level which is positively associated ($\beta = 0.682$; *p* < 0.01).

Surprisingly, from the LP constructs investigated, only “low setup” presented a significant positive association ($\beta = 0.299$; *p* < 0.05) with operational performance improvement which contradicts previous research (e.g. Shah and Ward, 2003; Shah and Ward, 2007; Taj and Morosan, 2011). However, in the Brazilian manufacturing context, the effect of pull and flow practices does not seem to be as pervasive as in other contexts. Saurin *et al.* (2010), Tortorella *et al.* (2015), Marodin *et al.* (2016) and Tortorella *et al.* (2017) stressed that LP implementation in Brazilian manufacturing companies is less extensive than in developed economies and most companies continue to struggle with implementing practices that will provide minimum process stability. Therefore, it is reasonable to assume that practices which demand a deeper comprehension of LP as a true value-creation system, such as pull and flow practices, might not be associated with performance improvement.

Furthermore, a direct effect of Industry 4.0 technologies was observed for the process-related technologies. These are primarily related to improving and facilitating manufacturing processes (material flow) and appear to have a positive relationship with operational performance improvement ($\beta = 0.194$; *p* < 0.05). On the other hand, the product/service-related technologies, which mainly focus on supporting and enhancing product development and service innovation (information flow), do not show a significant direct effect on performance improvement. This may be due the fact that manufacturing companies located in emerging countries usually have fewer financial means than those in developed economies. Hence, the few implemented investments are usually focussed on manufacturing processes (Chen *et al.*, 2011). Additionally, multinational companies located in emerging economies, as in our study, typically develop their manufactured products abroad, in sites with established engineering know-how and technological support (Bonaglia *et al.*, 2007). Therefore, it is quite reasonable that the direct

impact of product/service-related technologies on operational performance is still incipient and less significant than the direct effect of process-related ones.

However, when the interaction terms are taken into consideration, process-related technologies seem to moderate the effect of low setup negatively ($\beta = -0.296; p < 0.05$). This is contrary to common belief that Industry 4.0 technologies, which are primarily focussed on manufacturing processes, should positively reinforce the relationship between (lean) management practices and operational performance indicators (Subramaniam *et al.*, 2009; Dworschak and Zaiser, 2014). Since Industry 4.0 tends to emphasise the reduction of complexity by strict modularisation, one would expect that the concurrent implementation of such technologies with low setup practices will increase the positive effects on operational performance. Nevertheless, our results do not bear such a moderating assumption. One explanation is that, although both low setup practices and process-related technologies seem to positively affect performance when analysed separately, Brazilian companies may not understand yet how to benefit from their concurrent adoption. As indicated by David *et al.* (2016) and Landscheidt and Kans (2016), the isolated initiative of investing in cutting-edge technology, without dealing with systemic process improvement and design, does not imply better operational performance. In other words, the incorporation of an acknowledged technology into ill-structured manufacturing processes will not give the expected results. Another reason for this finding could be the misconception of the adoption of process-related technologies in terms of simply increasing the level of machine automation. If they are not designed properly, higher levels of machine automation in production lines could entail a more rigid layout, undermining the flexibility of changing over and so increase the costs related to the introduction of new products (Takeda, 2006; Baudin, 2007). In this sense, if a misguided adoption of process-related technologies occurs, companies may perceive these technologies as being contradictory to the underlying concepts of low setup practices, entailing a negative effect on operational performance.

In turn, technologies related to products or services appear to positively moderate the relationship between flow and operational performance improvement ($\beta = 0.366; p < 0.05$). In fact, if product development and service innovations are properly supported by these Industry 4.0 technologies, it is reasonable to expect a positive impact on the effect of flow practices, through the reduction of time-to-market and, hence, a more reliable flow of value. Furthermore, assertive prototyping together with an integrated design and commissioning approach may anticipate manufacturing issues due to the availability, processing and analysis of big data (Hermann *et al.*, 2016). These technologies might support problem-solving activities and thereby enable continuous flow strategies.

Overall, our study provides arguments for examining the interaction between both approaches, and suggests that LP implementation may, in part, benefit significantly from the adoption of Industry 4.0 technologies. Nevertheless, the pervasiveness of this relationship might change according to the context in which the manufacturing company is located (developed vs developing economy). Indeed, our results empirically support *H2b* and reject *H3a*. Regarding the remaining hypotheses, our findings do not demonstrate a significant moderation effect of Industry 4.0 technologies.

5. Conclusions

5.1 Theoretical implications

With the advent of the fourth industrial revolution, the integration of smart technologies with LP implementation is acquiring special importance. Lean practices tend to be more impactful since Industry 4.0 allows a better understanding of customers' demands and accelerates information sharing processes. This empowers employees' engagement which is key in LP (Van Dun and Wilderom, 2016) as well as throughout the value chain. Industry 4.0 can boost the outcomes of traditional LP implementation, resulting in distinguished

performance levels. Our study provides empirical evidence for such an association and enhancement, thereby adding to the understanding of the adoption of advanced manufacturing technology (Cheng *et al.*, 2018; Kamble *et al.*, 2018).

