Identifying pathways to a high-performing Lean Automation implementation: an empirical study in the manufacturing industry

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Abstract

This paper examines pathways to implement a high-performing Lean Automation (LA). We asked 61 manufacturers from Brazil and India that are undergoing a lean implementation together with the adoption of disruptive digital technologies from Industry 4.0 (I4.0) to indicate their implementation sequence. We then used multivariate data techniques to analyze the collected data. Our findings suggested three sets of lean practices and I4.0 technologies; namely: start-up, in-transition and advanced. Further, companies that presented a higher performance improvement have more extensively implemented start-up and in-transition practices/technologies. However, no significant difference was found for the adoption level of advanced practices/technologies between low- and high-performer companies. Since the integration of I4.0 technologies into Lean Manufacturing (LM) is a relatively recent phenomenon, our study provides guidelines related to a preferential implementation sequence within this portfolio of practices and technologies.

Keywords: Lean Automation, Lean Manufacturing, Industry 4.0, Performance.

1. Introduction

Lean thinking has been subscribed for decades by both manufacturing and services sector to improve their performance (Womack and Jones, 1997; Stone, 2012). One of the strong reasons for the consistent adoption of lean thinking across diverse sectors is the simplicity at which the different lean tools and techniques can be implemented even by the shop floor employees, by just relying on common sense (Holt, 2019). Lean Manufacturing (LM) was not only simple to implement but also delivered large returns for firms. It helped firms to significantly reduce non-value adding tasks and enhance value-adding tasks, which finally enhanced their operational performance (Shah and Ward, 2003; Chavez et al., 2013; Bortolotti et al., 2015a).

In the recent past, firms have started adopting Industry 4.0 (I4.0) by deploying smart components and machines that are integrated into a common digital network based on well-proven internet standards (Kolberg et al., 2017). Researchers have stated I4.0 as a new industrial paradigm that can enable firms to deliver higher financial, ecological and social performance (Stock et al., 2018). Through the deployment of digital technologies, I4.0 facilitates higher levels of mass customized processes, products and services (Zawadzki and Żywicki, 2016), new product and service developments (Dalenogare et al., 2018), and business model innovations (Frank et al., 2019) allowing firms to achieve improved performance levels.

As both LM and I4.0 have individually shown to enhance performance, firms have started integrating both approaches to achieve superior performance and competitive advantage over their competitors in the market (Tortorella et al., 2019a; 2019b). On the one hand, LM delivers its positive impact on performance through a systematic and continuous search for waste reduction and improvements (Narayanamurthy and Gurumurthy, 2016). On the other hand, I4.0 technologies introduce automation and interconnectivity that can mitigate pre-existing management difficulties (Tortorella et al., 2020a). Combining LM with I4.0 helps firms in achieving Lean Automation (LA), which according to Kolberg et al. (2017) aims for higher changeability and shorter information flows to meet future market demands. Therefore, it is clear that these two interventions introduce capabilities that can operate together to lead firms to new performance standards that are much higher than in the past.

However, even though literature converges on the potential of combining LM and I4.0 implementation together to achieve LA for higher performance, research has not focused on examining if the sequence of implementation of different LM practices and I4.0 technologies in a firm will have an impact on its operational performance. That the actual implementation sequence has an impact is indicated by Browning and Heath (2009) in the context of LM practices. Browning and Heath (2009) conducted a detailed case study research of Lockheed Martin's production system for the F22. They proposed that the cost reduction benefits achievable through the implementation of LM practices could vary depending on the timing of their implementation. This temporal aspect of LM practices implementation played such a crucial role that it can change the benefits to go from positive to negative (costs).

Similarly, research has discussed implementation patterns of I4.0 technologies. For instance, recently Frank et al. (2019) started by splitting I4.0 technologies into two broad categories, namely front-end (comprising of smart manufacturing, smart products, smart supply chain and smart working) and base technologies (comprising of cloud, IoT, big data and analytics). Then by applying cluster analysis, they defined patterns of adoption of these two layers of technologies in the surveyed companies and summarized the sequence of implementation in a framework. Yet, while the importance of the implementation sequence is widely recognized, no study to date empirically assessed the sequence in which LM and I4.0 are implemented in practice, and how the different pathways affect performance. Therefore, by extending the research on finding the optimal sequence of implementation of LM practices and I4.0 technologies individually, we answer the following research question:

> **RQ:** Which pathway of implementation of LM practices and I4.0 technologies can mature the LA intervention to achieve superior performance improvement?

To answer the above-stated research question, we randomly listed 21 LM practices suggested by Shah and Ward (2003) and 14 I4.0 technologies listed by Tortorella and Fettermann (2018) and Rossini et al. (2019). The respondents were asked to sequence the LM practices and I4.0 technologies in the order of their implementation and provide the response on their adoption level. Finally, respondents' perceptions on operational performance improvement during the last three years were recorded. The data was collected from manufacturing firms in India and Brazil using a questionnaire. The final sample comprised of 61 manufacturers from Brazil and India that were undergoing a lean implementation together with the adoption of digital technologies from I4.0. We used multivariate data techniques to analyze the collected data.

Our findings indicate that there is no clear path in terms of individual practices/technologies. Yet, there are sets of LA practices/technologies that are more prone to be implemented first than others, suggesting the existence of a precedence relationship. Our study identifies three sets of lean practices and I4.0 technologies using unique ranking data. Since the integration of I4.0 technologies into lean management is a relatively recent phenomenon, our study provides guidelines related to a preferential implementation sequence within this portfolio of practices and technologies. To the best of our knowledge, this study is the first one to use ranking data to answer the aforementioned question.

The paper is structured as follows. In section 2, we review the related literature to provide the background to our study. In section 3, we present the research method, including questionnaire development, data collection, and data analysis. In section 4, we discuss the results obtained and develop a schematic representation of the pathway to a high-performing LA implementation. Finally, in section 5, we conclude the research, outline implications for research and practice, and list the limitations and future research directions.

2. Background

In this section, we review literature that has discussed the importance of the sequence in which LM and I4.0 are implemented. Following it, we then review the literature that discusses the impact of LA on performance. Note that we do not aim to provide a systematic and comprehensive review of the literature. This would be far out of the scope of this study given the large amount of relevant literature. We rather seek to identify and discuss key papers to contextualize our study.

2.1. LM implementation

LM implementation is grounded on five broad tenets: (*i*) identify/define value, (*ii*) map the value stream, (*iii*) create flow, (*iv*) establish pull system, and (*v*) pursue perfection. Adopting these tenets in sequence allows value stream managers to spot inefficiencies, create better flow in work processes, enhance value for their customers, and develop a continuous improvement culture (Åhlström, 1998; Åhlström and Karlsson, 2000). It has been noticed in recent research that these tenets are operationalized differently by firms leading to a disconnect between theory and practice (Narayanamurthy et al., 2018).

According to Browning and Heath (2009), maturation of lean research has advanced more rapidly in philosophy than in actual theory and the mechanisms governing how and when to apply lean practices require further elucidation. The majority of lean practices help in achieving one of the two key objectives – controlling inventory buildup and reducing system variability. Hüttmeir et al. (2009) examine the choice firms have to make between lean practice *heijunka* (leanness) and just-in-sequence (responsiveness) to remain competitive. Based on the case study of a BMW engine plant, they propose a hybrid strategy with first using *heijunka* to smooth out the most extreme production values followed by JIS for the remainder of the production.

