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Lean manufacturing and business performance: testing the S-curve theory

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ABSTRACT

This article makes a case for the importance of exploring patterns in the relationship between the adoption of lean manufacturing practices and business performance. This relationship has been described as ambiguous, because it has variously appeared to be positive, insignificant, and negative. Accordingly, this article tests this relationship for non-linearity and shows that it follows the S-Curve theory. A survey of manufacturing companies in an industrial cluster in Brazil was undertaken. This region faces infrastructural challenges, such as geographic distance between purchasers and suppliers and a shortage of skilled Labour. Despite the conditions, these companies have significantly improved their operational, financial, and environmental performance through the adoption of lean practices. Thus, this article contributes to the literature on lean manufacturing by: (a) furthering the debate on the relationship between lean practices and business performance, and testing its adherence to the S-curve theory by means of survey research; and (b) simultaneously testing operational, financial and environmental performance as a result of the adoption of lean manufacturing practices. As a consequence of the S-shaped relationship demonstrated, managers need to be aware of the presence of inertial and saturation points in the adoption of lean manufacturing practices, so they can correctly allocate resources for improving the adoption of lean practices.

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KEYWORDS
Lean manufacturing; firm performance; operations management; emerging economies; non-linear relationships

1. Introduction

There is growing interest from scholars around the world in the effects that the adoption of lean manufacturing (LM) practices have on organisational/business performance (Abreu-Ledón et al. 2018; Villarreal et al. 2018; Tortorella, Miorando, and Marodin 2017). There are three main categories of results relating to the relationship between the adoption of lean manufacturing practices and business performance: (a) a positive and significant relationship (e.g., Netland and Ferdows 2016; Godinho Filho, Ganga, and Gunasekaran 2016; Chavez et al. 2015); (b) no significant relationship (e.g., Alcaraz et al. 2014; Green Jr. et al. 2014; Fullerton, Mcwatters, and Fawson 2003); and (c) a partially negative and significant relationship (e.g., Marin-Garcia and Bonavia 2015; Danese, Romano, and Bortolotti 2012; Callen, Fader, and Krinsky 2000). The dissonance between these findings shows that the relationship between lean practices and business performance still requires further investigation, and that testing for a non-linear relationship between lean practices and performance is an avenue which deserves investigation (Liu, Niu, and Li 2018).

This article will test for a non-linear relationship in the effects of lean manufacturing practices on business performance, in order to further explain the dynamic underlying this relationship. According to Netland, Ferdows, and Sanchez (2015) and Netland and Ferdows (2016), the relationship between lean manufacturing and business performance can be understood using the S-curve theory; i.e., as a non-linear relationship. However, more research is needed to validate this assertion; in particular, testing these findings in different settings and under different local conditions. Thus, this article focuses on testing this theory. It tests the previous findings of Netland, Ferdows, and Sanchez (2015) and Netland and Ferdows (2016) and validates the results using data collected from a sample which contains particular contextual features.

Articles driven by theory testing are especially relevant in the field of operations management because the management field commonly experiences a lack of consensus on paradigms (Colquitt and Zapata-Phelan 2007); therefore, further validation and explanation of a phenomenon is a valuable contribution to this research field (MacCarthy et al. 2013).

In general, the relationship between lean manufacturing and business performance has been analysed in terms of operational, financial, or market measures. However, the connection between lean and green practices cannot be neglected (Dües, Tan, and Lim 2013). Furthermore, according

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to Belhadi, Touriki, and Fezazi (2018), Danese, Manfè, and Romano (2018), Garza-Reyes et al. (2016) and Thanki and Thakkar (2016), there is a lack of studies focussing on the relationship between lean manufacturing and environmental performance. Accordingly, this article addresses this research gap.