In fact, a major theoretical contribution is the evidence that purely technological adoption does not lead to the expected results. LP practices help to install organisational habits and mindsets that favour systemic process improvements. Although Industry 4.0 may impact performance at a certain level (Zawadzki and Żywicki, 2016; Quezada *et al.*, 2017), its effect might change when LP practices are implemented simultaneously. In other words, the socio-technical organisational changes that coincide with LP reinforce practices and behaviours which, when combined properly with today's technological advancements, enable companies to compete successfully under the, at first sight, paradoxical scenario where high-tech applications and human-based simplicity exist concurrently. There is certainly an opportunity, while implementing LP, for companies to intelligently weigh the trade-offs when introducing novel technologies instead of simple standard operating procedures. Therefore, technology adoption does not necessarily lead to negative interactions with LP practices but, following Toyota's principle, it must be applied in such a way as to create value for people and processes (Morgan and Liker, 2006; Liker and Morgan, 2011).

Our study also reinforces the validation of two bundles of Industry 4.0 technologies: process-related technologies that support the flow of materials and product/service-related technologies that support the flow of information. The Brazilian National Confederation of Industry (2016), on which our measure was based, originally grouped these technologies into three categories according to their focus, namely: process, product development and new business model/service innovation. Our validation shows that the original second and third clusters converge into one bundle. The process-related technologies include sensors, remote monitoring and integrated engineering systems; the product/service-related technologies involve rapid prototyping, virtual modelling and cloud services. The empirical validation of bundles of technologies that address material and information flows is somewhat consistent with the frameworks proposed by Anderl (2014) and Lee *et al.* (2014). They discussed the benefits of certain groups of technologies on manufacturing, product development and business innovation, but without testing their concurrent effects. In this sense, our research provides empirical evidence for Industry 4.0 technologies that behave similarly and, hence, could be adopted together. Follow-up studies should include even more advanced Industry 4.0 technologies.

The insights from this study were also examined from the perspective of the contingency theory, since they clarify some usual misunderstandings related to the contingent nature of LP and Industry 4.0. First, our findings do not support the assumption that Industry 4.0 adoption can have an indistinct impact on operational performance. In fact, our research suggests that novel technologies which mainly focus on product development and innovation may not be as valued by manufacturers as expected, especially within the Brazilian industrial sector. This contingency also affects the referred LP practices, because our outcomes differ from studies performed in other socioeconomic contexts (e.g. Netland, 2016). Since this study was employed in Brazil, it adds to the predominantly US-based studies on context-practice-performance relationships that were published in the last 25 years in the *International Journal of Operations & Production Management* and the *Journal of Operations Management* (Boer *et al.*, 2017). Second, we identified that some contingencies, like technological intensity, company size and duration of LP implementation, may have a less extensive effect on the interaction between LP and Industry 4.0 than indicated by previous studies. In fact, our research shows that of the four contingencies, only tier level plays a significant role in the resulting model. Although unexpected, this converges with Marodin *et al.*'s (2016) findings, suggesting that similar tier-level effects can also be observed when integrating Industry 4.0 with LP implementation. It may well be that organisations higher up in the supply chain are nowadays required to

focus more on operational performance improvement than those downstream, which could be achieved via novel technology adoption.

However, Industry 4.0 is still a relatively new concept, especially in economically emerging countries (Mexican Ministry of Economy, 2016; Tortorella and Fettermann, 2018), thus misunderstandings about its concepts and benefits might lead to counterintuitive moderating effects. A similar pattern occurred with regards to LP (e.g. Saurin and Ferreira, 2009; Hines *et al.*, 2018): contrary effects ensued when the concepts were not understood well by the managers who implemented them. Our research emphasises that the integration of product/service-related Industry 4.0 technologies into flow practices can lead to significant operational performance improvements, but only if approached properly. Therefore, a better grasp of the meaning of Industry 4.0 technologies may support proactive initiatives that can potentially converge with previous efforts of implementing LP practices.

5.2 Managerial contributions

As manufacturers search for efficient and economic production systems, novel technologies can contribute to boosting their competitiveness. Industry 4.0 can facilitate the development of higher performance through new business models and services. However, its adoption entails additional challenges for companies, especially those in emerging economies. Therefore, our findings provide managers and practitioners with an indication of the right balance between the adoption of Industry 4.0 technologies and LP practices for improving operational performance within their companies. In fact, our study gives arguments to support managers' decision-making processes: if they install many flow-related LP practices, they should prioritise the adoption of product/service-oriented technologies such as cloud services, IoT, or big data analysis, in order to achieve high operational performance levels. With advanced information and communication systems in place, along with a LP operating system, a company has the potential to expand with new performance standards. Industries now have the opportunity of combining the benefits of real-time integration with minimal waste generation in the whole value stream. In sum, our findings can help managers to anticipate operational difficulties when integrating process-related new technologies with flow practices. This information helps to set fair expectations, which support a manager's investment decisions to achieve certain strategic objectives regarding Industry 4.0.