According to Chavez et al. (2013), complexity of the lean practices-performance link is yet not well understood and needs further exploration. Researchers have observed in the field that scope and focus of lean practices rollout is determined by workers perceptions, which are influenced by preexisting process characteristics and gender of employees (Losonci et al., 2011). They noticed that plants with more transparent processes achieved moderate lean transformation through work method and commitment, and plants with less transparent processes achieved radical lean transformation through communication and belief. By studying the impact of internal lean practices (comprised of pull-production systems, set-up time reduction, just-in-time and quality management) on operational performance, Chavez et al. (2013) explain under which circumstances lean practices are more effective by considering industry clockspeed contingency. While developing a methodology to assess systemic leanness of a value stream, Narayanamurthy and Gurumurthy (2016) explained that lean adoption undergoes three broad stages – lean implementation readiness, lean implementation and lean implementation assessment. Value streams transition from one stage to another in the lean adoption journey and poor maturity in the previous stage delivers inferior results in the stages to follow.

Replicating the overall success of lean practices implementation continues to remain infeasible in practice. This is attributed to the piecemeal approach of firms as they merely implement isolated lean practices and allow the means (the practices) to become ends in themselves. This pattern leads to falling short of the underlying philosophy of lean - to achieve an overall efficient and effective production system (Bortolotti et al., 2015). Driven by this need, the objective of this research is to examine the sequence in which lean practices should be implemented, especially in contexts where industry 4.0 technologies are simultaneously adopted by firms to achieve superior performance. It is hoped that this supports firms in replicating the overall success of lean practices implementation from one firm to another. Table 1 summarizes the literature on the implementation sequence of LM practices discussed in this section.

Table 1 – Literature on implementation sequence of LM practices

2.2. I4.0 adoption

The advent of I4.0 and the envisioned benefits from its adoption have motivated many researchers to develop strategic guidelines and roadmaps to support companies in their digital transformation (Pessl et al., 2017). In general, those guidelines and roadmaps encompass a set of design principles and digital technologies that aim at providing advice on the proper sequence for I4.0 adoption. However, some researchers (e.g. Erol et al., 2016; Ganzarain and Errasti, 2016) claim that those roadmaps should be tailored to each company's needs, being adapted and customized in a way that undermines a generalizable approach.

In this sense, a few studies have attempted to identify trends in I4.0 adoption, so that an implementation framework could be more assertively proposed. Based on a multi-method study encompassing a literature review and case study, Mishra et al. (2018) have suggested a conceptual I4.0 roadmap to support a sustainable growth in the industrial sector. More recently, Frank et al. (2019) have surveyed Brazilian manufacturers in order to identify I4.0 implementation patterns and empirically validate a conceptual framework. Nevertheless, companies' low readiness level on I4.0 has hindered the examination of basic digital technologies, such as big data and analytics.

Therefore, although the evidence on I4.0 adoption is prolific, most studies are either of a conceptual/theoretical nature or applications with a very narrow perspective. Overall, the scarcity of empirical evidence and the lack of understanding of what a full I4.0 adoption actually is, may obstruct the determination of a specific pathway for I4.0. Additionally, the required infrastructure and labor skills for I4.0 (Santos et al., 2017) do not contribute to a faster and wider adoption across companies and socioeconomic contexts (Ghobakhloo, 2018). This fact negatively influences the comprehension of I4.0 adoption from a system-wide perspective, suggesting that further investigation on the topic is needed. Finally, Table 2 summarizes the literature on the implementation sequence of I4.0 technologies discussed in this section.

Table 2 – Literature on implementation sequence of I4.0 technologies

2.3. Impact of LA on performance

Already in the early 1990s, initial attempts for integrating automation using technology into LM emerged (Kolberg et al., 2017). Robotics has been in use for at least three decades to improve quality, performance and efficiency in manufacturing industries (Hedelind and Jackson, 2011). With the ecosystem that is currently being offered through I4.0 technologies, lean automation is becoming more feasible and attractive for enhancing performance (Tortorella et al., 2019a). Easy integration and relationship maintenance between the business partners through internet and common cloud contributes to strong collaboration, synchronization and better communication which enables effective supplier feedback (Sanders et al., 2016). In addition, more advanced analytics and big data environments equip machines to be self-aware and self-maintained, thereby achieving significant improvements in their total productive and preventive maintenance (Dombrowski et al., 2017).

However, contradictory evidences on the impact of LA on performance are also found in literature (e.g. Sanders et al., 2016; Tortorella and Fettermann, 2018; Rossini et al., 2019), which call for deeper comprehension and exploration. For instance, it gets difficult to embrace JIT production, small batch-sizes, and continuous improvement when integrating industrial robots without a well-thought through strategy (Hedelind and Jackson, 2011), which, in turn, can negatively impact the overall performance. Therefore, it is important to delineate and understand the impact that the sequence in which LM and I4.0 are implemented can have on performance. Table 3 summarizes the literature on the impact of LA on performance discussed in this section.

Table 3 – Literature on the impact of LA on performance

3. Research method

This study aims at identifying pathways to implement a high-performing LA. For that, we conducted an empirical research, which is a recommended approach for exploratory studies (Goodwin, 2005). Among the existing ways of data collection for empirical research purposes, the survey method is frequently adopted due to its advantages, such as high level of representativeness, low cost, and provision of good statistical significance and standardized stimulus to all respondents (Montgomery, 2013). The quantification of empirical evidence gathered from respondents carefully selected is a usual approach in studies of similar nature (e.g. Tortorella and Fettermann, 2018; Rossini et al., 2019). Therefore, we conducted a survey-based study with practitioners so that we could answer the research question: "which pathway of implementation of LM practices and I4.0 technologies can mature the LA intervention to achieve superior performance improvement?". The proposed research method was comprised of three steps: questionnaire development, data collection and sample characterization, and data analysis. Each step is described in detail in the sections to follow.

3.1. Questionnaire development

In alignment with our research question the applied questionnaire was composed by four parts: (*i*) respondent information, (*ii*) implementation sequence of LM practices and I4.0

technologies, (*iii*) adoption level of those LM practices and I4.0 technologies and (*iv*) perception of operational performance.

The first part collected information of respondents (e.g. roles) and their respective companies (e.g. ownership, manufacturing strategy, country, size and sector). In the second part, respondents were asked to sequence the implementation order of LM practices and I4.0 technologies in their companies. For that, we listed the 21 LM practices suggested by Shah and Ward (2003) and the 14 I4.0 technologies listed by Tortorella and Fettermann (2018) and Rossini et al. (2019). These sets of practices and technologies were chosen since they were consistently referred to by other studies (e.g. Dahlgaard-Park and Pettersen, 2009; Marodin et al., 2016; Pagliosa et al., 2019). Thus, to represent the LA implementation, we combined those 21 LM practices with the 14 I4.0 technologies, and randomly displayed the 35 items in the questionnaire to avoid bias in the responses of the implementation sequence. Respondents should then assign '1' to the first practice/technology that they have implemented and then look for another practice/technology that was subsequently adopted, assigning the equivalent incremental number. If two or more practices/technologies were simultaneously implemented, respondents were asked to give them all the same number. In turn, practices/technologies that were not implemented at all should not receive any number. The third part assessed the adoption level of those LM practices and I4.0 technologies according to the 3-point scale proposed in Shah and Ward (2003): (1) no implementation; (2) some implementation; (3) extensive implementation. The fourth and last part of the questionnaire aimed at measuring respondents' perceptions on operational performance improvement during the last three years. Following Tortorella et al. (2018), we evaluated five performance indicators (i.e. productivity, delivery service level, inventory level, workplace accidents, and scraps and reworks). A 7-point Likert scale ranging from 1 (worsened significantly) to 7 (improved significantly) was applied in this part. We used a 7-point Likert scale since it allows for a better reflection of a respondent’s true evaluation than a 5-point Likert scale (Finstad, 2010). All items and measures are given in the Appendix.

