Bundles of Lean Automation practices and principles and their impact on operational performance

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Highlights:

- 23 LA practices grouped into 3 internally consistent bundles
- 18 LP and I4.0 principles grouped into 2 bundles of LA principles
- 5 operational performance indicators
- Bundles empirically validated and investigated their effects on operational performance
- Both the socio and technical components of LA drives performance

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Abstract

The objective of this paper is two-fold. First, it aims at empirically validating bundles of Lean Automation (LA) practices and principles. Second, it verifies their impact on operational performance improvement. For that, we surveyed 110 manufacturers who have been concomitantly implementing Lean Production (LP) and Industry 4.0 (I4.0). The collected responses were examined using multivariate data analysis techniques. We identified three bundles of LA named according to the focus of the corresponding practices (i.e. *workplace*, *value stream* and *extended value stream*), and two bundles of LA principles (sociocultural- and technology-oriented). Our findings indicated that LA practices positively mediate the relationship between LA principles and the company's operational performance, especially when considering practices applied at a workplace or value stream level. As the integration of I4.0 into LP becomes widespread, the LA paradigm tends to be a more relevant topic in the operations management field. Hence, more profound comprehension of LA practices and principles, and their implications on companies' operations may help achieve higher performance, setting the proper managerial expectations.

Keywords: Lean automation, Lean production, Industry 4.0, Performance.

1. Introduction

For over the last four decades, Lean Production (LP) has been deemed a strategic approach to continuously improving processes, products, services and organizations (Stone, 2012). Inspired by the Toyota Production System (Krafcik, 1988), LP fosters employee engagement through daily problem-solving activities that seek to minimize waste and enhance the efficiency of the flow of value (Womack and Jones, 1997; Dahlgaard-Park and Pettersen, 2009; Netland and Powell, 2017). According to Seppälä and Klemola (2004) and Souza and Alves (2018), LP implementation encompasses several management principles and practices, whose benefits have been reported in different industry sectors such as manufacturing (Shah and Ward, 2003; Marodin et al., 2015; Panwar et al., 2018), healthcare (Costa and Godinho Filho, 2016; Borges et al., 2019; Lindsay et al., 2019), services (Ahlstrom, 2004; Malmbrandt and Åhlström, 2013; Cavdur et al., 2019), among others. LP consists of a low-tech approach that seeks for simple and effective solutions aligned with the business vision (Marodin et al., 2019).

More recently, with the Fourth Industrial Revolution, also denoted as Industry 4.0 (I4.0), new information and communication technologies (ICTs) emerged aiming at facilitating data collection, storage, sharing and processing in organizations (Lasi et al., 2014; Xu et al., 2018). According to Lu (2017) and Rojko (2017), the digital transformation implied by I4.0 will significantly change products, processes, services and business models through increased interconnectivity and modularity achieved through vertical, horizontal, and end to end integration of the value chain (Chiarini and Kumar, 2020). Disruptive ICTs, such as Internet-of-Things, big data, machine learning and cloud computing establish the fundamental basis for these innovative changes (Frank et al., 2019; Tortorella et al., 2020a). This has motivated several companies to integrate I4.0 technologies and principles into existing management approaches, such as LP (Pagliosa et al., 2019; Chiarini and Kumar, 2020).

The incorporation of I4.0 technologies into LP has been named as Lean Automation (LA). Although the term LA became popular in the 1990s with the incorporation of Computer Integrated Manufacturing (CIM) and Flexible Manufacturing System (FMS), it lost relevance over the years (Jackson et al., 2011; Hedelind and Jackson, 2011). After introducing I4.0, the LA concept gained another connotation, expanding its meaning and contribution (Kolberg et al., 2017). Some authors (e.g. Sanders et al., 2016; Buer et al., 2018; Rossini et al., 2019) examined the association between LP practices and I4.0 technologies as a basis for developing the LA concept. Tortorella et al. (2020b) proposed a LA framework, but it was not empirically validated. Hence, the exact bundles of practices and principles that characterize LA are not yet fully known. This gap is wider when considering the effect of LA implementation on companies' operational performance. Against this context, two research questions are addressed in this paper:

(i) What are the main bundles of LA practices and principles?

(ii) How do these LA bundles impact on operational performance?

To answer these questions, 110 practitioners from manufacturing companies that have been implementing both LP and I4.0 over the past years were surveyed. They were asked to respond to a four-part questionnaire: Q1, which detailed the companies' context and respondents' characteristics; Q2, which examined the implementation level of 31 LA measures; Q3, which identified the observed frequency of the LP and I4.0 principles in the companies' decisions and employees' behaviors; and Q4, which evaluated the operational performance improvement in the companies in the last three years. The collected responses were analyzed through multivariate data techniques, and the results were used to verify our hypotheses' validity. The contribution of this work is two-fold. First, we empirically validate bundles of LA practices and principles, allowing the identification of a LA framework. No previous studies proposing comprehensive definitions of the bundles of practices and principles involved in LA were found. Second, we examine the contribution of those bundles to companies' operational performance. Although a few studies reported the benefits of LA (e.g. Ma et al., 2017; Yamazaki et al., 2017), those were conducted from a narrow perspective, approaching specific practices and technologies and disregarding the effect of a systemic implementation.

A successful LA implementation may encompass changes on both tangible (i.e. management practices and technologies) and intangible (i.e. behaviors and organizational culture) aspects of an organization (Soliman and Saurin, 2017; Srinivasan et al., 2020). Thus, this study was grounded on socio-technical systems (STS) theory. STS theory argues for the joint optimization of the social and the technical systems, without prioritising one over the other (Appelbaum, 1997). Therefore, it offers a proper lens for the investigation of LA. This is not a simplistic approach that aims to replace human work by automation, but rather using it in line with core lean principles focused on people development (Ropohl, 1999; Baxter and Sommerville, 2011). According to Srinivasan et al. (2020), the social aspect has become even more critical in the I4.0 era. The digital connectivity in the value chain will require employees to have the technical knowledge and develop foundational skills in communication, socialization, and empathy required to interact with stakeholders in the value chain, including end-customer.

The remaining of this article is organized as follows. Section 2 brings the theoretical background on the underlying concepts of this study. Section 3 develops the hypotheses and theoretical model under analysis. Section 4 described the applied method, whose results are presented and discussed in section 5. Section 6 concludes the paper, indicating limitations and future research opportunities.

2. Background

2.1. Lean Production

The literature on LP is prolific and much has been studied on its implementation. Although the benefits from LP are widely acknowledged, most companies still struggle with sustaining them in the long term (Roth, 2011; Pakdil and Leonard, 2017). This led researchers to specialize and explore different LP facets to better understand what its implementation entails (Grigg et al., 2020). A common approach is to deploy LP into a set of practices and principles. The principles are the strategic components that refer to the ideals of the system (Papadopoulou and Ozbayrak, 2005; Souza and Alves, 2018). The practices are the components that operationalize such principles (Tortorella et al., 2017a). As required in any socio-technical system, the proper alignment between LP practices and principles is crucial to successful lean implementation (Gambatese et al., 2017).