5.3 Limitations and future research

Our sample has certain limitations. First, our sample only confirmed some of the moderating effects of Industry 4.0 technologies on LP practices implementation. Hence, there is a need to develop and empirically test models with larger samples. Increasing the sample by replicating the study in different countries would support the inference of more generalisable results, regardless of the socioeconomic context. We used operational performance indicators as a proxy for financial performance, since financial results are often carefully protected by companies and difficult to obtain and the performance of certain financial indicators is only shared among senior managers. However, the observed improvements in the operational performance indicators probably had a direct impact on the company's financial performance, mitigating any concerns related to that. Additionally, we examined operational performance as a single dimension comprised of five different indicators. Further studies could analyse the individual association of each of these indicators with LP and Industry 4.0 to understand how exactly a company's performance is affected by both approaches.

Second, as discussed in Section 3.3, we took various countermeasures to curb the biases that may have resulted from our (cross-sectional) research design. Guide and Ketokivi (2015) recommended utilising multiple respondents per firm in order to mitigate common method bias. Although this approach was not feasible in our study, we invite others to determine firm-level outcomes based on multiple respondents.

Third, the different experiences of the companies using LP was also a sample limitation, possibly influencing respondents' perceptions of LP practices implementation as their mindsets might have been at different lean maturity stages. Nevertheless, most participating companies had more than two years of lean implementation experience. A comparative study of companies in the same lean phase (Netland and Ferdows, 2016) could avoid any potential errors from the collected data. Also, further studies could include archival data (i.e. publicly available company-level financial reports) to validate the self-reported performance data. They could address the association between LP and Industry 4.0 from a practice level, providing additional details that complement our study. We may have lost specific aspects of the relationship by using EFA to combine individual technologies into multi-dimensional constructs that represent Industry 4.0.

Future longitudinal studies ought to collect more objective output measures or involve front-line supervisors in the rating of the implementation levels of LP and Industry 4.0. This also includes additional LP variables (e.g. the level of employee involvement, suppliers' and customers' relationship, total quality management and human resources management practices) or the use of multiple levels of analysis to observe the composed influence of these variables over time. Moreover, in-depth case studies that address common barriers or difficulties with LP implementation and Industry 4.0 adoption may allow a better understanding of the inherent challenges on implementing these approaches concurrently. The lack of empirical research in this emerging field (Kamble *et al.*, 2018) provides ample opportunities for further investigation across different socio-economic contexts.

Note

1. To rule out the existence of any cross-loadings between the LP practices and I4.0 technologies measures in our survey, we ran an additional EFA with all 21 items. No cross-loadings were found (factor loadings ≥ 0.45).

References

- Abdulmalek, F. and Rajgopal, J. (2007), "Analyzing the benefits of lean manufacturing and value stream mapping via simulation: a process sector case study", *International Journal of Production Economics*, Vol. 107 No. 1, pp. 223-236.
- Albers, A., Gladysz, B., Pinner, T., Butenko, V. and Stürmlinger, T. (2016), "Procedure for defining the system of objectives in the initial phase of an industry 4.0 project focusing on intelligent quality control systems", *Procedia CIRP*, Vol. 52, pp. 262-267.
- Anderl, R. (2014), "Industrie 4.0: advanced engineering of smart products and smart production", *Proceedings of the 19th International Seminar on High Technology, Technological Innovations in the Product Development, Piracicaba, 15-16 June*.
- Armstrong, J. and Overton, T. (1977), "Estimating nonresponse bias in mail surveys", *Journal of Marketing Research*, Vol. 14 No. 3, pp. 396-402.
- Bagozzi, R. and Yi, Y. (1988), "On the evaluation of structural equation models", *Journal of the Academy of Marketing Science*, Vol. 16 No. 1, pp. 74-94.
- Baudin, M. (2007), *Working with Machines: The Nuts and Bolts of Lean Operations with Jidoka*, Productivity Press, New York, NY.
- Bhasin, S. (2012), "Performance of lean in large organisations", *Journal of Manufacturing Systems*, Vol. 31 No. 3, pp. 349-357.
- Boer, H., Boer, H.E.E., Demeter, K. and Szász, L. (2017), "Towards a contingency theory of operations management", *International EurOMA Conference, Edinburgh, 1-5 July*.
- Bonaglia, F., Goldstein, A. and Mathews, J. (2007), "Accelerated internationalization by emerging markets' multinationals: the case of the white goods sector", *Journal of World Business*, Vol. 42 No. 4, pp. 369-383.