Taking into account the above, this article aims to address the following research question: is the relationship between the adoption of lean manufacturing practices and business performance significant, and does it follow an S-curve pattern, under particular contextual circumstances? This article answers the research question by testing for a non-linear relationship between lean practices and business performance, using a sample of manufacturing companies located in the Amazon region of Brazil. This region faces infrastructural challenges, such as logistical limitations, which inhibit the timely transport of goods between suppliers and companies, and an absence of skilled workers.

This article contributes to the lean manufacturing literature by: (a) furthering the debate on the relationship between lean practices and business performance, clarifying the form of this relationship and, as a consequence, guiding managers towards effective decision-making regarding investment in lean practices; (b) simultaneously testing operational, financial and environmental performance in relation to the adoption of lean manufacturing practices, since environmental performance, in particular, has previously been neglected in studies in this field (Danese, Manfè, and Romano 2018; Garza-Reyes et al. 2018) and, as a result, the breadth of the effects of lean practices on business performance has not been fully understood; and finally (c) analysing the theme of lean manufacturing based on the established theoretical perspective of contingency theory, as recommended by Danese, Manfè, and Romano (2018), in order to enable the theoretical advancement of the lean manufacturing field and to validate the work of Netland, Ferdows, and Sanchez (2015) and Netland and Ferdows (2016).

This paper is organised as follows: Section 2 includes the literature review, the formulation of the research hypothesis and the research framework; Section 3 describes the research method applied; Section 4 reports the results of the statistical analysis; Section 5 discusses the main findings; and Section 6 provides the conclusions, the implications of the research and future research suggestions.

2. Theoretical background

2.1. Literature review and formulation of research hypothesis

This literature review summarises the findings of articles which have previously conducted surveys of manufacturing companies in exploring the adoption of lean practices and their relationship with business performance, furthering the work of Negrão, Godinho Filho, and Marodin (2016).

The majority of the articles identified state that there is a positive relationship between the adoption of lean practices and operational and financial performance (e.g., Gijo, Palod, and Antony 2018; Bevilacqua, Emanuele, and Sanctis 2017; Hong and Leffakis 2017; Chavez et al. 2015; Wiengarten et al. 2015). According to these articles, the main indicators of operational and financial performance that showed improvement after LM adoption were productivity, lead times, inventory levels, quality, on-time delivery, manufacturing unit cost, profitability, return on investment and market share. A positive and significant relationship was also found between lean practices and environmental performance (e.g., Garza-Reyes et al. 2018, Kumar and Rodrigues 2017; Inman and Green 2018; Ruben, Vinodh, and Asokan 2017).

However, other articles have not found a significant relationship between lean practices and business performance (e.g., Chen 2015; Green Jr. et al. 2014; Danese, Romano, and Bortolotti 2012). The key performance indicators that did not show improvement after LM adoption, according to these articles, were productivity, quality, flexibility, on-time delivery, lead time, profitability and manufacturing unit cost. The possible reasons given for this non-improvement include (e.g., Green Jr. et al. 2014; Swink, Narasimhan, and Kim 2005; Fullerton, Mcwatters, and Fawson 2003):

- Varying levels of implementation of lean practices
- The time required to perceive the effects of lean practices
- The different industrial sectors studied
- Absence of necessary organisational culture
- Short-sighted vision and lack of knowledge about lean manufacturing
- The absence of strategic business integration in the supply chain

Other research (e.g., Marin-Garcia and Bonavia 2015; Danese, Romano, and Bortolotti 2012) shows that some lean practices (e.g., statistical process control, continuous flow, total productive maintenance, kaizen and JIT delivery by suppliers) present a negative relationship with some operational performance indicators (e.g., productivity, flexibility, quality, lead time, and on-time delivery). According to these articles, these results are most likely due to the high variability of demand, companies' strategic goals and the lack of theoretical basis in the implementation of lean manufacturing.

It can be inferred from the previously reported findings that: (a) there is most likely a significant relationship between the adoption of lean manufacturing practices and business performance; and (b) the relationship between the adoption of lean practices and business performance appears to follow a non-linear pattern, since this relationship has variously been found to be positive, not significant, and negative.