Regarding LP principles, several commonalities are found in previous studies. For instance, Toyota (2001) indicated the existence of two main principles: (*i*) continuous improvement, which refers to the utilization of specific practices to continually seek for and implement improvements; and (*ii*) respect for people, suggesting that people are relevant resources to the business. These two principles were utilized as a basis for the studies from Kumar et al. (2018) and Coetzee et al. (2019), respectively. Complementarily, Womack and Jones (2003) suggested five LP principles: (*i*) identify value, (*ii*) map the value stream, (*iii*) create flow, (*iv*) establish pull, and (*v*) seek perfection. Those principles are widely acknowledged by both academics and practitioners from different fields (Netland and Powell, 2017). Another proposition on LP principles was performed by Liker (2004), which described fourteen underlying principles to the LP culture. Such principles adoption must promote individual behaviors and an organizational culture that fosters the implementation of LP practices (Fullerton and Wempe, 2009; Paro and Gerolamo, 2017).

In turn, several studies examined the fundamental bundles of lean practices that characterize a systematically LP implementation. Shah and Ward (2003) posed four bundles of practices: just-in-time (JIT), total quality management (TQM), total preventive maintenance (TPM), and human resource management (HRM). Later, Shah and Ward (2007) expanded this by empirically identifying ten operational constructs comprised of 41 LP practices. Bortolotti et al. (2015) proposed the categorization of LP bundles into hard (i.e. lean technical and analytical tools) and soft (i.e. lean practices concerning people and relations) practices. Specifically oriented to supply chain management improvement, Tortorella et al. (2017b) validated four bundles composed of 22 practices.

Possibly as a result of the large number of practices, which implies additional complexity, the application of LP practices still occurs in a fragmented way, disregarding their interactions (Negrão et al., 2017). Panwar et al. (2018) highlighted that a fragmented LP implementation might entail a marginal impact on the operational performance of process industries. Despite those differences found in the literature, there seems to be a consensus on the main bundles of practices encompassed in a LP implementation.

2.2. Industry 4.0

Research on I4.0 has been intense in the past few years (Xu et al., 2018; Oztemel and Gursev, 2020). Motivated by the envisioned competitive advantages derived from I4.0 disruptive ICTs, academia, companies, and government have developed joint efforts to better understand this new production paradigm (Sung, 2018). I4.0 enables manufacturers to efficiently enhance their operations by quickly identifying wastes and improvement opportunities through digital connectivity that allows visualization of abnormalities and wastes in the value chain. It denotes the technological transition from embedded systems to cyber-physical systems (Liao et al., 2017). In other words, I4.0 encompasses the digitization of the industry with the integration of all existing processes of the value chain, featured by its adaptability, flexibility and efficiency that enables it to meet customer's requirements in the current scenario (Dalenogare et al., 2018).

A few authors investigated the underlying design principles that foster extensive I4.0 adoption. Hermann et al. (2015; 2016) identified four main I4.0 design principles: (*i*) interconnection, which refers to the ability to connect machines, devices, sensors, and people through IoT and wireless communication technologies; (*ii*) information transparency, which is enabled by the fusion of the physical and virtual world for real-time process information provision; (*iii*) decentralized decisions, which combines interconnected and decentralized decision-makers to utilize both local and global information for better decision-making and increasing overall productivity; and (*iv*) technical assistance, which refers to an effective, successful, and safe support of humans in physical tasks through a smooth and intuitive human-machine interaction. Lu (2017) indicated that I4.0 principles comprise interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity. Ghobakhloo (2018) proposed twelve I4.0 design principles, complementing the previous works by adding a smart product, smart factory, vertical integration, horizontal integration, product personalization and corporate social responsibility.

Similarly, several works have discussed the main I4.0 technologies and implementation frameworks. Fatorachian and Kazemi (2018), for instance, proposed a theoretical I4.0 framework comprising six technological enablers and six drivers for their implementation. Frank et al. (2019) suggested that I4.0 comprises a systematic integration of front-end technologies, in which Smart Manufacturing plays a central role. Despite the specificities of each proposal, researchers tend to converge to similar outcomes, which denotes a certain degree of consensus on the body of knowledge on the topic.

2.3. Lean Automation

LA is characterized by the integration of I4.0 into LP (Kolberg et al., 2017). With the ecosystem currently offered by novel ICTs, LA is becoming more viable and appealing to the enhancement of company's performance (Tortorella et al., 2019a). However, because LA is a recent phenomenon, both researchers and practitioners still struggle with its conceptualization and practical implications (Sanders et al., 2016; Ma et al., 2017; Buer et al., 2018). This poor understanding may lead to misguided implementation approaches that usually fall short of achieving the expected benefits, wasting organizational efforts (Satoglu et al., 2018; Shahin et al., 2020).

In terms of LA implementation, a few studies indicated guidelines to better structure it. Dombrowski et al. (2017) used 260 cases in Germany to identify the relationships between I4.0 and LP, providing evidence on the synergistic pairwise relationships. Wagner et al. (2017) conceptually conceived a matrix relating LP practices and I4.0 technologies based on the perceptions of experts. Tortorella et al. (2020b) proposed 31 LA measures grouped into nine operational constructs. Nevertheless, the convergent and discriminant validity of those constructs were not checked, hence, lacking empirical validation. A similar flaw was observed in Tortorella et al. (2020c), which identified three clusters of LA measures according to the preferred implementation sequence in companies (i.e. start-up, in-transition and advanced). Therefore, literature is still scarce on the definitions of the bundles of practices and principles encompassing LA.

3. Hypotheses development

The literature on both LP (e.g. Soliman and Saurin, 2017; Tortorella et al., 2017a) and I4.0 (e.g. Davies et al., 2017; Beier et al., 2020) indicates the socio-technical nature of these approaches. As LA derives from both, we assumed conceptual similarities and framed our research on STS theory. STS theory concerns the joint optimization and shared emphasis on the development of both social and technical components to the raising of productivity and wellbeing (Cooper and Foster, 1971). Therefore, best performance arises from accounting for both the social and the technical dimensions, without overemphasizing one over the other (Ropohl, 1999; Baxter and Sommerville, 2011). STS also acknowledges the external environment's influence (e.g. political, economic, legal, cultural) as a permanent source of uncertainty (Hendrick and Kleiner, 2001).

LA combines principles from LP and I4.0, introducing ideals and fostering capabilities that can be managed together to support companies achieving superior performance (Tortorella et al., 2020c). However, the rules of conduct and guiding beliefs that serve as the foundation for a LA implementation are still unknown. Further, the impact of the integration of LP and I4.0 principles on performance is not clear (Mrugalska and Wyrwicka, 2017; Buer et al., 2018). Despite that, previous studies that individually focused on either LP or I4.0 principles have reported a positive association with performance improvement. If we extend the same rationale to LA, one might assume that the concurrent adoption of those principles might result in similar implications on operational performance. Nevertheless, some contradictory aspects of both LP and I4.0 may entail unexpected results from LA implementation. For instance, I4.0 technologies might be highly disruptive (Frank, et al., 2019) and resource-consuming, which may divert attention from LP practices and principles (Buer et al., 2018). This disruptive character somewhat conflicts with the

LP idea of utilizing reliable and exhaustively tested technologies (Liker, 2004; Liker and Hoseus, 2008). Additionally, LP heavily relies on people involvement and creativity (Bortolotti et al., 2015), which may lose its emphasis with the over-reliance on I4.0 technologies. Hence, to investigate that, we formulate the following hypothesis:

H1: *The adoption of LA principles positively impacts on operational performance.*

Previous research on LP practices (e.g. Shah and Ward, 2003; Bortolotti et al., 2015; Marodin et al., 2019) and I4.0 technologies (e.g. Dalenogare et al., 2018; Fatorachian and Kazemi, 2020) indicated their positive contribution to operational performance. Additionally, studies that investigated the concomitant implementation of LP and I4.0 (e.g. Dombrowski et al., 2017; Tortorella and Fettermann, 2018; Rossini et al., 2019; Chiarini and Kumar, 2020) suggested a synergistic effect on companies' performance. The few existing studies that specifically emphasized the effect of LA adoption on performance improvement (e.g. Kolberg et al., 2017; Shigematsu et al., 2018; Tortorella et al., 2020c), were either narrow in terms of the analyzed practices or did not discriminate the individual impact of each bundle of practices. Although these studies allow a similar effect of LA practices to be assumed on performance, no empirical evidence has been found to support this claim. To examine this relationship, the following hypothesis was formulated:

H2: *The implementation of LA practices positively impacts on operational performance improvement.*

According to Drucker (1995), the difference between a practice and a principle is that practice is the repetition of an activity to improve a skill, while a principle is a fundamental assumption that generates the act of practice. Based on this definition, LA principles may feature the social (intangible) aspects, while LA practices might compose the technical (tangible) elements required for a successful implementation. Ideally, LA principles should be widely established in an organization, so that individuals' mindsets were properly adjusted before the actual implementation of LA practices. The constant application of Lean practice bundles over the years has helped organisations to implicitly embrace and follow Lean principles of putting the customer at the heart of all improvement activities. However, as posed by Liker (2004) and highlighted by Liker and Hoseus (2008), the socio-technical change inherent to a lean transformation tends to be more effective when new practices are inserted into the work routine. In other words, authors suggest that it is easier to change individuals' beliefs and mindsets by introducing new practices than changing workplace practices by simply discussing those beliefs and ideals. In this sense, LA practices may act as mediators of LA principles, facilitating the relationship with operational performance. Based on this, we propose the following hypothesis:

H3: *The implementation of LA practices positively mediates the impact of the adoption of LA principles on operational performance improvement.*

4. Method

We followed an empirical approach, which allowed us to gain knowledge through direct/indirect observation or experience (Goodwin, 2005). The quantification of empirical evidence gathered from respondents that satisfy selection criteria is a frequent procedure in the research of the same nature (e.g. Marodin et al., 2018; Li et al., 2019). The survey method is commonly applied to collect data for empirical research purposes since it presents a high level of representativeness, reduced cost, potential statistical relevance and standardized stimulus to all participants (Montgomery, 2013). Hence, the proposed method comprises four main steps (see Figure 1): (*i*) measures and instrument development; (*ii*) sample selection and data collection; (*iii*) constructs' validity and reliability; and (*iv*) data analysis. The subsequent sections provide detailed information on these steps.

Figure 1 – Proposed method steps

4.1. Measures and instrument development

The proposed questionnaire consisted of four parts. First, we gathered information on respondents' characteristics (role, lean experience, professional experience and I4.0 knowledge) and organizations (tier level, size and sector) to identify the demographic profile of the sample. Second, respondents had to indicate the adoption level of 31 LA measures proposed by Tortorella et al. (2020b) in their organizations. This is one of the first attempts to propose a LA framework and, hence, was used as a basis for these measures. For that, we applied a five-point Likert scale that varied from 1 (not used) to 5 (fully adopted). Third, we combined the 14 LP principles proposed by Liker (2004) and extensively used in other studies (e.g. Bhasin and Burcher, 2006; Paro and Gerolamo, 2015; Tortorella et al., 2019b) with six I4.0 design principles consolidated from the works of Hermann et al. (2015; 2016) and Ghobakhloo (2018). Respondents were supposed to indicate through a 5-point scale (1 meant 'almost never' and 5 'almost always') the observed frequency of those principles in the companies' decisions and employees' behaviors. The last part of the questionnaire aimed at examining the improvement level in companies' operational performance over the past three years. Performance variations are more easily identified and other empirical studies (Shah and Ward, 2003; Marodin et al., 2018; 2019; Rossini et al., 2019) have also used them as a proxy for organizational performance. We utilized five indicators to measure the improvement level of operational performance; they were: safety (work accidents), quality (scrap and rework), delivery service, productivity and inventory. These indicators were evaluated through a Likert scale that ranged from 1 (worsened significantly) to 5 (improved significantly).

Face and content validity were verified through a pre-test of the instrument done with three experts (2 academicians and 1 practitioner) (Kothari, 2004). Minor improvements were suggested in terms of taxonomy and questions. We addressed a few procedures to curb potential common method variance (Huber and Power, 1985). Regarding the design of the questionnaire, we located the dependent variables far from independent ones (Podsakoff and Organ, 1986). We also added a statement at the beginning of the questionnaire informing about the anonymous and confidential nature of the investigation, and the fact that there were no right nor wrong responses (Podsakoff et al., 2003).

4.2. Sample selection and data collection

To ensure the quality of our sample and the legitimacy of respondents' perception, we conducted a non-random approach using predefined selection criteria (Smith, 1983). Respondents should be experienced in LP and aware of I4.0 technologies. The sample was comprised of companies from different industrial sectors due to the low amount of companies implementing both LP and I4.0, as observed by Tortorella and Fettermann (2018). Additionally, even though lean implementation is mainly associated with high-volume and discrete parts manufacturers, the pervasiveness of practices across the industrial spectrum is unknown (Marodin et al., 2015), justifying the cross-industry sample. All involved companies systematically monitor their performance results, allowing a clear perception when responding to the questionnaire.

Because the researchers have already developed an extensive network with organizations through previous collaboration activities (e.g. consultancy, research and education), the identification of potential respondents was facilitated. The questionnaire was first sent to 658 respondents from companies located in Brazil during October and November 2020. From those, 110 responses were received, resulting in a response rate of 16.7%. As shown in Table 1, 56.4% of the sample was from companies with less than 500 employees and from tiers 1 or 2 in their respective supply chain. Participants were predominantly from the chemical and automotive sectors, and had more than 10 years of professional experience (53.6%). The majority of respondents were engineers or analysts in their companies (38.2%), and claimed to have a moderate knowledge on I4.0 (i.e. they could engage in a technical discussion about adopting I4.0 technologies, giving an opinion about its applicability in a certain known context). In terms of LP experience, the sample was perfectly balanced between those who had more than 5 years of experience and the ones with less than 5 years.

As an additional verification for common method bias, a statistical analysis using Harman's single-factor test was conducted, including all measures (Malhotra et al., 2006). Results indicated a first factor representing 29.6% of the total variance, suggesting that no single factor was responsible for most of the responses' variance. Thus, we disregarded issues related to common method bias.

Table 1 – Sample characteristics (n = 110)

4.3. Constructs' validity and reliability

We carried out three Exploratory Factor Analysis (EFA) using Principal Component (PC) extraction to validate constructs using collected responses (Fabrigar et al., 1999). EFA is recommended when there is no a *priori* hypothesis about components or patterns of measured items (Finch and West, 1997), which was our case.