- Bortolotti, T., Boscari, S. and Danese, P. (2015), "Successful lean implementation: organizational culture and soft lean practices", *International Journal of Production Economics*, Vol. 160, pp. 182-201.
- Brazilian National Confederation of Industry (2016), "Industry 4.0: a new challenge for Brazilian industry", *CNI Indicators*, Vol. 17 No. 2, pp. 1-13.
- Brettel, M., Friederichsen, N., Keller, M. and Rosenberg, M. (2014), "How virtualization, decentralization and network building change the manufacturing landscape: an Industry 4.0 perspective", *International Journal of Mechanical, Industrial Science and Engineering*, Vol. 8 No. 1, pp. 37-44.
- Buer, S., Strandhagen, J. and Chan, F. (2018), "The link between Industry 4.0 and lean manufacturing: mapping current research and establishing a research agenda", *International Journal of Production Research*, Vol. 56 No. 8, pp. 2924-2940.
- Chen, F., Hope, O., Li, Q. and Wang, X. (2011), "Financial reporting quality and investment efficiency of private firms in emerging markets", *The Accounting Review*, Vol. 86 No. 4, pp. 1255-1288.
- Cheng, Y., Matthiesen, R., Farooq, S., Johansen, J., Hu, H. and Ma, L. (2018), "The evolution of investment patterns on advanced manufacturing technology (AMT) in manufacturing operations: a longitudinal analysis", *International Journal of Production Economics*, Vol. 203, pp. 239-253.
- Danese, P., Manfè, V. and Romano, P. (2018), "A systematic literature review on recent lean research: state-of-the-art and future directions", *International Journal of Management Reviews*, Vol. 20 No. 2, pp. 579-605.
- David, R., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å. and Gorecky, D. (2016), "Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies", *Proceedings of International Conference on Computers & Industrial Engineering (CIE46), Tianjin, 29-31 October*.
- Doolen, T. and Hacker, M. (2005), "A review of lean assessment in organizations: an exploratory study of lean practices by electronics manufacturers", *Journal of Manufacturing Systems*, Vol. 24 No. 1, pp. 55-67.
- Dora, M., Kumar, M. and Gellynck, X. (2016), "Determinants and barriers to lean implementation in food-processing SMEs: a multiple case analysis", *Production Planning & Control*, Vol. 27 No. 1, pp. 1-23.
- Duggan, K. (2012), *Creating Mixed Model Value Streams: Practical Lean Techniques for Building to Demand*, CRC Press, London.
- Dworschak, B. and Zaiser, H. (2014), "Competences for cyber-physical systems in manufacturing: first findings and scenarios", *Procedia CIRP*, Vol. 25, pp. 3-8.
- Erol, S., Schumacher, A. and Sihm, W. (2016), "Strategic guidance towards Industry 4.0: a three-stage process model", *Proceedings of International Conference on Competitive Manufacturing (COMA16), Stellenbosch*.
- Erthal, A. and Marques, L. (2018), "National culture and organisational culture in lean organisations: a systematic review", *Production Planning & Control*, Vol. 29 No. 8, pp. 668-687.
- Fatorachian, H. and Kazemi, H. (2018), "A critical investigation of Industry 4.0 in manufacturing: theoretical operationalisation framework", *Production Planning & Control*, Vol. 29 No. 8, pp. 633-644.
- Fettermann, D., Cavalcante, C., Almeida, T. and Tortorella, G. (2018), "How does Industry 4.0 contribute to operations management?", *Journal of Industrial and Production Engineering*, Vol. 35 No. 4, pp. 255-268.
- Forbes India (2016), "Industry 4.0: the next industrial revolution demystified", available at: www.forbesindia.com/article/nasscom-india-leadership-forum-2016/industry-4-0-the-next-industrial-revolution-demystified/42239/1 (accessed 2 March 2018).
- Fornell, C. and Larcker, D. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.
- Furlan, A., Vinelli, A. and Dal Pont, G. (2011), "Complementarity and lean manufacturing bundles: an empirical analysis", *International Journal of Operations & Production Management*, Vol. 31 No. 8, pp. 835-850.