Non-linear relationships imply that the relationship between two variables is not directly proportional, and such non-linear relationships can be either U-shaped or S-shaped (including inverted versions of both shapes). An inverted U-shape, for example, shows that low levels of an independent variable initially lead to an increase in a dependent variable. However, at some point, the effect of increasingly high levels of the independent variable reverses the direction of the relationship, and the value of the dependent variable starts to decrease (Jaccard and Jacoby 2010). An S-shaped

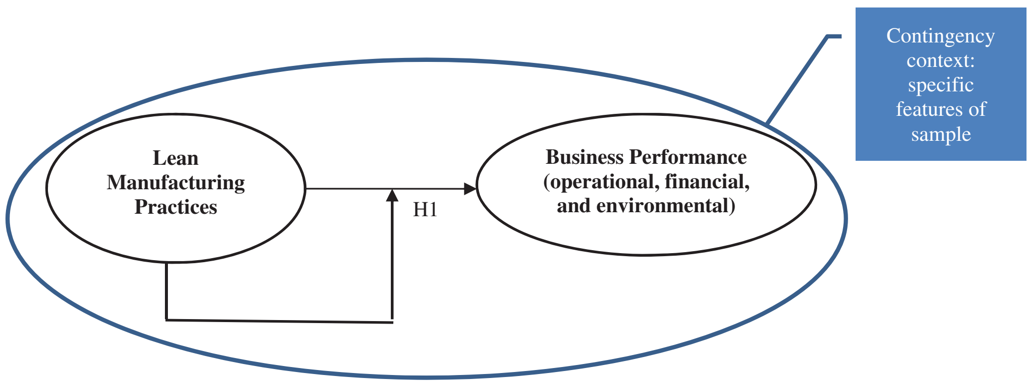

Figure 1. Research framework.

relationship means that "at low levels of an independent variable, there is a floor effect such that changes in the independent variable have no impact on a dependent. Then at some point, increases in the independent variable begin to lead to increases in the dependent variable. This continues up to a point, when a ceiling effect kicks in, and further changes in the independent variable have no subsequent effect on the dependent variable" (Jaccard and Jacoby 2010, p. 105). Based on previous findings, the research hypothesis of this article is:

> **H1**: The adoption of lean manufacturing practices has a non-linear effect on business performance, following an S-curve pattern.

The S-shaped pattern can be applied in the field of lean manufacturing in order to understand the features of the different maturity phases of lean manufacturing implementation and how these different stages of implementation impact on operational performance over time (Netland, Ferdows, and Sanchez 2015; Netland and Ferdows 2016). This article tests the S-shaped pattern in order to validate the findings of Netland, Ferdows, and Sanchez (2015) and Netland and Ferdows (2016). In addition, this research tests these findings utilising a sample from a different setting to that studied by Netland and Ferdows (2016). Therefore, this article may further explain the relationship between lean manufacturing practices and business performance.

2.2. Research framework

Previous studies that have identified no relationship between the adoption of lean practices and business performance claim that this result is due to certain contingency factors (Zhu and Lin 2018). Contingency theory can guide the effectiveness of performance-improvement programmes by providing an understanding of the contextual conditions in which improvement programmes are adopted (Sousa and Voss 2008). Therefore, clarity around the contextual conditions under which lean practices are adopted can deepen understanding of the conflicting results on lean manufacturing and business performance.

The confirmation of a non-linear pattern for the relationship between the adoption of lean manufacturing practices and business performance would require testing this relationship in a certain previously established contingency context. According to Oliver et al. (1994), the central features of lean manufacturing include, among others, flexible and multi-skilled operators who will be able to tackle problems and suggest solutions, and a position of proximity to suppliers.