The first EFA was performed using operational performance indicators. Through a varimax rotation of axes, high factor loadings for the five performance indicators were obtained in the first PC (eigenvalue of 3.632 and 72.63% of the total variance), as shown in Table 2. We checked construct reliability based on the Cronbach's alpha, whose result was 0.815. This indicated high reliability in responses, as it was higher than the Meyers et al. (2006)'s alpha threshold of 0.6.

Table 2 – EFA to validate the Performance construct

We ran a second EFA utilizing the adoption level of the 31 LA measures. The objective was to identify bundles of LA practices. We found three components whose eigenvalues were larger than 1 through a varimax rotation. The components' loadings allowed the verification of three bundles of practices named after their application focus. We replicated the results through an oblique rotation as a check for orthogonality, which led to similar components. Cronbach's alpha was determined to test reliability (see Table 3). Values for each bundle were defined using the weighted average of original responses with factor loadings as weights. Eight measures were excluded since they did not satisfactorily load in any of the three components; i.e. factor loadings were all below 0.45 for each component (Hair et al., 2014).

The first bundle was comprised of eleven LA practices mainly oriented to a workplace [WPL] level (micro-level), such as '*our employees practice setups to reduce the time required supported by collaborative engineering systems*' and '*we maintain all our equipment regularly using data collected from machine digital automation sensors*'. These practices aim at ensuring the basic stability of the workstations through the combination of LP practices and I4.0 technologies. The second bundle consisted of six LA practices that might help improve the supply chain (macro-level). This bundle particularly involves both customers and suppliers in the development of a more efficient extended value stream [EVS], justifying its denomination. The third bundle of LA grouped six practices that are mostly applied at a value stream level [VS]. In this sense, this bundle focuses on the flow improvement within the organization (meso-level).

Table 3 – EFA to validate the LA constructs

The third EFA was performed with responses to the observed frequency of the 14 LP principles and 6 I4.0 principles in the companies' decisions and employees' behaviors. We applied an EFA with varimax rotation to extract the two components in Table 4 (eigenvalues ≥ 1). Two bundles were obtained based on the analysis of their factor loading, with exception of two LP principles, whose loadings were all below 0.45 and, hence, excluded from both components. As LA implies in significant shifts in the organization's operations, following indications from the STS theory (Sovacool and Hess, 2017) we named these bundles of principles according to their orientation; i.e. sociocultural- [SOCIO] or technology-oriented [TECH]. Sociocultural-oriented principles mostly concern the behavioral and cultural elements of the LA implementation, such as 'build a culture of stopping to fix problems', 'respect your network of partners' and 'make decision slowly by consensus, implement them rapidly'. It is worth mentioning that the ten principles belonging to this bundle are all derived from LP principles. Technology-oriented principles refer to the tangible components related to the design of the LA implementation, such as 'use only reliable, tested technology', 'easily accessible information to all relevant stakeholders' and 'quick adaptation to market changes supported by information and communication technologies'. From the eight principles assigned to this bundle, two were originally proposed for LP and six are I4.0 design principles, empirically indicating the combination between LP and I4.0 principles.

Table 4 – EFA to validate the Principles constructs

Complementarily, a Confirmatory Factor Analysis (CFA) including all bundles of LA practices and principles was conducted (see Table 5) to check their convergent validity and unidimensionality (Tabachnik and Fidell, 2007). Due to the sample size, two CFA models were determined (Bentler and Chou, 1987): one full model including all bundles, and another for each single bundle. We examined the goodness-of-fit of the CFA using Chi-squared test result (χ^2/df), Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR). CFI values greater than 0.90 combined with SRMR values lower than 0.08 were applied as thresholds (Hu and Bentler, 1999). All items presented loadings greater than 0.45 on their respective constructs, whose Cronbach's alpha values were acceptable. Discriminant validity was tested using the average variance extracted (AVE). Values for each bundle were greater than the squared correlation coefficients (Fornell and Larcker, 1981; Bagozzi and Yi, 1988), meeting the required thresholds. Each bundle had its composite reliability (CR) assessed. All CR results were greater than 0.7, ensuring their convergent validity (Hair et al., 2014). Hence, we calculated the values for each bundle on a continuous scale using their corresponding factor loadings as weights. Finally, we checked the pairwise correlations for all constructs (see Table 6), whose significant correlation coefficients (p-value < 0.05) were all positive.

Table 5 – Bundles of LA practices and principles, measures and CFA factor loadings

Table 6 – Pearson correlation

4.4. Data analysis

To verify our hypotheses, we conducted a set of Ordinary Least Square (OLS) hierarchical linear regression models. Four models were tested. The first three models individually and respectively regressed each of the three bundles of LA practices on the control variables 'tier level' and 'company size' (Models 1A, 2A and 3A) and bundles of LA principles (Model 1B, 2B and 3B). In the fourth model, we first regressed the operational performance construct on the control variables. Then, we inserted the bundles of LA principles (independent variables), which generated Model 4B. In Model 4C, Operational Performance (dependent variable) was regressed on both independent and mediating (bundles of LA practices) variables.

We also verified all models with the insertion of dummy industry sector variables, since the nature of the processes and contextual characteristics associated with the industry sector might influence the companies' readiness on both LP and Industry 4.0. Coefficients of these dummies were not significant, remaining the same results when these variables were excluded from the regression models. Hence, to enhance the degrees of freedom and significance of our models, we did not consider the industry sector in the regression (Tortorella et al., 2018). Furthermore, the variance inflation factors (VIF) for all variables was used to check multicollinearity of the estimated coefficients. Since VIF values were all below five, multicollinearity issues were not a concern (Belsley et al., 2005).

Assumptions of normality, linearity, and homoscedasticity between independent, mediating and dependent variables were verified (Hair et al., 2014). Residuals were used to check the normality of the error term distribution. Linearity was confirmed through plots of the partial regression for each model. No model rejected the hypothesis of adherence to the normal distribution of residuals (Kolmogorov-Smirnov test p-value < 5%). We plotted the standardized residuals against the predicted values to visually examine homoscedasticity. All checks showed the required conditions for the OLS regression analyses.

It is also worth noting that, with respect to our sample size, determining a minimum representative sample size at which the results of a dataset analysis would be unchanged from those obtained with larger sample sizes has been a major practical concern for multivariate data analysis techniques application (Forcino, 2012; Forcino et al., 2015). Although there is no certain rule, some researchers support a rule of thumb when using the sample size. In regression analysis, which is the procedure conducted in our study, many researchers (e.g. Concato et al., 1995; Peduzzi et al., 1995; Vittinghoff and McCulloch, 2007) suggest that there should be at least 10 observations per variable. In our regression models, the most critical model was 4C, in which we regressed the operational performance on seven variables (i.e. control, independent and mediating variables). As our sample consisted of 110 respondents, we met the suggested 10 to 1 ratio between sample size and variables. Furthermore, other recent survey-based studies that approached novel phenomena utilized a similar cross-industry sample size to perform their multivariate data analyses, such as

Tortorella et al. (2020a) with a dataset comprised by 135 respondents, Frank et al. (2019) which had a 92-respondent sample, Marodin et al. (2018) with a sample of 110 responses, and Tortorella et al. (2017b) with a sample of 89 companies. This evidence reinforces the indication that our sample size and composition satisfactorily allows the conduction of the proposed data analysis.