- Ganzarain, J. and Errasti, N. (2016), "Three stage maturity model in SME's towards Industry 4.0", *Journal of Industrial Engineering and Management*, Vol. 9 No. 5, pp. 1119-1128.
- García-Alcaraz, J., Prieto-Luevano, D., Maldonado-Macías, A., Blanco-Fernández, J., Jiménez-Macías, E. and Moreno-Jiménez, J. (2015), "Structural equation modeling to identify the human resource value in the JIT implementation: case maquiladora sector", *The International Journal of Advanced Manufacturing Technology*, Vol. 77 Nos 5-8, pp. 1483-1497.
- Gjeldum, N., Mladineo, M. and Veza, I. (2016), "Transfer of model of innovative smart factory to Croatian economy using lean learning factory", *Procedia CIRP*, Vol. 54, pp. 158-163.
- Goldsby, T., Michael Knemeyer, A., Miller, J. and Wallenburg, C. (2013), "Measurement and moderation: finding the boundary conditions in logistics and supply chain research", *Journal of Business Logistics*, Vol. 34 No. 2, pp. 109-116.
- Guide, V. Jr and Ketokivi, M. (2015), "Notes from the editors: redefining some methodological criteria for the journal", *Journal of Operations Management*, Vol. 37 No. 1, pp. v-viii.
- Hair, J., Black, W., Babin, B. and Anderson, R. (2014), *Multivariate Data Analysis*, Pearson New International Edition, 7th ed., Pearson, Harlow.
- Hermann, M., Pentek, T. and Otto, B. (2016), "Design principles for industrie 4.0 scenarios", *Proceedings of the 49th Hawaii International Conference on System Sciences, IEEE*, pp. 3928-3937.
- Hines, P. and Rich, N. (1997), "The seven value stream mapping tools", *International Journal of Operations & Production Management*, Vol. 17 No. 1, pp. 46-64.
- Hines, P., Holweg, M. and Rich, N. (2004), "Learning to evolve: a literature review of contemporary lean thinking", *International Journal of Operations and Production Management*, Vol. 24 No. 10, pp. 994-1011.
- Hines, P., Taylor, D. and Walsh, A. (2018), "The lean journey: have we got it wrong?", *Total Quality Management & Business Excellence* (forthcoming).
- Hines, P., Rich, N., Bicheno, J., Brunt, D., Taylor, D., Butterworth, C. and Sullivan, J. (1998), "Value stream management", *The International Journal of Logistics Management*, Vol. 9 No. 1, pp. 25-42.
- Hofmann, E. and Rüsçh, M. (2017), "Industry 4.0 and the current status as well as future prospects on logistics", *Computers in Industry*, Vol. 89, pp. 23-34.
- Hoseus, M. and Liker, J. (2008), *Toyota Culture: The Heart and Soul of the Toyota Way*, McGraw Hill, New York, NY.
- Hu, L. and Bentler, P. (1999), "Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 6 No. 1, pp. 1-55.
- Junior, M. and Godinho Filho, M. (2010), "Variations of the kanban system: literature review and classification", *International Journal of Production Economics*, Vol. 125 No. 1, pp. 13-21.
- Kamble, S., Gunasekaran, A. and Gawankar, S. (2018), "Sustainable Industry 4.0 framework: a systematic literature review identifying the current trends and future perspectives", *Process Safety and Environmental Protection*, Vol. 117, pp. 408-425.
- Karim, A. and Arif-Uz-Zaman, K. (2013), "A methodology for effective implementation of lean strategies and its performance evaluation in manufacturing organizations", *Business Process Management Journal*, Vol. 19 No. 1, pp. 169-196.
- Kolberg, D. and Zühlke, D. (2015), "Lean automation enabled by industry 4.0 technologies", *IFAC-PapersOnLine*, Vol. 48 No. 3, pp. 1870-1875.
- Kolberg, D., Knobloch, J. and Zühlke, D. (2017), "Towards a lean automation interface for workstations", *International Journal of Production Research*, Vol. 55 No. 10, pp. 2845-2856.
- Kroes, J., Manikas, A. and Gattiker, T. (2018), "Operational leanness and retail firm performance since 1980", *International Journal of Production Economics*, Vol. 197, pp. 262-274.
- Kull, T., Yan, T., Liu, Z. and Wacker, J. (2014), "The moderation of lean manufacturing effectiveness by dimensions of national culture: testing practice-culture congruence hypotheses", *International Journal of Production Economics*, Vol. 153, pp. 1-12.

- Landscheidt, S. and Kans, M. (2016), "Automation practices in wood product industries: lessons learned, current practices and future perspectives", *Proceedings of the 7th Swedish Production Symposium SPS, Lund, October 25–27*.
- Lasi, H., Fettke, P., Kemper, H., Feld, T. and Hoffmann, M. (2014), "Industry 4.0", *Business & Information Systems Engineering*, Vol. 6 No. 4, pp. 239-242.
- Lee, J., Kao, H. and Yang, S. (2014), "Service innovation and smart analytics for industry 4.0 and big data environment", *Procedia CIRP*, Vol. 16, pp. 3-8.
- Liao, Y., Deschamps, F., Loures, E. and Ramos, L. (2017), "Past, present and future of industry 4.0: a systematic literature review and research agenda proposal", *International Journal of Production Research*, Vol. 55 No. 12, pp. 3609-3629.
- Liker, J. and Morgan, J. (2011), "Lean product development as a system: a case study of body and stamping development at Ford", *Engineering Management Journal*, Vol. 23 No. 1, pp. 16-28.
- Lu, J., Yang, T. and Wang, C. (2011), "A lean pull system design analysed by value stream mapping and multiple criteria decision-making method under demand uncertainty", *International Journal of Production Research*, Vol. 24 No. 3, pp. 211-228.
- Lummus, R., Vokurka, R. and Rodeghiero, B. (2006), "Improving quality through value stream mapping: a case study of a physician's clinic", *Total Quality Management & Business Excellence*, Vol. 17 No. 8, pp. 1063-1075.
- Malhotra, N., Kim, S. and Patil, A. (2006), "Common method variance in IS research: a comparison of alternative approaches and a reanalysis of past research", *Management Science*, Vol. 52 No. 12, pp. 1865-1883.
- Mann, D. (2005), *Creating a Lean Culture: Tools to Sustain Lean Conversion*, Productivity Press, New York, NY.
- Marodin, G.A., Frank, A.G. and Tortorella, G.L. (2016), "Contextual factors and lean production implementation in the Brazilian automotive supply chain", *Supply Chain Management: An International Journal*, Vol. 21 No. 4, pp. 417-432.
- Marodin, G.A., Saurin, T., Tortorella, G.L. and Denicol, J. (2015), "How context factors influence lean production practices in manufacturing cells", *The International Journal of Advanced Manufacturing Technology*, Vol. 79 Nos 5-8, pp. 1389-1399.
- Marsh, H. and Hocevar, D. (1985), "Application of confirmatory factor analysis to the study of self-concept: first-and higher order factor models and their invariance across groups", *Psychological Bulletin*, Vol. 97 No. 3, pp. 562-572.
- Maskell, B., Baggaley, B. and Grasso, L. (2011), *Practical Lean Accounting: A Proven System for Measuring and Managing the Lean Enterprise*, CRC Press, NJ.
- Mexican Ministry of Economy (2016), *Crafting the Future: A Roadmap for Industry 4.0 in Mexico*, 1st ed., Mexican Ministry of Economy, Mexico City, available at: www.promexico.mx/documentos/mapas-de-ruta/industry-4.0-mexico.pdf
- Moef, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S. and Barbaray, R. (2018), "The industrial management of SMEs in the era of Industry 4.0", *International Journal of Production Research*, Vol. 56 No. 3, pp. 1118-1136.
- Morgan, J. and Liker, J. (2006), *The Toyota Product Development System*, Productivity Press, New York, NY.
- Narayanamurthy, G., Gurumurthy, A., Subramanian, N. and Moser, R. (2018), "Assessing the readiness to implement lean in healthcare institutions: a case study", *International Journal of Production Economics*, Vol. 197, pp. 123-142.
- Netland, T. (2016), "Critical success factors for implementing lean production: the effect of contingencies", *International Journal of Production Research*, Vol. 54 No. 8, pp. 2433-2448.
- Netland, T. and Ferdows, K. (2016), "The s-curve effect of lean implementation", *Production and Operations Management*, Vol. 25 No. 6, pp. 1106-1120.
- Netland, T., Schloetzer, J. and Ferdows, K. (2015), "Implementing lean: the effect of takt time", *Proceedings of EurOMA, Nèuchâtel, 26 June-1 July*.