The availability of skilled Labour and viable logistics seem to be key elements of lean manufacturing principles. Thus, this article tests the research hypothesis using a sample of manufacturing companies located in the Amazon region of Brazil, which faces many infrastructural challenges, such as logistical limitations which inhibit fast transport of goods between suppliers and companies, and an absence of skilled workers. Therefore, if the relationship between lean manufacturing and business performance remains significant in this sample, it would indicate that the relationship is indeed significant in general. Accordingly, these geographical conditions will allow for a better understanding of the findings of the research, which aims to test Netland and Ferdows (2016)'s work. The research framework of this article is presented in Figure 1.

3. Research method

3.1. Sampling

The sample population used in this study is composed of manufacturing companies located in the Metropolitan Region of Belém, Pará, in the Amazon region of Brazil, and includes a total of 1387 companies.

Pará is a state located in the north of Brazil, in an area known as the Amazon region. It occupies a land mass area of approximately 1.3 million square kilometres, bigger than many major European countries, such as Germany, UK, Spain and France (IBGE 2015). Pará has a number of particular characteristics in terms of socio-economic factors and logistics. Only around 30% of the population has experience of formal employment (IBGE 2015), and only 6% of the population has an undergraduate degree. The majority of the population only has secondary education (FAPESPA, 2014). Pará faces various logistical challenges because of its geographical location; for example, fluvial transport is the main mode of freight in the region. In addition, the road infrastructure is relatively underdeveloped, meaning that the movement of goods by road is difficult. The fact that fluvial freight is the

Table 1. Characterisation of companies.

Industry	n	%	Process	n	%	Number of employees	n	%
Food products	58	27	MTS	177	81.6	Up to 19	37	17
Beverages	14	6.5	MTO	32	14.7	20 to 99	120	55
Wood products	32	15	ETO	8	3.7	100 to 499	48	22
Chemicals	14	6.5				More than 500	12	6
Rubber products and plastic	16	7						
Non-metallic mineral products	26	12						
Metal products, except machinery and equipment	24	11						
Others[a]	33	15						
Total	217	100	Total	217	100	Total	217	100

[a]Textile products, Articles of clothing and accessories, Leather and leather goods, Pharmaceutical chemicals and pharmaceuticals, Pulp paper and paper products, Other transport equipment except motor vehicles, Machinery and equipment, Metallurgy, Miscellaneous products.

principal mode of transport has consequences for the planning of deliveries in terms of timing and quantity, which means that proximity to suppliers, a core principle of lean manufacturing, is a huge challenge.

These characteristics might well affect the adoption of lean manufacturing practices among the companies studied. Thus, these companies provide an interesting subject for testing and validating Netland and Ferdows' (2016) findings, as they provide a different context. Therefore, this article may further explain the relationship between lean manufacturing practices and business performance.

Table 1 shows the characteristics of the companies studied. In total, 16 sectors of the manufacturing industry were represented, with a predominance of food manufacturers (27%) and wood products (15%), among other areas. Production inventory ('make to stock', or MTS) is the main production type adopted by these companies (81.6%). According to IBGE (2015), small businesses are those which employ fewer than 100 employees, medium-size companies employ up to 200 people and large firms have more than 200 employees. In this sample, 72% of companies fall into the small category.

3.2. Measures included in the research instrument

Previous empirical studies list a large number of lean practices. White and Ruch (1990) originally identified ten lean elements and White, Ojha, and Kuo (2010) subsequently organised these into four practices: quality; reliability of delivery; flexibility of volume; low cost. Panizzolo (1998) lists 48 lean operating elements arranged into six practices: process and equipment; manufacturing, planning and control; human resources; product design; supplier relationships; customer relationships. Shah and Ward (2003) categorise 22 elements into four lean practices: just in time; total productive maintenance; total quality management; human resource management. Shah and Ward later (2007) proposed 41 key elements that reflect a comprehensive set of ten lean practices.