3.2. Data collection and sample characterization

To ensure the participation of appropriate respondents, we defined a few selection criteria. First, following the suggestion from Tortorella et al. (2019a), all respondents should be knowledgeable about LM and I4.0 with a minimum experience of 2 years with both approaches. Second, respondents should play key roles in their companies to allow them to conduct a wider judgement of LA implementation within their companies. In this sense, we focused on either senior/middle managers, who could perceive the company as a whole, or engineers/analysts, who were directly in charge of LA implementation in their companies. Third, because we aimed to assess LA implementation in an manufacturing environment, we only included respondents that worked for product-oriented manufacturers. This criterion helped to increase the likelihood of a more experienced respondents in terms of LA, as both LM and I4.0 were initially conceived in this industrial context (Womack et al., 2007; Lasi et al., 2014). However, no specific manufacturing sector was targeted due to the limited number of companies in both countries (Brazil and India) that are concurrently adopting LM practices and I4.0 technologies.

The questionnaire was first sent by e-mail in October 2019 to 255 potential respondents that met the aforementioned criteria. We received 45 responses, from which 8 were excluded due to unsatisfactory completion of the questionnaire. Then, a follow-up email was sent in November 2019, adding a further 27 responses to our dataset from which 3 were withdrawn due to lack of information. The final sample thus comprised 61 respondents, which results in a response rate of 23.9%. To check for non-response bias, we analyzed differences in means between early (n_1 = 37) and late (n_2 = 24) respondents through Levene's test for equality of variances and a t-test for the equality of means (Armstrong and Overton, 1977). Results indicated significance levels higher than 0.05, which allowed us to disregard the possibility of differences in means and variances.

It is worth mentioning that the sample size of 61 respondents was below our expectations. However, the establishment of rigorous sample selection criteria, such as a minimum 2-year experience with both LM and I4.0, may have affected the number of responses in our dataset. As noticed by Tortorella and Fettermann (2018), few manufacturing companies have concurrently implemented LM and I4.0 for a significant amount of time. Further, the combination of both approaches become even rarer when considering the context of emerging economies, such as Brazil and India, which significantly restricts the number of respondents that meet such criteria. Still these criteria are necessary to ensure qualified responses.

The final sample was reasonably balanced with regards to respondents' characteristics, as shown in Table 4. Most respondents had an Engineer or Analyst (57.4%) role within their companies. Most companies were located in Brazil (59.0%) and had more than 500 employees (59.0%). The majority of manufacturers were national (52.5%), i.e. owned by either Brazilian or Indian companies, and belonged to the food sector (32.8%). Regarding their manufacturing strategies, surprisingly, most companies had either a 'made-to-order' or 'engineered-to-order' strategy, with 37.7% of respondents each.

Table 4 – Sample characteristics (n = 61)

To best of our knowledge, there is no measure to assess the validity of partial complete heterogenous ranking data as collected in the second part of our questionnaire. Similar, the third part on the adoption level does not measure any concept or construct. Only results from the fourth part, performance improvements, were therefore checked for reliability using Cronbach's alpha. A value of 0.781 infers a high reliability of responses according to Meyers et al.'s (2006) threshold of 0.6 or higher.

3.3. Data analysis

There was no significant implementation sequence for our initial analyses at the item level. Hence, we looked for clusters based on the performance improvement levels, and the implementation sequence of LM practices and I4.0 technologies. Clustering tools are designed to examine the relationships within a database to determine whether it is possible to describe such data using a small number of observations of similar classes (Gordon, 1999). According to Rencher (2002), the objects within a cluster must be similar to the other inserted into the same cluster (homogeneity), and different from other objects embedded in other clusters (denoting heterogeneity). We performed two clustering analyses: one aiming to identify different levels of operational performance improvement among respondents, and another one considering the sequence of implementation of LM practices and I4.0 technologies as clustering variables.

For the first clustering analysis, we used observations related to operational performance improvement as clustering variables. To identify the most adequate number of clusters, we applied Ward's hierarchical method (Rencher, 2002). Next, using *k*-means method, we rearranged observations into the number of clusters previously identified (Hair et al., 2006). It is worth mentioning that we performed an analysis of variance (ANOVA) as a *post hoc* procedure to check for differences in means across clustering variables calculated using data from each cluster.

We also tested for differences in frequencies of observations between clusters according to each company characteristic; i.e. company size, manufacturing strategy and ownership. These variables were considered as categorical since we were utilizing the dimensions obtained from the clustering analysis for performance improvement and companies' characteristics, which allowed for the application of the chi-square test with contingency tables and adjusted residuals. This procedure was applied to test the hypothesis that frequencies in the contingency table were independent (Tabachnick and Fidell, 2013). It allowed to verify whether clusters' composition was associated with performance improvement or not. We considered associations to be significant when the adjusted residual values were larger than |1.96| and |2.58|, which corresponds to a significance level of 0.05 and 0.01, respectively (Hair et al., 2006).

The second clustering analysis utilized the implementation sequence of LM practices and I4.0 technologies as clustering variables for the LA implementation sequence. This is partial complete heterogenous ranking data. To create complete ranking data for further analysis, whenever a practice or technology had its response empty (i.e. was not implemented), we purposefully assigned the value of '35' to its implementation sequence, since we have in total 35 practices/technologies and this would be the last possible number. There is no recommended procedure for clustering heterogenous ranking data. Our ranking data represent time which in turn can be represented as a geometrical distance. We therefore considered Ward's hierarchical method that focus on the squared Euclidean distance to be appropriate for our data.

Differences in the mean implementation levels of each one of the clusters of LA implementation were verified according to performance improvement levels (based on the performance improvement clusters identified previously). For that, we applied One-way ANOVAs, testing the null hypothesis that states that samples in all groups are drawn from populations with the same mean values. The ANOVA produces an *F*-statistic, which is the ratio of the variance calculated among the means to the variance within the samples. A higher ratio therefore implies that the samples were drawn from populations with different mean values (Howell, 2012).

4. Results and discussion

4.1 Presentation of results – Performance Clustering

Figure 1 depicts the dendogram for the clustering analysis based on the improvement level of operational performance; two clusters were identified. Then, using the *k*-means method and fixing *k* equals to two, clusters were rearranged (see Table 5), and the ANOVA results indicated that all five performance indicators presented significant differences in means (*p*-values < 0.05). The 23 observations assigned to cluster 1 displayed lower mean values for all performance indicators, suggesting that these respondents perceived a lower level of performance improvement in their companies in the last three years. Hence, this cluster was labeled as 'Low Performance Improvement' (LPI). The remaining 38 respondents grouped in cluster 2 perceived significantly higher means, indicating that these companies had a higher improvement level of their performance. This cluster was consequently labeled as 'High Performance Improvement' (HPI).