- Nicholas, J. (2015), *Lean Production for Competitive Advantage: A Comprehensive Guide to Lean Methodologies and Management Practices*, Productivity Press, New York, NY.
- Oberski, D. (2014), "Lavaan. survey: an R package for complex survey analysis of structural equation models", *Journal of Statistical Software*, Vol. 57 No. 1, pp. 1-27.
- OECD (2011), "ISIC REV. 3 technology intensity definition", available at: www.oecd.org/sti/ind/48350231.pdf (accessed 10 June 2017).
- Ohno, T. (1988), *Toyota Production System: Beyond Large-scale Production*, CRC Press, New York, NY.
- Podsakoff, P. and Organ, D. (1986), "Self-reports in organizational research: problems and prospects", *Journal of Management*, Vol. 12 No. 4, pp. 531-544.
- Podsakoff, P., MacKenzie, S., Lee, J. and Podsakoff, N. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.
- Qin, J., Liu, Y. and Grosvenor, R. (2016), "A categorical framework of manufacturing for industry 4.0 and beyond", *Procedia CIRP*, Vol. 52, pp. 173-178.
- Quezada, L., da Costa, S. and Tan, K. (2017), "Operational excellence towards sustainable development goals through Industry 4.0", *International Journal of Production Economics*, Vol. 190, pp. 1-2.
- Romero-Silva, R., Santos, J. and Hurtado, M. (2018), "A note on defining organisational systems for contingency theory in OM", *Production Planning & Control*, Vol. 29 No. 16, pp. 1343-1348.
- Rossini, M., Costa, F., Tortorella, G.L. and Portoli-Staudacher, A. (2019), "The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers", *The International Journal of Advanced Manufacturing Technology*, Vol. 102 Nos 9-12, pp. 3963-3976.
- Rother, M. and Harris, R. (2001), *Creating Continuous Flow: An Action Guide for Managers, Engineers and Production Associates*, Lean Enterprise Institute, London.
- Rother, M. and Shook, J. (1999), *Learning to See: Value Stream Mapping to Add Value and Eliminate Muda*, The Lean Enterprise Institute, London.
- Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P. and Harnisch, M. (2015), "Industry 4.0: the future of productivity and growth in manufacturing industries", *Boston Consulting Group*, Vol. 9 No. 1, pp. 54-89.
- Sanders, A., Elangeswaran, C. and Wulfsberg, J. (2016), "Industry 4.0 implies lean manufacturing: research activities in industry 4.0 function as enablers for lean manufacturing", *Journal of Industrial Engineering and Management*, Vol. 9 No. 3, pp. 811-833.
- Sanders, A., Subramanian, K., Redlich, T. and Wulfsberg, J. (2017), "Industry 4.0 and lean management: synergy or contradiction?", *Proceedings of IFIP International Conference on Advances in Production Management Systems Springer, Cham*, pp. 341-349.
- Saurin, T. and Ferreira, C. (2009), "The impacts of lean production on working conditions: a case study of a harvester assembly line in Brazil", *International Journal of Industrial Ergonomics*, Vol. 39 No. 2, pp. 403-412.
- Saurin, T., Ribeiro, J. and Marodin, G.A. (2010), "Identification of research opportunities based on a survey on lean production implementation conducted in Brazilian and foreign companies", *Gestão & Produção*, Vol. 17 No. 4, pp. 829-841.
- Schermelleh-Engel, K., Moosbrugger, H. and Müller, H. (2003), "Evaluating the fit of structural equation models: tests of significance and descriptive goodness-of-fit measures", *Methods of Psychological Research Online*, Vol. 8 No. 2, pp. 23-74.
- Schumacher, A., Erol, S. and Sihn, W. (2016), "A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises", *Procedia CIRP*, Vol. 52, pp. 161-166.
- SEBRAE (2010), "Criteria for classifying manufacturing companies in Brazil", available at: www.sebrae-sc.com.br/leis/default.asp?vcdtexto=4154 (accessed 5 May 2016).
- Seth, D. and Gupta, V. (2005), "Application of value stream mapping for lean operations and cycle time reduction: an Indian case study", *Production Planning & Control*, Vol. 16 No. 1, pp. 44-59.