This study was carried out using the model suggested by Shah and Ward (2007), adapted by Godinho Filho, Ganga, and Gunasekaran (2016), which finally comprises 45 operational elements grouped into 10 lean practices, as detailed in Tables 2 and 3 and in Appendix A. This model was chosen because it was the most widely used model in the comprehensive literature review conducted for this article. In our research, all operational elements that make up the lean practices were rated on a seven-point Likert scale ranging from (1) "strongly disagree" to (7) "strongly agree". Seven-point Likert scales have been widely used in modern operations management research; for example, Caniato et al. (2018). In addition, according to Hensley (1999), reliability increases as the number of scale points increases from five to seven points.

The performance indicators investigated in this study are provided in Appendix B. These performance measures, chosen from the literature review, show the effect of lean practices on business performance, especially in studies that show the relationship between lean manufacturing and operational performance (e.g., Godinho Filho, Ganga, and Gunasekaran 2016; Dora et al. 2013; Ghosh 2012), financial performance (e.g., Chavez et al. 2015; Dora et al. 2014; Fullerton, Kennedy, and Widener 2014; Yang, Hong, and Modi 2011) and environmental performance (Yang, Hong, and Modi 2011). All performance indicators were again rated on a seven-point Likert scale: (1) worsened by more than 50%; (2) worsened by 30% to 50%; (3) worsened by 10% to 30%; (4) remained the same; (5) improved by up to 30%; (6) improved by 30% to 50%; (7) improved by more than 50%. This type of scale has previously been used in other studies, such as Godinho Filho, Ganga, and Gunasekaran (2016) and Yang, Hong, and Modi (2011).

3.3. Data collection

The questionnaire was handled by the Federation of Industries of the State of Pará (FIEPA). Data collection occurred between September and December 2014. The survey was initially sent by e-mail to 1387 companies, but 62 of these messages were returned as the email address was invalid. A month after sending out the questionnaire, a follow-up reminder email was sent. The same procedure was repeated twice more, with the questionnaire attached to the electronic message each time, following recommendations for employing internet research methods (Dillman, Smyth, and Christian 2014). In December 2014, after the third e-mail reminder, 217 valid and completed questionnaires had been returned, and their responses were analysed.

The final response rate for the survey was 16.4% of the sample population. This rate is similar to other large-scale research studies in operations management (e.g., Braunscheidel and Suresh 2009; Hult, Ketchen, and Arrfelt

Table 2. Construct indicators and measurement model of lean manufacturing practices.