Figure 1 – Dendrogram of operational performance improvement clusters

Table 5 – ANOVA between performance improvement variables of each cluster

Table 6 shows the contingency table and chi-square results for all companies' characteristics (i.e. company size, manufacturing strategy and ownership) according to the perceived performance improvement level of manufacturers. Frequencies indicated the number of companies assigned to each cluster (LPI or HPI) that present certain characteristics; for example, there are 11 companies that adopt an engineered-to-order strategy within the LPI cluster. Adjusted residual values indicated that the effect of companies' characteristics on the perceived improvement level is less pervasive than expected. In fact, only company size seems to be significantly associated ($\chi^2 = 6.036$; *p*-value < 0.05) with the improvement level in operational performance. In other words, larger manufacturers ($\geq$ 500 employees) have perceived a more prominent performance improvement in the past few years, as these companies are significantly more frequent in HPI cluster than smaller ones (< 500 employees). No significant association was found between the other characteristics and performance improvement.

Table 6 - Chi-square test among contextual variables according to operational performance improvement

On the one hand, the identification of the influence of company size on operational performance has been evidenced by many studies (e.g. Yeung, 2008; Aras et al., 2010; Hui et al., 2013). However, indications and extension of this effect may vary (i.e. positive or negative) depending on the performance metric that is considered. Our results suggested that the improvement level of those five performance indicators is more likely to be higher when considering large-sized companies. According to Muscalu et al. (2013) and Schreck and Raithel (2018), although large companies usually present more complex organizational communication channels, their operational performance control and results dissemination among employees are generally more structured, allowing a more in-depth understanding and, hence, accurate perception of the variation of these indicators. This might explain the positive association between company size and the perceived performance improvement.

On the other hand, this result is somewhat convergent to the indications from Anand et al. (2009) and Singh and Singh (2014), which have argued that the effect of contextual variables on performance improvement might be less intense when companies have a structured and formal approach for continuous improvement. This suggests that the observed performance improvement is unlikely to be influenced by companies' characteristics. Consequently, performance improvements might be better explained by the practices and technologies companies have been adopting over the years. Thus, understanding the sequence and level of implementation of LA may shed some light on the variation in performance among these companies. This will be discussed in Section 4.3 below.

4.2 Presentation of results – Implementation Sequence Clustering

Regarding the clustering analysis for the LM practices and I4.0 technologies, we initially identified three clusters of LA implementation, as shown in Figure 2. As aforementioned, whenever a practice and/or technology has not been implemented at all, respondents should not assign any value to such item in the second part of the questionnaire. This resulted in the implementation rate, which represented the percentage of respondents that claimed to implement that practice/technology at a certain moment within their organizations. The details of the second clustering analysis of the 35 practices and technologies are shown in Table 7. In total three clusters were identified as follows:

- *Cluster 1 (Start-up)* was comprised by 10 practices and technologies that presented the lowest mean values for the implementation sequence order and the highest mean implementation rate (71.1%). This indicates that, in general, these practices are the first to be adopted in a LA implementation. It is worth noticing that all 10 are LM practices from

Shah and Ward's (2003). This suggests that these LM practices establish the fundamental basis for a LA implementation; hence, this cluster was denoted as 'Start-up' practices.

- *Cluster 2 (In-transition)* was composed by 5 I4.0 technologies and 6 LM practices, whose mean values for implementation sequence order varied from 15.0 to 21.4. The mean implementation rate of these 11 practices and technologies was 44.6% and their mean values for implementation sequence were considered intermediate. Practices (e.g. pull system/Kanban, self-directed teams and lot size reductions) and technologies (e.g. real-time data sharing with suppliers/customers and RFID tags at products) encompassed in this cluster present a slightly higher complexity when compared to the practices in the *Start-up* cluster. However, they are not cutting-edge practice/technologies in manufacturing environments. Thus, it becomes reasonable to expect that this cluster represents practices and technologies that support the transition of a manufacturer to a more advanced level of LA implementation, which led us to label this cluster as 'In-transition' practices/technologies.
- *Cluster 3 (Advanced)* encompassed the remaining 5 LM practices and 9 I4.0 technologies, which had the highest mean values for the implementation sequence order (varying from 24.4 to 33.7). Practices and technologies from this cluster also had the lowest mean implementation rate (31.9%), which corroborates the indication that these are typically adopted last in a LA implementation. A possible explanation is the high-complexity and the strict requirements necessary to implement those practices/technologies. Further, contrary to what was observed in previous clusters, this cluster is mainly comprised by I4.0 technologies that specifically need more sophisticated infrastructure and labor skills to work appropriately, such as cloud computing system and augmented reality. Based on these arguments, this cluster was denoted as 'Advanced' practices/technologies.

Figure 2 – Dendrogram of practices/technologies based on implementation sequence order

Table 7 – Clusters of LA practices/technologies based on implementation sequence

Finally, Table 8 gives the results from the One-way ANOVA used to verify the differences in the mean implementation levels of each of the three clusters of LA implementation according to performance improvement levels (LPI and HPI). Contrarily to companies' characteristics, performance improvement appears to be closely related to LA implementation level. For instance, when considering the *Start-up* practices/technologies, the implementation level seems to be positively associated with performance improvement (F-value = 2.694; p-value < 0.05). In other words, companies that have been adopting these practices/technologies more extensively are more likely to perceive larger leaps in their operational performance over the years. As *Start-up* practices/technologies are usually implemented first and mainly comprised by LM practices, this result reinforces that the establishment of a robust LA basis helps to ensure relevant increments in performance, even when considering a medium-term perspective (i.e. three years). Such outcome converges to indications from Kolberg et al. (2017) and Tortorella et al. (2020b), which have emphasized that LM implementation provides a solid process and behavioral foundation on which I4.0 technologies may build and potentialize results.

A similar trend was observed with respect to *In-transition* practices/technologies, as its implementation level appears to be positively related to companies' performance improvement level (F-value = 3.599; p-value < 0.05). Practices and technologies bundled in this LA set may face additional challenges. According to Negrão et al. (2020), one of the most critical moments for a lean implementation occurs after the "honeymoon" period, which is typical of the beginner stage. After the short-term wins, companies need to perform fundamental changes in their sociotechnical systems so that they keep evolving and improving their processes (Narayanamurthy and Gurumurthy, 2016; Tortorella et al., 2017). In other words, the successful implementation of *In-transition* practices/technologies usually goes beyond the technicalities, being affected by the way people behave and internalize the required sociocultural changes (Cassell et al., 2006; Bortolotti et al., 2015b). Nevertheless, our results evidenced that the extensive adoption of these *In-transition* practices/technologies may lead to a superior performance, underpinning the assumption that they may positively bridge the transition of a manufacturer from a beginner to an advanced LA transformation.

In opposition, *Advanced* practices/technologies did not show a relationship with the same significance level as the previous ones. No association was found between their implementation level and the variation in operational performance.

Table 8 – One-way ANOVA results for mean implementation levels of practices/technologies according to operational performance improvement

4.3 Discussion of results: schematic pathway development

Our results raised interesting insights that deserve further discussion. First, the fact that *Start-up* and *In-transition* practices/technologies are indeed associated with higher performing companies empirically confirms that LA implementation does have a positive impact on operational outcomes. This finding consistently converges to Tortorella and Fetterman's (2018) and Rossini et al.'s (2019) works, which have verified the effect of the integration between I4.0 and LM on companies' performance. However, it adds to these studies as we suggested a preferential implementation sequence (i.e. pathway) for LA, which provides clearer guidelines for managers and academicians with respect to how to successfully adopt these practices and technologies.