5. Results and discussion

Table 7 presents the standardized $\hat{\beta}$ coefficients for the OLS regression analyses. Models 1, 2 and 3 examined the effect of the adoption of the LA principles bundles [SOCIO] and [TECH] on the LA practices bundles [WPL], [VS] and [EVS], respectively. In all these models, both bundles of LA principles (independent variables) seem to positively contribute to the implementation of LA practices (mediating variables), with the exception of the [EVS] bundle for which only [TECH] displayed a significant association ($\hat{\beta}$ = 0.822; p-value < 0.01). In the fourth model, we regressed operational performance improvement on the control (Model 4A), independent (Model 4B) and mediating variables (Model 4C). Only Models 4B and 4C were significant models (p-value < 0.01). Nevertheless, Model 4C showed the highest predicting capacity for operational performance improvement with an adjusted R^2 of 0.565, significantly enhancing the prediction of Model 4B. In Model 4C, both bundles of LA principles and two bundles of LA practices (WPL and VS) were positively associated with the dependent variable, while no significant effect was found for any of the control variables and [EVS]. The relationships empirically identified are illustrated in Figure 2.

Table 7 – Standardized $\hat{\beta}$ coefficients for hierarchical regression analyses

Figure 2 – Empirically validated relationships

Regarding the LA principles (SOCIO and TECH), our findings have shown their significant direct and indirect impact on operational performance. Such relevant effect suggests that companies undergoing an LA implementation must invest efforts to ensure their employees really understand the need behind the undergoing changes and the intrinsic values and beliefs that the company is looking for. Although the observation of how those principles are inserted into individuals' routine is very subtle due to their intangible nature (Tortorella et al., 2019b), our findings evidenced that it is fundamental to have those principles as key elements of the LA implementation. This result corroborates to the indications from Maleyeff (2006), Losonci et al. (2011) and Yadav et al. (2017), which emphasized that the adoption of those principles guide how companies must be managed and structured towards a better performance.

Furthermore, our work has indicated that an effective LA implementation requires not only principles related to the sociocultural aspects, which have been extensively discussed in previous studies, but also the ones oriented to the technological elements. This indication is reasonable considering the digital transformation implied by I4.0 (Lasi et al., 2014; Liao et al., 2017; Frank et al., 2019), which may reinforce the role of design principles that support a systematic integration of novel ICTs into existing management practices (Ghobakhloo and Hong, 2014). This outcome adds to the literature on LA, which has poorly approached the relevance of the [TECH] principles to a successful implementation. In fact, results showed that [TECH] principles appear to have a major impact on [EVS] practices, highlighting their role at a supply chain level. Hence, companies implementing LA must equally care of the development of both [SOCIO] and [TECH] principles, which is strongly aligned with STS assumptions (Cooper and Foster, 1971; Baxter and Sommerville, 2011). This result fully supports *H1*.

Results for LA practices partially confirm *H2* and *H3*. LA practices applied at a workplace and value stream levels seem to positively mediate the effect of LA principles on operational performance. These outcomes are somewhat aligned with the works from Kolberg et al. (2017) and Tortorella et al. (2020c), which have approached LA's implications from a micro and meso level, respectively. Surprisingly, LA practices focused on a macro level (EVS) did not appear to significantly impact on operational performance. This result is somewhat contrary to indications from Marodin et al. (2017) and Fatorachian and Kazemi (2020). While the former suggested a positive effect of LP at a supply chain level, the latter argued a beneficial contribution of I4.0 to supply chain performance. However, as observed by Pepper and Spedding (2010) and Jones and Womack (2016), lean thinking and practice have been evolving during the past decades. The understanding of the concepts and structures that drive them has changed, expanding the awareness of both practitioners and academics. More specifically, Hines et al. (2004) and Tortorella et al. (2017b) suggested that lean implementation at a supply chain level is usually lagging behind the implementation at a shop floor level, which may blur practitioners' perceptions when responding questions associated with this application focus. We argue that this might be the case for LA practices at a supply chain level, justifying their unexpected lack of significant effect on operational performance.

6. Conclusions

This research examined the effects of the bundles of LA practices and principles on companies' operational performance improvement. This study indicates two major findings. First, LA principles could be grouped into two separate bundles, depending on their orientation. Similarly, LA practices could be combined into three bundles according to their application focus. Second, these bundles of LA practices and principles have a positive and significant relationship with operational performance. More specifically, LA practices seem to mediate the effect of LA principles, acting as facilitators for operational performance. A more in-depth discussion of these findings is provided subsequently.

6.1. Theoretical implications

Some studies (e.g. Buer et al., 2018; Tortorella et al., 2020b) have found different frameworks for guiding the integration of I4.0 into LP, giving rise to LA. However, the combination of LA practices and principles into bundles and their empirical validation has not yet been evidenced. Thus, the first implication of our investigation is the identification of two specific bundles for LA principles and three bundles of LA practices, empirically validating them.

The bundle of sociocultural-oriented principles combines 10 LA principles mainly focused on providing guidance on the behavioral and cultural elements that must be incorporated into the organization. All these principles originate from LP principles, hence, fostering the behaviors and mindsets required to sustain improvements in the long term. In opposition, the bundle of technology-oriented principles mixes two principles from LP and six from I4.0. These principles establish the fundamental design ideals that should guide the digitization side of the LA implementation. The empirical identification of this bundle and its proposition as part of the LA principles is one of the theoretical uniqueness of this work. The LA principles are aligned with the focus of the STS theory that emphasizes a balance between technical and social systems to have a greater impact on the organizational performance.

Regarding the bundles of LA practices, our research presents a different approach to their categorization. Works from Shah and Ward (2003; 2007) and Bortolotti et al. (2015) identified the bundles of LP practices that were grouped and named according to their functionality. Similarly, Tortorella et al. (2020b) conceptually conceived nine bundles of LA practices based on their functions. In turn, we empirically validated bundles of LA practices that were named according to their context of the application (i.e. workplace, value stream, extended value stream). Pagliosa et al. (2019) have suggested a similar categorization of LP practices and I4.0 technologies; though, they did not validate this structure and considered LP and I4.0 as separate dimensions. Similarly, Chiarini and Kumar (2020) has also inductively developed an integrated LP and I4.0 practice bundles by conducting interviews in Italian manufacturing firms; those items still need to be empirically tested and validated through survey research. Their study also omitted to measure the impact of LP and I4.0 practices on operational performance. As most continuous improvement initiatives tend to start cautiously, encompassing a few workstations as implementation pilots, then moving to some production lines and, eventually, expanding to upstream and downstream partners (Duggan, 2012; Netland and Aspelund, 2014; Netland et al., 2015), it becomes reasonable to group LA practices under this rationale. Toyota first organized and streamlined its own processes and practices by adopting the Toyota Production System (TPS), before asking their suppliers to improve their performance using TPS principles and practices. This clearly shows the importance of micro- and meso-level focus first to organize and improve your own work before shifting the focus to improving the supply chain (i.e. macro-level focus), as evidenced in our findings as well.