- Seth, D., Seth, N. and Dhariwal, P. (2017), "Application of value stream mapping (VSM) for lean and cycle time reduction in complex production environments: a case study", *Production Planning & Control*, Vol. 28 No. 5, pp. 398-419.
- Shah, R. and Ward, P. (2003), "Lean manufacturing: context, practice bundles, and performance", *Journal of Operations Management*, Vol. 21 No. 2, pp. 129-149.
- Shah, R. and Ward, P. (2007), "Defining and developing measures of lean production", *Journal of Operations Management*, Vol. 25 No. 4, pp. 785-805.
- Shingo, S. (1988), *Non-stock Production: The Shingo System of Continuous Improvement*, CRC Press, New York, NY.
- Shrouf, F., Ordieres, J. and Miragliotta, G. (2014), "Smart factories in industry 4.0: a review of the concept and of energy management approached in production based on the internet of things paradigm", *Proceedings of the 2014 IEEE, Sydney, 10-14 June*.
- Sibatrova, S. and Vishnevskiy, K. (2016), "Present and future of the production: integrating lean management into corporate foresight", working paper, National Research University Higher School of Economics (HSE), Moscow, available at: <https://wp.hse.ru/data/2016/10/24/1110750731/66STI2016.pdf> (accessed 2 March 2018).
- Sim, K. and Rogers, J. (2009), "Implementing lean production systems: barriers to change", *Management Research News*, Vol. 32 No. 1, pp. 37-49.
- Soliman, M., Saurin, T. and Anzanello, M. (2018), "The impacts of lean production on the complexity of socio-technical systems", *International Journal of Production Economics*, Vol. 197, pp. 342-357.
- Sousa, R. and Voss, C. (2008), "Contingency research in operations management practices", *Journal of Operations Management*, Vol. 26 No. 6, pp. 697-713.
- Spear, S. (2009), *Chasing the Rabbit: How Market Leaders Outdistance the Competition and How Great Companies can Catch up and Win*, McGraw Hill, New York, NY.
- Stone, K. (2012), "Four decades of lean: a systematic literature review", *International Journal of Lean Six Sigma*, Vol. 3 No. 2, pp. 112-132.
- Subramaniam, S., Husin, S., Singh, R. and Hamidon, A. (2009), "Production monitoring system for monitoring the industrial shop floor performance", *International Journal of Systems Applications, Engineering & Development*, Vol. 3 No. 1, pp. 28-35.
- Tabachnik, B. and Fidell, L. (2007), *Using Multivariate Statistics*, Allyn and Bacon, Boston, MA.
- Taj, S. and Morosan, C. (2011), "The impact of lean operations on the Chinese manufacturing performance", *Journal of Manufacturing Technology Management*, Vol. 22 No. 2, pp. 223-240.
- Takeda, H. (2006), *The Synchronized Production System: Going Beyond Just-in-Time Through Kaizen*, Kogan Page, London.
- Thoben, K., Wiesner, S. and Wuest, T. (2017), "Industrie 4.0 and smart manufacturing: a review of research issues and application examples", *International Journal of Automation Technology*, Vol. 11 No. 1, pp. 4-16.
- Tortorella, G.L. and Fettermann, D. (2018), "Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies", *International Journal of Production Research*, Vol. 56 No. 8, pp. 2975-2987.
- Tortorella, G.L., Giglio, R. and Van Dun, D.H. (2018), "Industry 4.0 as a moderator on the relationship between lean and operational performance", *25th International Annual EurOMA Conference: To Serve, to Produce and to Servitize in the Era of Networks, Big Data and Analytics, Budapest, June*.
- Tortorella, G.L., Miorando, R. and Tlapa, D. (2017), "Implementation of lean supply chain: an empirical research on the effect of context", *The TQM Journal*, Vol. 29 No. 4, pp. 610-623.
- Tortorella, G.L., Fettermann, D., Frank, A.G. and Marodin, G.A. (2018), "Lean manufacturing implementation: leadership styles and contextual variables", *International Journal of Operations & Production Management*, Vol. 38 No. 5, pp. 1205-1227.
- Tortorella, G.L., Marodin, G.A., Miorando, R. and Seidel, A. (2015), "The impact of contextual variables on learning organization in firms that are implementing lean: a study in Southern Brazil", *The International Journal of Advanced Manufacturing Technology*, Vol. 78 Nos 9-12, pp. 1879-1892.