Second, it was observed that, as LA implementation advances, companies tend to move from an exclusively LM approach to an I4.0 technologies orientation. This means that most high-performing companies begin their LA implementation based on a solid understanding and adoption of LM practices. To continue progressing on their continuous improvement approach, these manufacturers start integrating I4.0 technologies of medium complexity, such as 'RFID tags at products', 'sensors for monitoring the production process' and 'machines with digital interfaces and sensors', observing consistent and positive enhancements on their performance level. Nevertheless, this integration does not exempt the need to refine LM comprehension since they keep adopting higher-complexity practices, such as 'pull system/kanban' and 'self-directed work teams'. This transient LA stage is very much aligned with the exploitation phase suggested by Netland and Ferdows (2016), in which companies are realizing the benefits from integrating I4.0 into LM. *In-transition* practices/technologies are expected to support further developments for a full LA implementation. The final stage for LA implementation comprehends the adoption of *Advanced* practices/technologies. Contrary to *Start-up*, here companies may spend more efforts in adopting I4.0 technologies, since LM practices were substantially addressed in previous stages. In this sense, *Advanced* LA implementation concerns the adoption of highly complex and more infrastructure-demanding technologies (e.g. cloud computing system, additive manufacturing, rapid prototyping and 3D printing) that are likely to aid LM practices that emphasize the improvement of flow within manufacturers (e.g. cellular manufacturing, JIT/continuous flow production and quick changeover techniques). According to Womack and Jones (1997), an efficient and defect-free flow of value is a key aspect of a lean system and usually the ultimate goal of an organization, which is reasonably supported by the adoption of *Advanced* practices and technologies. However, these practices and technologies did not yield the same level of performance improvement as observed in the first two stages.

In fact, another insightful finding was the absence of a statistically significant relationship between the adoption of *Advanced* practices/technologies and performance improvement. A possible explanation is the law of diminishing returns, i.e. as improvement moves a manufacturing plant nearer and nearer to its operating or asset frontier more and more resources must be expended in order to achieve each additional increment of benefit (Schmenner and Swink, 1998). While new technology shifts the asset frontier, there is a final frontier given by the current technological process. This highlights that it is important for managers to be aware of diminishing performance returns when moving along our pathway to a high-performing LA implementation schematized in Figure 3.

Figure 3 – Schematic representation of the pathway to a high-performing LA implementation

5. Conclusions

This study aimed at investigating pathways to implement a high-performing LA. Our findings have relevant implications for both theory and practice, which are detailed as follows.

With regards to theory, the identification of three sets of LA practices/technologies that should be subsequently implemented suggests an interdependence and precedence relationship between them. This time dimension is typically neglected in the literature which tends to observe the implementation level of practices and technologies at one moment in time. Such outcome indicates the existence of stages through which companies need to pass so that a full LA implementation is achieved. Furthermore, our findings highlight that much still needs to be unveiled, especially in terms of the impact of LA on performance improvement as companies achieve more advanced levels of implementation.

In practical terms, most studies that investigate LA (or the integration of novel technologies into LM) approach the topic without recommending a clear implementation sequence of practices and technologies. Although most of these studies have suggested a positive correlation between LM and I4.0 towards a successful LA implementation, to the best of our knowledge none of them have indicated such pathway. In this sense, managers and practitioners from companies undergoing a LA implementation may find here guidelines that can support them to prioritize efforts and more objectively focus on the proper set of practices and technologies. This is particularly valid when companies realize their actual readiness level and the next steps to continuously improve their products, processes and services are not quite evident. Meanwhile, it is important that managers are aware that there will be diminishing performance returns as the LA transition progresses and the company approaches the final asset frontier given by current technological possibilities.

It is worth mentioning that there are also some limitations to this study. The first comprises our sampling process. Our indications are limited to manufacturers located in Brazil and India. However, LA has been implemented in different industry sectors worldwide and additional insights could probably be gained if sample size was increased and the sample diversified. This would also allow the utilization of more sophisticated statistical techniques, which could lead to complementary findings. Another key limitation concerns the sets of LA practices/technologies. The actual validation of these sets still needs further empirical and experimental analysis, which could be extensively carried out by future studies. Additionally, companies might implement other practices/technologies that were not contemplated in our study, which could potentially raise additional insights. These issues could also motivate future studies on the topic. Finally, the transition throughout the proposed LA pathway is subtle and not explicit between sets of practices/technologies (i.e. stages). Therefore, methods that help companies assess their readiness level would complement our study, avoiding jumping ahead to stages for which companies are not yet mature.

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Table 1 – Literature on implementation sequence of LM practices

Reference	Research questions	Methodology	Findings
Åhlström (1998)	Whether to implement improvement initiatives (i.e. elimination of waste, zero defects, pull scheduling, multifunctional teams, delayering, team leaders, vertical information systems, and continuous improvement) in parallel or sequentially?	Longitudinal case study of a Sweden-based company by spending 130 days over a period of two and a half years.	Zero defects and delayering are starting principles - Requires management effort and resources early on in the implementation. Elimination of waste, multifunctional teams, and pull scheduling are core principles - Requires management effort and resources throughout implementation. Vertical information systems and team leaders are supporting principles - Requires management effort and resources throughout the whole implementation, but less than the core principles. Continuous improvement principle after the base has been laid - Management devoted effort and resources late during implementation.
Åhlström and Karlsson (2000)	When during manufacturing improvement a delayering of the organization should take place?	Longitudinal case study started in February 1993 and ended in August 1995. Data were collected through three ways: participant observation, interviews and documents.	Management devoted effort and resources to delayering mostly early in the adoption process.
Browning and Heath (2009)	How novelty, complexity, instability, and buffering affect the relationship between lean implementation and production costs?	Case/field study of Lockheed Martin's production system for the F22.	Develop a revised framework that reconceptualizes the effect of lean on production costs and use it to develop propositions about how the timing, scale, and extent of lean implementation can regulate the benefits of lean.
Hüttmeir et al. (2009)	Is it better for a manufacturing plant to use heijunka to maximize its leanness, or to use JIS to maximize its responsiveness?	Stylized simulation model with a case study of a BMW engine plant.	A hybrid approach where heijunka is used to smooth out the most extreme production values and JIS is used for the remainder of production carried out.
Losonci et al. (2011)	How intrinsic factors (commitment, belief) and external factors (lean work method, communication) affect the success of lean implementation from worker's point of view?	Combination of case study and survey methodologies	Intrinsic factors (commitment, belief) and external factors (lean work method, communication) have direct impact on workers' perceptions of lean success. The effects are contingent on the scope and focus of changes and is influenced by process characteristics.
Chavez et al. (2013)	To what extent do internal lean practices impact on multiple operational performance? To what extent is the relationship between internal lean practices and multiple operational performance contingent upon IC?	Regression analysis on empirical data gathered from 228 manufacturing companies in the Republic of Ireland.	Internal lean practices are positively related to quality, delivery, flexibility and cost. Industry clockspeed moderates this relationship except with cost.
Bortolotti et al. (2015)	Which lean practices support cumulative performance and is there a particular sequence of practices that will support it?	Structural equation modeling on data gathered from 317 plants in three industries and ten countries.	Fitness bundles establish the foundation for layering the development of JIT and TQM bundles that are more specific and targeted. While adapting TQM and JIT bundles to firm's own context, it has to further develop its capabilities associated with fitness bundles.
Narayanamurthy and Gurumurthy (2016)	How to conduct systemic leanness assessment by incorporating the interactions between lean elements for achieving continuous improvement of lean implementation?	Graph-theoretic approach.	A scale has been developed to assist firms in assessing and comparing their systemic leanness index.
Narayanamurthy et al. (2018)	How to properly select the value stream on which LM should be implemented first?	The 8A framework is proposed by reviewing the literature on lean implementation case studies. Single case study methodology has been adopted to validate the application of 8A framework. A multi-criteria decision-making approach has been employed for choosing the value stream.	Utility of the proposed 8A framework for value stream selection was confirmed through its successful application in an educational institute. Qualitative cross-validation and sensitivity analysis also confirmed the robustness of the value stream selection made using the 8A framework.