Finally, results show that the adoption of LA principles (SOCIO and TECH) and practices (WPL and VS) positively affect operational performance. Nevertheless, LA practices that act at a supply chain level (EVS) do not seem to have a similar and relevant effect. In general, our study provided evidence that similar to LP and I4.0, LA implementation also comprises socio-technical changes, in which both its practices (tangible elements) and principles (intangible aspects) have a relevant role in achieving enhanced operational performance. This work has evidenced that, although LA is a recent phenomenon given the emergence of novel ICTs, it may be an upcoming trend for continuously improve companies in the Fourth Industrial Revolution era.

6.2. Contributions to practice

This research also has some practical implications to organizations undergoing a LA implementation. Due to the validation of bundles of LA, organizations might benefit from the concomitant implementation of these interrelated practices and principles. Since LA requires changes in the socio-technical factors, determining which practices and principles have a synergistic interaction might reduce efforts and catalyze the expected benefits. The validation of bundles of LA practices and principles determines an implementation framework that conducts more assertively organizations' continuous improvement initiatives in the Fourth Industrial Revolution era.

Moreover, the identification of a positive association between LA bundles and operational performance evidences the advantages that LA may entail in manufacturers. Understanding how the interaction between the bundles of LA practices and principles impacts performance is undoubtedly of management's interest. As managers become aware of the benefits of the LA, they are more prone to foster and support its implementation. The comprehension of such effects also enables the customization of LA adoption, preventing from ineffective "one-size-fits-all" approaches.

Practitioners can benefit from our findings by particularly ensuring that they attend to the 'socio' side of implementing I4.0 technologies within a LA approach, as well as the technical. Within companies that already have a strong socio-technical lean orientation and 'respect for people' in their culture, this is likely to be how they implement LA. Yet for companies that wish to introduce I4.0 as part of a LA approach that does not have a pre-existing strong 'respect for people' in place, our results would indicate that tending to the human aspects of LA implementation would be especially important and beneficial to the performance outcomes, in lifting the likelihood and magnitude of success chances (Srinivasan et al., 2020).

6.3. Limitations and future research

An important limitation of this research regards the LA implementation itself. I4.0 was formally acknowledged in 2011, and many studies on LA have been developed since then. Nevertheless, most research on LA is in the early stages, characterized by specific applications in a few processes. Hence, the extent and readiness of LA vary across organizations, affecting practitioners' perceptions when responding to the questionnaire. Although countermeasures to mitigate biases were performed, larger sample sizes would allow researchers to curb such issues and obtain more robust results. Moreover, since this was a cross-sectional survey, the maturity level variation is more challenging to capture. Longitudinal research would support the identification of the evolution of both social and technical aspects during LA implementation. This would demand the expansion of the data collection and different analysis procedures, motivating future studies. We also acknowledge the need for future studies to extend the sampling procedures to other industry sectors that can also benefit from LA implementation (e.g. services, construction, etc.), which could raise complementary insights to both theory and practice.

We also propose that further and different types of studies, both qualitative and quantitative, can and will add much to the body of evidence needed to support business decisions to invest effectively in LA. Case studies will further expand knowledge of how LA works best by illuminating the causal mechanisms of the principles, practices and outcomes more deeply and directly. Such work will increase the confidence that practitioners have through their illustrative power. Event studies also have the potential to test and provide evidence of the relationship between LA and bottom line outcomes. With the advent and move towards maturity of applications of I4.0 in combination with LP in progress, such additional types of research will increasingly provide for 'triangulation' about LA impacts, and hence more efficient and effective LA initiatives.

Finally, the impact of LA was investigated using a set of practices and principles. As the literature on LA evolves, other practices and principles may emerge as part of the LA, leading to additional bundles whose association with operational performance can vary, indicating an opportunity for researchers. Operational performance indicators applied in the questionnaire could also be complemented through the inclusion of financial indicators (e.g. profit, revenue, etc.), which is a sensitive issue for companies.

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Table 1 – Sample characteristics (*n* = 110)

Company size			Respondents' Lean experience		
< 500 employees	62	56.4%	< 5 years	55	50.0%
> 500 employees	48	43.6%	> 5 years	55	50.0%
Tier level			Industry sector		
1 or 2	72	65.5%	Chemical	13	11.8%
3 or 4	38	34.5%	Automotive	13	11.8%
Respondents' role			Metal-mechanics	12	10.9%
Analyst/Engineer	42	38.2%	Machine and equipment	5	4.6%
Supervisor/Coordinator	35	31.8%	Textile	5	4.6%
Manager/Director	33	30.0%	Food	4	3.6%
Resnpondents' I4.0 Knowledge			Others	58	52.7%
Basic	33	30.0%	Respondents' professional experience		
Moderate	40	36.4%	< 10 years	51	46.4%
Advanced	37	33.6%	> 10 years	59	53.6%

Table 2 – EFA to validate the Performance construct

Performance Indicators	Mean	Std. dev.	Communalities	Factor loadings
Safety (work accidents)	3.494	1.053	0.679	**0.824**
Quality (scrap and rework)	3.323	0.830	0.730	**0.855**
Delivery service	3.424	0.846	0.775	**0.880**
Productivity	3.393	0.878	0.811	**0.901**
Inventory	3.323	0.793	0.636	**0.798**
Extraction sums of squared loadings				3.632
% of variance				72.632
Cronbach's alpha				0.815
Kaiser-Meyer-Olkin measure of sampling adequacy				0.846
Bartlett's test of sphericity (χ^2 / df)				322.843 / 10*

Notes: Extraction method: Principal Component Analysis; * *p*-value < 0.01.