-
- Tortorella, G.L., Miorando, R., Caiado, R., Nascimento, D. and Portioli Staudacher, A. (2018), "The mediating effect of employees' involvement on the relationship between Industry 4.0 and operational performance improvement", *Total Quality Management & Business Excellence* (forthcoming).
- Vacek, J. (2016), "Socio-economic aspects of Industry 4.0", *Innovation Management, Entrepreneurship and Corporate Sustainability (IMECS 2016)*, *Vysoká škola ekonomická v Praze*, pp. 731-741.
- Van de Ven, A., Ganco, M. and Hinings, C. (2013), "Returning to the frontier of contingency theory of organizational and institutional designs", *Academy of Management Annals*, Vol. 7 No. 1, pp. 393-440.
- Van Dun, D.H. and Wilderom, C.P.M. (2012), "Human dynamics and enablers of effective lean team cultures and climates", in Hodgkinson, G. and Ford, J. (Eds), *International Review of Industrial and Organizational Psychology*, John Wiley and Sons, Chichester, pp. 115-152.
- Van Dun, D.H. and Wilderom, C.P.M. (2016), "Lean-team effectiveness through leader values and members' informing", *International Journal of Operations & Production Management*, Vol. 36 No. 11, pp. 1530-1550.
- Walker, H.L., Radnor, Z., Chicksand, D. and Watson, G. (2015), "Theoretical perspectives in operations management: an analysis of the literature", *International Journal of Operations & Production Management*, Vol. 35 No. 8, pp. 1182-1206.
- Wan, J., Cai, H. and Zhou, K. (2015), "Industrie 4.0: enabling technologies", *Proceedings of Intelligent Computing and Internet of Things (ICIT), 2014 International Conference on IEEE, January*, pp. 135-140.
- Womack, J. and Jones, D. (2003), *Lean Thinking: Banish Waste and Create Wealth in your Corporation*, Simon & Schuster, New York, NY.
- Xu, L., Xu, E. and Li, L. (2018), "Industry 4.0: state of the art and future trends", *International Journal of Production Research*, Vol. 56 No. 8, pp. 2941-2962.
- Zawadzki, P. and Żywicki, K. (2016), "Smart product design and production control for effective mass customization in the Industry 4.0 concept", *Management and Production Engineering Review*, Vol. 7 No. 3, pp. 105-112.
- Zühlke, D. (2010), "Smart factory: towards a factory-of-things", *Annual Reviews in Control*, Vol. 34 No. 1, pp. 129-138.

Appendix. Applied survey

1 – Please indicate below how the following operational performance indicators evolved in the last three years in your company:

** Scale from 1 (Worsened significantly) to 5 (Improved significantly)*

Performance evolution

1-Productivity	
2-Delivery service level	
3-Inventory level	
4-Quality (scrap and rework)	
5-Safety (accidents)	

2 – Please indicate below the characteristics of your company:

(a) Industry sector: _____

(b) Company size: () Up to 499 employees
() More than 500 employees

(c) Tier level: () 1st () 2nd () 3rd or more

(d) Time of Lean Production implementation in the company: () ≤ 2 years
() > 2 years

(e) Your experience with Lean Production implementation: () ≤ 2 years
() > 2 years

(f) Your job title within your company: () Engineer or Analyst
() Supervisor or Coordinator
() Manager or Director

2 – Please indicate for each statement below the agreement level according to your company's reality:

** Scale from 1 (Fully disagree) to 5 (Fully agree)*

Agreement
level

1-Production is pulled by the shipment of finished goods	
2-Production at stations is pulled by the current demand of the next station	
3-We use a pull production system	
4-We use kanban, squares, or containers of signals for production control	
5-Products are classified into groups with similar processing requirements	
6-Products are classified into groups with similar routing requirements	
7-Equipment is grouped to produce a continuous flow of families of products	
8-Families of products determine our factory layout	
9-Our employees practise setups to reduce the time required	
10-We are working to lower setup times in our plant	
11-We have low set up times of equipment in our plant	

3 – Please indicate below the adoption level of the following digital technologies within your company’s processes:

** Scale from 1 (Not used) to 5 (Fully adopted)*

Adoption
level

1-Digital automation without sensors	
2-Digital automation with process control sensors	
3-Remote monitoring and control of production through systems such as Manufacturing Execution System and Supervisory Control and Data Acquisition	
4-Digital automation with sensors for product and operating conditions identification, flexible lines	
5-Integrated engineering systems for product development and product manufacturing	
6-Additive manufacturing, rapid prototyping or 3D printing	

7-Simulations/analysis of virtual models (finite elements, computational fluid dynamics, etc.) for design and commissioning	
8-Collection, processing and analysis of large quantities of data (big data)	
9-Use of cloud services associated with the product	
10-Incorporation of digital services into products (Internet-of-Things or Product Service Systems)	

Corresponding author

Guilherme Luz Tortorella can be contacted at: gtortorella@bol.com.br