Table 2 – Literature on implementation sequence of I4.0 technologies

Reference	Research questions	Methodology	Findings
Erol et al. (2016)	How to align companies' strategy with the challenges imposed by I4.0?	Framework proposition based on workshop sessions with experts.	Results show a strong need for guided support in developing a company-specific Industry 4.0 vision and roadmap.
Ganzarain and Errasti (2016)	How to address the challenges regarding the concept of I4.0 and the diversification methodology based on the vision and strategy of the company?	Involves industry within the pilot program; from the diversification and capacity assessment analysis of the company`s profile, skills and technologies that dominates.	The application of maturity models to the I4.0 may help organizations to integrate this methodology into their culture. Results show a real need for guided support in developing a company-specific I4.0 vision and specific project planning.
Santos et al. (2017)	How do key I4.0 technologies and concepts have been addressed over time?	Review of some major European industrial guidelines, roadmaps and scientific literature.	The move towards I4.0 has presented new and reconverted some relevant concepts; which has partially been either substituted or improved by some new technologies.
Pessl et al. (2017)	How does a company's maturity help to identify their own targets to develop a specific I4.0 implementation plan?	A detailed theoretical and practical perspective is given for the procedure model for the field of action human.	Results for an Austrian company are presented showing that organizational changes within this field are still a bottom up driven process instead of a management indicated holistic change process.
Mishra et al. (2018)	How does I4.0 help to exchange data efficiently for a sustainable growth in the industrial sector?	A literature review combined with a case study have been conducted.	A roadmap towards achieving the goals of I4.0 has been proposed.
Ghobakhloo (2018)	What are I4.0's key design principles and technology trends?	Systematic and content-centric review of literature based on a six-stage approach to identify key design principles and technology trends of I4.0.	I4.0 is an integrative system of value creation that is comprised of 12 design principles and 14 technology trends. I4.0 is no longer a hype and manufacturers need to get on board sooner rather than later.
Frank et al. (2019)	What are the current I4.0 technologies adoption patterns in manufacturing companies?	A survey in 92 manufacturers was conducted to study the implementation of these technologies.	I4.0 is related to a systemic adoption of the front-end technologies, in which Smart Manufacturing plays a central role. Implementation of base technologies is challenging companies, since big data and analytics are still low implemented in the sample studied.

Table 3 – Literature on the impact of LA on performance

Reference	Research questions	Methodology	Findings
Hedelind and Jackson (2011)	How industrial robotics fits into LM systems?	Case study with interviews, observations and data collection on performance measures and historical production data.	Differences between how Swedish and Japanese companies work with industrial robotics are highlighted. Create a guideline for how to design industrial robotic work cells that can easily be integrated into LM systems.
Sanders et al. (2016)	How LM can be implemented through the technologies of I4.0?	Literature review.	Bridges the gap between I4.0 and LM by identifying exactly which aspects of I4.0 contribute towards respective dimensions of LM.
Dombrowski et al. (2017)	How are I4.0 technologies and principles of LM systems interdependent on each other?	260 I4.0 use cases, presented on the "Platform I4.0" have been analyzed regarding the application of I4.0 elements.	Several I4.0 elements have been structured into technologies, systems and process related characteristics. Large interdependence between I4.0 technologies and lean practices were found for avoidance of waste and cloud computing, zero defect and big data, visualization and cloud computing.
Kolberg et al. (2017)	What is the ongoing work towards a common, unified communication interface to digitize LM methods using cyber physical systems?	Review of 41 methods of LM and a demonstration of Kanban method to evaluate the feasibility of unified communication interface.	Based on the model-view-controller-pattern, an architecture for the cyber-physical systems to loosely couple workstations to vendor-independent third-party solutions has been introduced. This is expected to lower the integration efforts and thereby assist in transitioning to lean automation solutions.
Tortorella and Fettermann (2018)	What is the relationship between LM practices and the implementation of I4.0 in Brazilian manufacturing companies?	Multivariate analysis on data from a survey carried out with 110 companies.	LM practices are positively associated with I4.0 technologies and their concurrent implementation leads to larger performance improvements.
Tortorella et al. (2019a)	How does I4.0 adoption (Process-related & product/service-related) moderate the relationship between LM practices (pull, flow and low setup) and operational performance improvement (safety, delivery, quality, productivity and inventory) in a developing economy context?	Multivariate data analyses including ordinary least square hierarchical linear regression models on data gathered from 147 manufacturing companies.	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.
Rossini et al. (2019)	What is the interrelation between the adoption of I4.0 technologies and the implementation of lean practices on the improvement level of European manufacturers' operational performance?	Multivariate analysis on data from a survey carried out with 108 European manufacturers.	Higher adoption levels of I4.0 may be easier to achieve when lean practices are extensively implemented in the company. When continuous improvement practices are not established, companies' readiness for adopting novel technologies may be lower.

Table 4 – Sample characteristics (n = 61)

Company's ownership			Manufacturing sector		
National	32	52.5%	Food	20	32.8%
Foreigner	29	47.5%	Pharmaceutical	10	16.4%
Company size			Metallurgy	7	11.5%
< 500 employees	25	41.0%	Equipment	6	9.8%
≥ 500 employees	36	59.0%	Plastic	4	6.6%
Respondent's role			Automotive	3	4.9%
Manager or Director	8	13.1%	Packaging	2	3.3%
Supervisor or Coordinator	18	29.5%	Furniture	2	3.3%
Engineer or Analyst	35	57.4%	Others	7	11.4%
Country			**Manufacturing strategy**		
Brazil	36	59.0%	Made-to-stock	15	24.6%
India	25	41.0%	Made-to-order	23	37.7%
			Engineered-to-order	23	37.7%

Table 5 – ANOVA between performance improvement variables of each cluster

Performance indicators	LPI (n = 23)		HPI (n = 38)		ANOVA
	Mean	Std. Dev.	Mean	Std. Dev.	F-value
Safety (accidents)	4.70		6.55		29.67**
Delivery service level	4.39		6.29		64.40**
Quality (scrap and rework)	4.65		6.21		32.31**
Productivity	4.52		6.42		36.74**
Inventory level	4.17		5.39		6.83*

Note: * p-value < 0.05; ** p-value < 0.01.