Table 3 – EFA to validate the LA constructs

	LA measures	Mean	Std. dev.	Communalities	1	2	3	Focus
la_{1}	Suppliers are directly involved in the new product development process through integrated and collaborative engineering systems, such as Manufacturing Execution System (MES), Supervisory Control and Data Acquisition (SCADA) and digital sensors.	2.303	1.190	0.769		*Excluded*		
la_{2}	Our key suppliers deliver to plant on JIT aided by remote control of production, digital interfaces and IoT.	2.363	1.110	0.720		*Excluded*		
la_{3}	We have a formal supplier certification program supported by digital automation without sensors.	2.313	1.166	0.850		*Excluded*		
la_{4}	Our suppliers are contractually committed to annual cost reductions by identifying abnormal product/operating conditions through sensors and IoT.	2.262	1.191	0.875		*Excluded*		
la_{14}	Products are classified into groups with similar routing requirements through integrated and collaborative engineering systems.	2.585	1.097	0.657		*Excluded*		
la_{19}	We have low set up times of equipment in our plant, which are monitored by digital sensors integrated into collaborative engineering systems, obtained through utilization of additive manufacturing and augmented reality.	2.484	1.304	0.748		*Excluded*		
la_{23}	We use fishbone type diagrams aided by collaborative engineering systems to identify causes of quality problems.	2.838	1.314	0.666		*Excluded*		
la_{26}	Shop floor employees lead product/process improvement efforts based upon digital sensors, remote control of production and collaborative engineering systems.	2.333	1.228	0.749		*Excluded*		
la_{17}	Our employees practice setups to reduce the time required supported by collaborative engineering systems.	2.717	1.125	0.694	**0.507**		0.496	
la_{20}	Large number of equipment/processes on shop floor are currently under statistical process control and monitored through digital sensors integrated into collaborative engineering systems.	2.787	1.255	0.760	**0.556**		0.553	
la_{21}	Extensive use of statistical techniques to reduce process variance through digital sensors and remote control of production integrated with collaborative engineering systems, which identify abnormal product/operating conditions.	2.666	1.324	0.740	**0.585**		0.489	
la_{22}	Charts showing defect rates are used as tools on the shop floor aided by digital interfaces integrated into collaborative engineering systems.	2.737	1.139	0.845	**0.779**			
la_{24}	We conduct process capability studies aided by collaborative engineering systems before product launch.	2.777	1.374	0.722	**0.669**			
la_{25}	Shop floor employees drive suggestion programs utilizing machine digital interfaces integrated into collaborative engineering systems by means of IoT.	2.626	1.242	0.743	**0.639**	0.521		Workplace (Micro level) [WPL]
la_{27}	Shop floor employees undergo cross functional training utilizing digital interfaces, remote control of production, collaborative engineering systems to identify abnormal conditions, and IoT.	2.656	1.162	0.881	**0.722**			
la_{28}	We dedicate a portion of everyday to planned equipment maintenance related activities based upon data from digital sensors integrated into engineering systems, MES or SCADA.	2.535	1.280	0.845	**0.769**		0.451	
la_{29}	We maintain all our equipment regularly using data collected from machine digital automation sensors.	2.697	1.265	0.793	**0.754**			
la_{30}	We maintain excellent records of all equipment maintenance related activities using data collected from machine digital automation sensors.	2.585	1.245	0.892	**0.845**			
la_{31}	We post equipment maintenance records on shop floor for active sharing with employees through machine digital interfaces integrated into collaborative engineering systems, MES or SCADA.	2.282	1.204	0.831	**0.815**			
la_{5}	We have corporate level communication on important issues with key suppliers aided by integrated digital interfaces and engineering systems through IoT.	2.292	1.108	0.791		**0.620**		
la_{6}	We take active steps to reduce the number of suppliers in each category using collaborative engineering systems.	2.414	1.020	0.825		**0.657**		
la_{7}	We evaluate suppliers on the basis of total cost and not per unit price, identifying their product/operating conditions by means of digital sensors.	2.474	1.163	0.910		**0.881**		Extended Value Stream or Supply Chain (Macro level) [EVS]
la_{8}	Our customers are actively involved, through digital interfaces and remote control of production, in current and future product offerings.	2.626	1.074	0.702	0.479	**0.588**		
la_{9}	Our customers are directly involved in current and future product offerings through utilization of process-oriented technologies, such as digital automation, remote control sensors and integrated engineering systems.	2.494	1.163	0.825		**0.784**		
la_{10}	Our customers frequently share current and future demand information with marketing department utilizing integrated digital interfaces and engineering systems with sensors.	2.555	1.144	0.871		**0.894**		
la_{11}	Production is pulled by the shipment of finished goods through integrated and collaborative systems.	2.787	1.180	0.771	0.456	0.456	**0.514**	
la_{12}	Production at stations is pulled by the current demand of the next station through integrated and collaborative systems.	2.666	1.160	0.855			**0.667**	
la_{13}	Products are classified into groups with similar processing requirements through integrated and collaborative engineering systems.	2.899	1.129	0.735	0.488		**0.570**	Value Stream (Meso level) [VS]
la_{15}	Equipment is grouped to produce a continuous flow of families of products through integrated and collaborative engineering systems.	2.899	1.083	0.772		0.505	**0.566**	
la_{16}	Families of products determine our factory layout through integrated and collaborative engineering systems.	2.656	1.136	0.834			**0.647**	
la_{18}	We are working to lower setup times in our plant utilizing integrated engineering systems.	3.141	1.169	0.854			**0.804**	
Extraction sums of squared loadings					19.829	2.404	1.201	
% of variance					63.963	7.756	3.875	
Rotation sums of squared loadings					8.132	7.246	5.537	
% of variance					26.232	23.374	17.862	
Cronbach's alpha (n = 110)					0.803	0.821	0.798	
Kaiser-Meyer-Olkin measure of sampling adequacy						0.827		
Bartlett's test of sphericity (χ^2 / df)						4,900.769 / 465*		

Notes: Extraction method: Principal Component Analysis; Rotation Method: Varimax with Kaiser normalization; *p-value < 0.01. The bold numbers indicate which practices were allocated to which constructs. Factor loadings below 0.45 were suppressed.

Table 4 – EFA to validate the Principles constructs

	Principles	Mean	Std. dev.	Communalities	1	2	Focus
pr_9	Develop leaders who live the philosophy	3.292	1.118	0.910	*Excluded*		
pr_{10}	Develop exceptional people and teams	3.272	1.123	0.874	*Excluded*		
pr_2	Create a continuous flow to bring problems to the surface	3.191	1.065	0.784	**0.790**		Sociocultural-oriented [SOCIO]
pr_3	Use "pull" systems to avoid overproduction	2.959	1.159	0.822	**0.747**		
pr_4	Level out the workload	2.919	1.112	0.581	**0.751**		
pr_5	Build a culture of stopping to fix problems	2.717	1.134	0.856	**0.906**		
pr_6	Standardized tasks are the foundation of continuous improvement	3.323	1.132	0.840	**0.833**		
pr_7	Use visual controls so no problems are hidden	3.111	1.086	0.812	**0.824**		
pr_{11}	Respect your network of partners	3.434	1.179	0.825	**0.750**		
pr_{12}	See for yourself to understand the situation	3.272	1.150	0.758	**0.751**		
pr_{13}	Make decision slowly by consensus, implement them rapidly	2.888	1.141	0.829	**0.839**		
pr_{14}	Become a learning organization through relentless reflection	3.010	1.025	0.839	**0.695**		
pr_1	Base management decisions on a long-term philosophy, even at the expense of short-term financial goals	3.242	1.125	0.582	0.454	**0.485**	Technology-oriented [TECH]
pr_8	Use only reliable, tested technology	3.393	0.987	0.606	0.486	**0.583**	
pr_{15}	Digitally interconnected machines, devices, sensors and people	2.727	1.132	0.773		**0.787**	
pr_{16}	Easily accessible information to all relevant stakeholders	2.979	0.999	0.768		**0.780**	
pr_{17}	Technological support to assist decision making in problem solving, such as digital twins	2.606	1.067	0.761	0.469	**0.709**	
pr_{18}	Capability to perform tasks as autonomously as possible supported by cyber-physical systems	2.697	1.281	0.855		**0.914**	
pr_{19}	Real-time capability of data collection, store and analysis	2.979	1.106	0.709		**0.787**	
pr_{20}	Quick adaptation to market changes supported by information and communication technologies	3.171	1.088	0.722		**0.686**	
	Extraction sums of squared loadings				11.953	2.518	
	% of variance				59.764	12.588	
	Rotation sums of squared loadings				7.530	5.253	
	% of variance				37.650	26.266	
	Cronbach's alpha (n = 110)				0.709	0.788	
	Kaiser-Meyer-Olkin measure of sampling adequacy				0.847		
	Bartlett's test of sphericity (χ^2 / df)				2,408.762 / 190*		

Notes: Extraction method: Principal Component Analysis; Rotation Method: Varimax with Kaiser normalization; *p-value < 0.01. The bold numbers indicate which practices were allocated to which constructs. Factor loadings below 0.45 were suppressed.