Table 6 - Chi-square test among contextual variables according to operational performance improvement

Contextual variables		LPI (n = 23)			HPI (n = 38)			Total frequency	Pearson chi-square
		Frequency		Adjusted residual	Frequency		Adjusted residual		
Company size	< 500 employees	14	56.0%	2.5*	11	44.0%	-2.5*	25	6.036**
	≥ 500 employees	9	25.0%	-2.5*	27	75.0%	2.5*	36	
	Total frequency	23	37.7%		38	62.3%		61	
Manufacturing strategy	Made-to-stock	4	26.7%	-1.0	11	73.3%	1.0	15	1.865
	Made-to-order	8	34.8%	-0.4	15	65.2%	0.4	23	
	Engineered-to-order	11	47.8%	1.3	12	52.2%	-1.3	23	
	Total frequency	23	37.7%		38	62.3%		61	
Ownership	National	10	31.3%	-1.1	22	68.8%	1.1	32	1.194
	Foreigner	13	44.8%	1.1	16	55.2%	-1.1	29	
	Total frequency	23	37.7%		38	62.3%		61	

Note: * significant at 5%.

Table 7 – Clusters of LA practices/technologies based on implementation sequence

Cluster	Practices/Technologies	Implementation rate[a]	Mean implementation sequence order	Mean implementation level[b]	Denomination[c]
1 (n_1 = 10)	Planning and scheduling strategies	86.9%	3.0	1.60 (0.79)	Start-up (71.1%)
	Preventive maintenance	77.0%	4.6	1.68 (0.47)	
	Quality management programs	68.9%	6.8	1.91 (0.94)	
	Safety improvement programs	65.6%	8.4	1.76 (1.02)	
	Continuous improvement programs	72.1%	9.4	1.68 (0.68)	
	Process capability measurement	68.9%	10.6	1.56 (0.62)	
	New process equipment/technologies	65.6%	10.9	1.70 (1.09)	
	Cross-functional work force	59.0%	11.4	1.79 (0.98)	
	Cycle time reductions	70.5%	12.7	1.63 (0.64)	
	Bottleneck removal (production smoothing)	77.0%	13.9	1.63 (0.85)	
2 (n_2 = 11)	Pull system/Kanban	37.7%	15.0	1.56 (0.56)	In-transition (44.6%)
	Focused factory production	39.3%	15.2	1.80 (0.41)	
	Self-directed work teams	44.3%	16.4	1.42 (0.50)	
	Lot size reductions	42.6%	17.2	1.41 (0.50)	
	Real-time data sharing with suppliers/customers	42.6%	18.2	1.35 (0.49)	
	RFID tags at products	34.4%	19.1	1.59 (0.50)	
	Highly Automated Machines	41.0%	19.5	1.69 (0.47)	
	Maintenance optimization	50.8%	19.7	1.41 (0.64)	
	Total quality management	54.1%	19.9	1.53 (0.65)	
	Sensors for monitoring the production process	49.2%	20.0	1.26 (0.76)	
	Machines with digital interfaces and sensors	54.1%	21.4	1.28 (0.68)	
3 (n_3 = 14)	Additive manufacturing, rapid prototyping, 3D printing	21.3%	24.4	0.96 (0.64)	Advanced (31.9%)
	Augmented reality	19.7%	25.2	0.83 (0.71)	
	Artificial intelligence and machine learning algorithms	19.7%	26.0	0.70 (0.72)	
	Robotic stations on automated production line	23.0%	26.9	0.90 (0.79)	
	Reengineered production process	27.9%	27.7	1.14 (0.74)	
	Autonomous production processes (MES, SCADA, etc.)	34.4%	28.7	1.03 (0.86)	
	Big Data	34.4%	29.2	1.13 (0.72)	
	Competitive benchmarking	39.3%	29.6	1.52 (0.69)	
	Internet of Things (IoT)	27.9%	30.5	1.04 (0.69)	
	Cellular manufacturing	26.2%	30.7	0.96 (0.76)	
	JIT/continuous flow production	39.3%	31.6	1.13 (0.78)	
	Quick changeover techniques	47.5%	32.3	1.39 (0.69)	
	Cloud computing system	45.9%	33.2	1.29 (0.77)	
	Integrated engineering systems (CAD, CAM, etc.)	39.3%	33.7	1.09 (0.88)	

Notes: [a] Rate calculated out of a sample of 61 respondents.
[b] Numbers within parentheses represent the standard deviation of the implementation level of each practice/technology.
[c] Numbers within parentheses represent the mean implementation rate of practices and technologies of the cluster.

Table 8 – One-way ANOVA results for mean implementation levels of practices/technologies according to operational performance improvement

Practices/ technologies	LPI (n = 23)				HPI (n = 38)				ANOVA F-value
	Mean implementation level	Std. dev.	95% conf. interval Lower bound	95% conf. interval Upper bound	Mean implementatio n level	Std. dev.	95% conf. interval Lower bound	95% conf. interval Upper bound	
Start-up (n = 10)	**1.13**	0.86	0.75	1.50	**1.42**	0.52	1.25	1.59	**2.694***
In-transition (n = 11)	**0.75**	0.99	0.33	1.18	**1.20**	0.83	0.93	1.48	**3.599***
Advanced (n = 14)	0.77	1.12	0.29	1.26	1.16	0.92	0.85	1.46	2.098

Note: * p-value < 0.05.

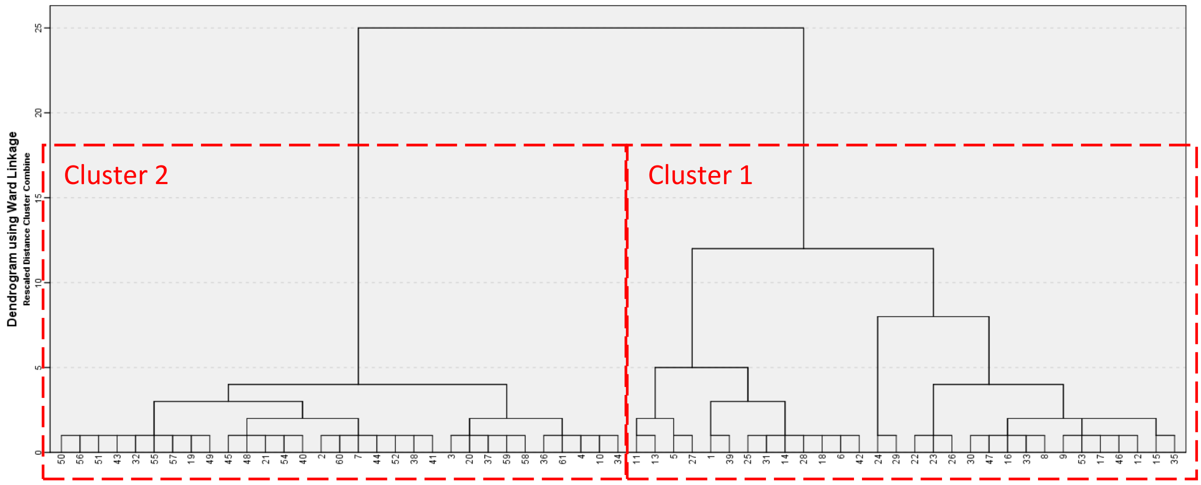

Figure 1 – Dendrogram of operational performance improvement clusters

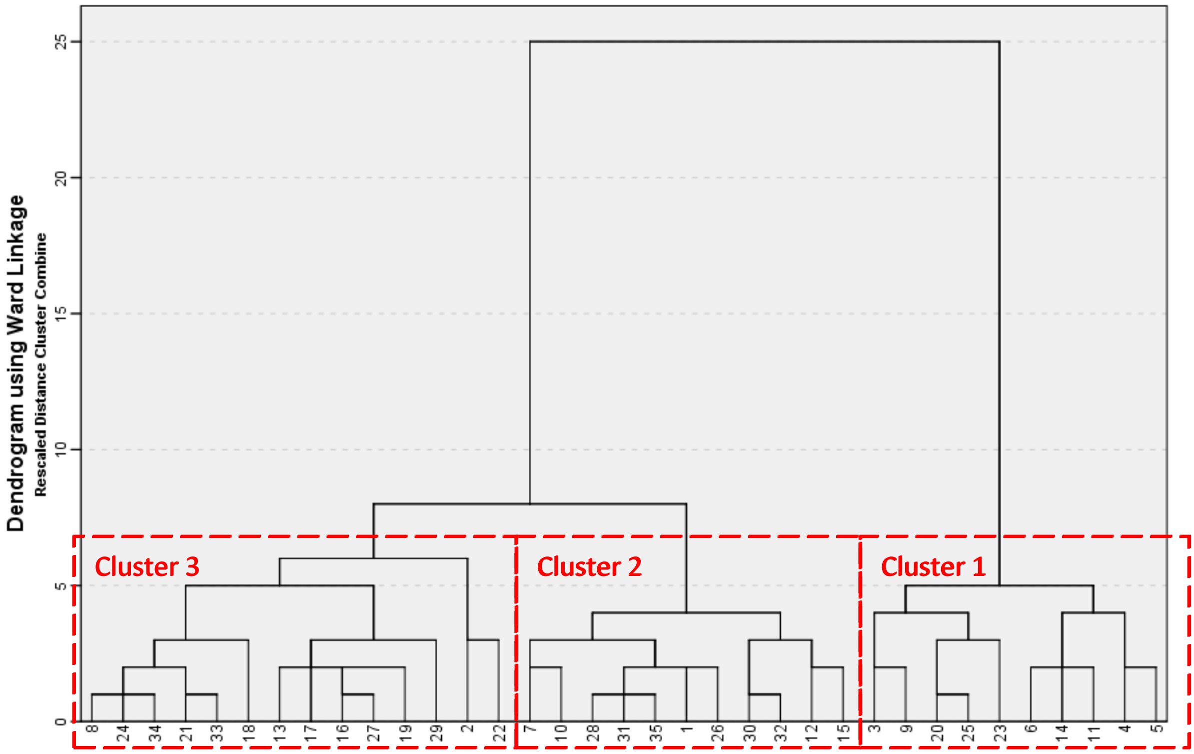

Figure 2 – Dendrogram of practices/technologies based on implementation sequence order

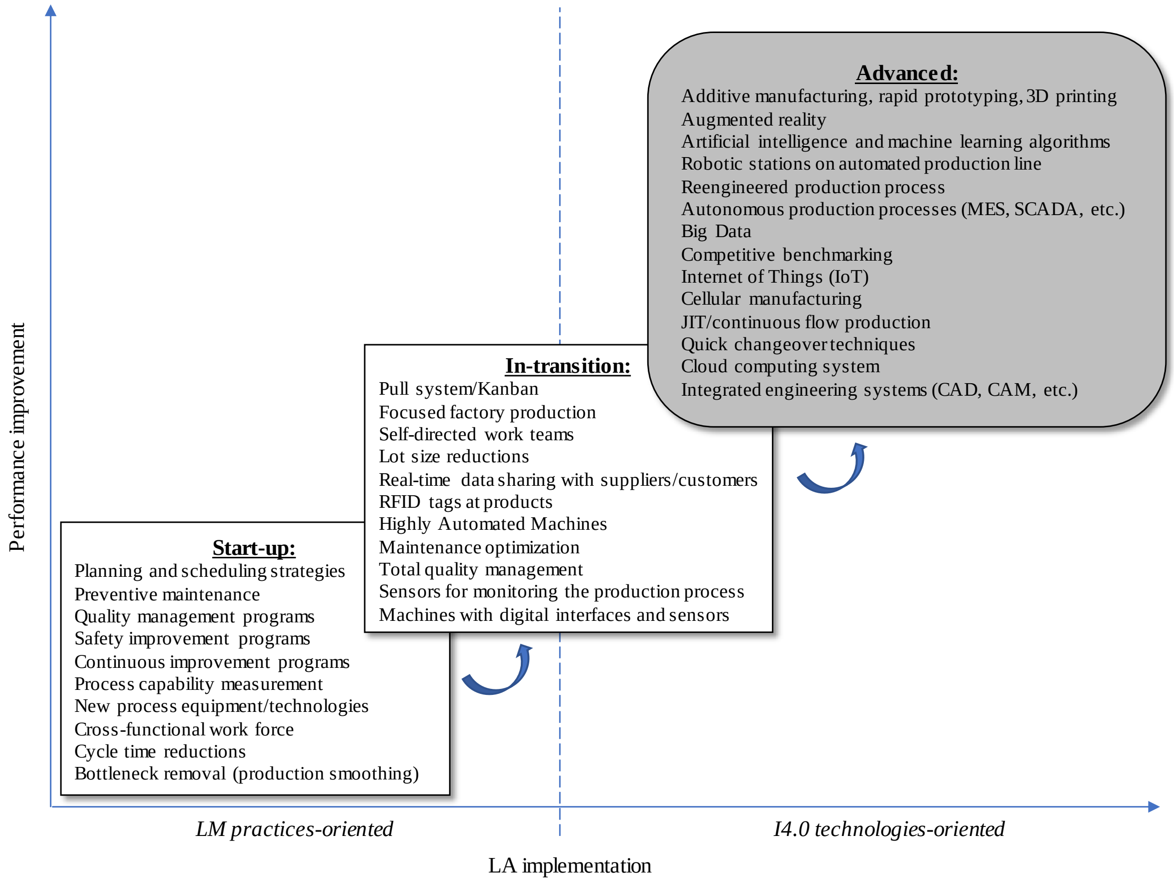

Figure 3 – Schematic representation of the pathway to a high-performing LA implementation

Appendix – Questionnaire measures

Industry 4.0 technologies (Tortorella and Fettermann, 2018; Rossini et al., 2019)	**Lean manufacturing practices (Shah and Ward, 2003)**
Robotic stations on automated production line	Bottleneck removal (production smoothing)
Highly Automated Machines	Cellular manufacturing
RFID tags at products	Competitive benchmarking
Sensors for monitoring the production process	Continuous improvement programs
Machines with digital interfaces and sensors	Cross-functional work force
Collaboration with suppliers/customers through real-time data sharing	Cycle time reductions
Autonomous production processes (MES, SCADA etc.)	Focused factory production
Artificial intelligence and machine learning algorithms	JIT/continuous flow production
Integrated engineering systems (CAD, CAM etc.)	Lot size reductions
Additive manufacturing, rapid prototyping or 3D printing	Maintenance optimization
Augmented reality, 3D etc.	New process equipment/technologies
Big data	Planning and scheduling strategies
Cloud computing system	Preventive maintenance
Internet of Things (IoT)	Process capability measurement
Operational performance improvement (Tortorella et al., 2019)	Pull system/kanban
Safety (work accidents)	Quality management programs
Delivery service level	Quick changeover techniques
Quality (scrap and rework)	Reengineered production process
Productivity	Safety improvement programs
Inventory level	Self-directed work teams
	Total quality management