Table 5 – Bundles of LA practices and principles, measures and CFA factor loadings

Bundles	Measures	Coef.	AVE	χ^2/df	CFI	SRMR	CR
WPL	la_{17}	0.511	0.714	41.871/9	0.912	0.059	0.798
	la_{20}	0.561					
	la_{21}	0.597					
	la_{22}	0.760					
	la_{24}	0.688					
	la_{25}	0.654					
	la_{27}	0.702					
	la_{28}	0.734					
	la_{29}	0.705					
	la_{30}	0.811					
	la_{31}	0.789					
EVS	la_5	0.602	0.670	18.005/4	0.918	0.075	0.802
	la_6	0.675					
	la_7	0.819					
	la_8	0.602					
	la_9	0.792					
	la_{10}	0.849					
VS	la_{11}	0.505	0.705	17.002/4	0.924	0.061	0.808
	la_{12}	0.679					
	la_{13}	0.512					
	la_{15}	0.569					
	la_{16}	0.654					
	la_{18}	0.812					
SOCIO	pr_2	0.765	0.551	38.081/8	0.911	0.062	0.753
	pr_3	0.743					
	pr_4	0.719					
	pr_5	0.889					
	pr_6	0.851					
	pr_7	0.816					
	pr_{11}	0.779					
	pr_{12}	0.723					
	pr_{13}	0.846					
	pr_{14}	0.687					
TECH	pr_1	0.497	0.532	26.002/6	0.905	0.072	0.783
	pr_8	0.545					
	pr_{15}	0.768					
	pr_{16}	0.749					
	pr_{17}	0.712					
	pr_{18}	0.900					
	pr_{19}	0.751					
	pr_{20}	0.664					

Table 6 – Pearson correlation

	1	2	3	4	5	6	7	8
1-PERFORMANCE	-	0.074	-0.043	0.729**	0.544**	0.374**	0.496**	0.380**
2-Size		-	-0.004	0.007	-0.014	0.011	0.028	-0.058
3-Tier			-	-0.051	0.176*	0.091	0.172*	0.248**
4-SOCIO				-	0.616**	0.610**	0.620**	0.455**
5-TECH					-	0.666**	0.726**	0.812**
6-WPL						-	0.839**	0.666**
7-VS							-	0.731**
8-EVS								-

Note: * Correlation coefficient significant at 5%; ** Correlation coefficient significant at 1%.

Table 7 – Standardized $\hat{\beta}$ coefficients for hierarchical regression analyses

Variables	WPL		VS		EVS		PERFORMANCE		
	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B	Model 4A	Model 4B	Model 4C
Size	0.012	0.016	0.029	0.034	-0.057	-0.045	0.074	0.072	0.067
Tier	0.091	0.027	0.172^{*}	0.096	0.247^{**}	0.101^{*}	-0.043	-0.041	-0.052
SOCIO		0.328^{***}		0.302^{***}		-0.046		0.622^{***}	0.665^{***}
TECH		0.459^{***}		0.523^{***}		0.822^{***}		0.169^{*}	0.237^{*}
WPL									0.388^{***}
VS									0.273^{**}
EVS									-0.040
F-value	0.407	24.365^{***}	1.503	33.069^{***}	3.311^{**}	48.552^{***}	0.354	28.987^{***}	19.174^{***}
R^2	0.008	0.509	0.030	0.585	0.065	0.674	0.007	0.552	0.596
Adj. R^2	-0.012	0.488	0.010	0.567	0.045	0.660	-0.013	0.533	0.565
Change in R^2		0.501^{***}		0.554^{***}		0.609^{***}		0.545^{***}	0.044^{**}

Notes: * p-value < 0.10; ** p-value < 0.05; *** p-value < 0.01.

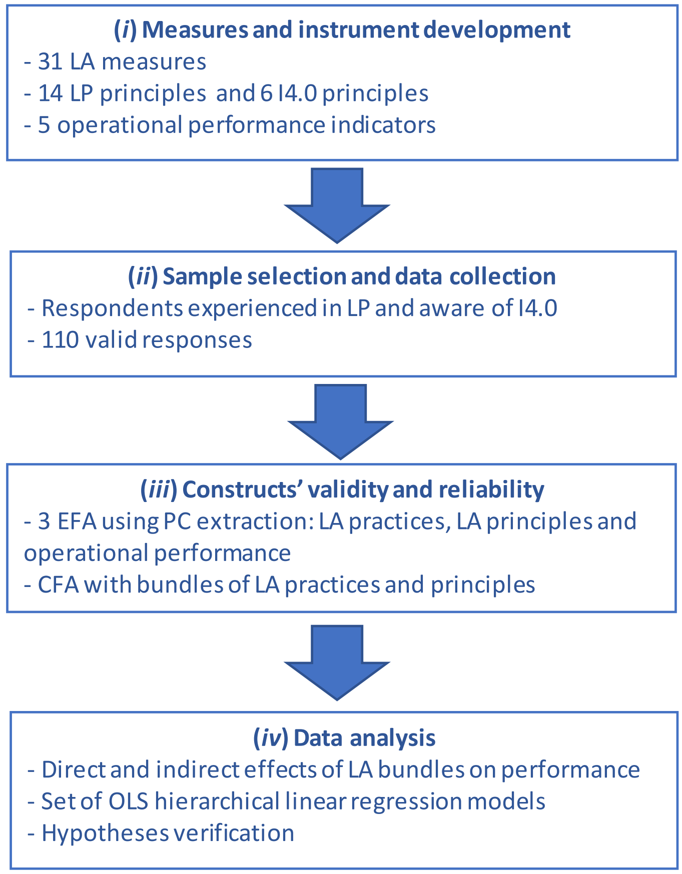

Figure 1 – Proposed method steps

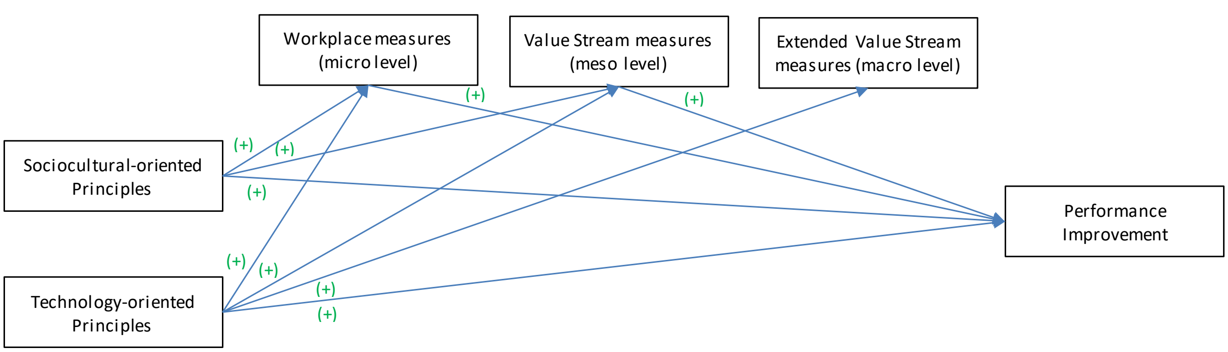

Figure 2 – Empirically validated relationships