Indicator/Item	Code	FL	AVE	α	ρ_A
A) Supplier Feedback (Suppfeed)			0.674	0.879	0.899
We are frequently in close contact with our suppliers	Suppfeed_1	0.754			
Our suppliers frequently visit our plants	Suppfeed_2	0.810			
We frequently visit our suppliers' plants	Suppfeed_3	0.782			
We give our suppliers feedback on quality and delivery performance	Suppfeed_4	0.857			
We strive to establish long-term relationships with our suppliers	Suppfeed_5	0.896			
B) JIT Delivery by Suppliers (SuppJIT)			0.572	0.725	0.742
Suppliers are directly involved in the new product development process	SuppJIT_1	0.766			
Our key suppliers deliver to plant or JIT bases	SuppJIT_2	0.677			
We have a formal supplier certification programme	SuppJIT_3	0.818			
C) Supplier Development (Suppdevt)			0.607	0.774	0.781
Our suppliers are contractually committed to annual cost reductions	Suppdevt_1	0.785			
We have corporate level communication on important issues with key suppliers	Suppdevt_3	0.847			
We evaluate suppliers on the basis of total cost and not per unit price	Suppdevt_6	0.698			
D) Customer Involvement (Custinv)			0.605	0.781	0.788
We are frequently in close contact with our customers	Custinv_1	0.760			
Our customers give us feedback on quality and delivery performance	Custinv_3	0.692			
Our customers frequently share current and future demand information with our marketing department	Custinv_6	0.813			
We regularly conduct customer satisfaction surveys	Custinv_7	0.839			
E) Pull (Pull)			0.941	0.937	0.937
Production is "pulled" by the shipment of finished goods	Pull_1	0.970			
Production at stations is "pulled" by the current demand of the next station	Pull_2	0.970			
F) Continuous Flow (Flow)			0.625	0.846	0.849
Products are classified into groups with similar processing requirements	Flow_1	0.730			
Products are classified into groups with similar routeing requirements	Flow_2	0.815			
Equipment is grouped to produce a continuous flow of families of products	Flow_3	0.887			
Families of products determine our factory layout	Flow_4	0.849			
Pace of production is directly linked with the rate of customer demand	Flow_5	0.650			
G) Single Minute Exchange of Dies (SMED)			0.718	0.865	0.865
Our employees' practices are set up to reduce the time required	SMED_1	0.844			
We are working to lower setup times in our plant	SMED_2	0.920			
We have low setup times of equipment in our plant	SMED_3	0.906			
Low supply lead times allow for quick responses to customer requests	SMED_4	0.701			
H) Single Minute Exchange of Dies (SMED)			0.718	0.865	0.865
Our employees' practices are set up to reduce the time required	SMED_1	0.844			
We are working to lower setup times in our plant	SMED_2	0.920			
We have low setup times of equipment in our plant	SMED_3	0.906			
Low supply lead times allow for quick responses to customer requests	SMED_4	0.701			
I) Statistical Process Control (SPC)			0.752	0.890	0.893
Large amounts of equipment/processes on the shop floor are currently under SPC	SPC_1	0.853			
Extensive use of statistical techniques to reduce process variance	SPC_2	0.897			
We use fishbone type diagrams to identify causes of quality problems	SPC_4	0.812			
Charts showing defect rates are used as tools on the shop floor	SPC_5	0.904			
J) Human Resource Management (HRM)			0.919	0.956	0.956
Shop-floor employees are key to problem solving teams	HRM_1	0.948			
Shop-floor employees drive suggestion programmes	HRM_2	0.960			
Shop-floor employees lead product/process improvement efforts	HRM_3	0.968			
K) Total Productive/Preventive Maintenance (TPM)			0.730	0.875	0.882
We dedicate a portion of everyday to planned equipment maintenance related activities	TPM_1	0.760			
We maintain al our equipment regularly	TPM_2	0.867			
We maintain excellent records of all equipment maintenance related activities	TPM_3	0.921			
We post equipment maintenance records on shop floor for active sharing with employees	TPM_4	0.861			

FL is factor loading; AVE: Average variance extracted; α: Cronbach's Alpha; ρ_A: Dijkstra-Henseler's rho_A.

Table 3. Construct indicators and measurement model of business performance.

Indicator/Item	Code	FL	AVE	α	ρ_A
A) Operational Performance (COP)			0.680	0.904	0.909
Perfect order	Perford	0.870			
Lead time	Leadtime	0.746			
Levels of stock of finished products	FGS	0.860			
Levels of raw material stock	RMS	0.829			
Rework rates	Rework	0.735			
Levels of inventory of materials in process	WIP	0.894			
B) Environmental Performance (CEP)			0.596	0.772	0.774
Consumption of hazardous/harmful/toxic materials	CHTM	0.665			
Energy consumption	Energy	0.867			
C) Financial Performance (CFP)			0.704	0.790	0.794
Sales	Sales	0.808			
Market share	MKS	0.853			
Profitability	Profit	0.854			

FL is factor loading; AVE: Average variance extracted; α: Cronbach's Alpha; ρ_A: Dijkstra-Henseler's rho_A.

Table 4. Non-response bias test.

Construct	Sig. Levene's test	Sig. t-test for equality of means
Supplier Feedback (Suppfeed)	0.161	0.058
JIT Delivery by Suppliers (SuppJIT)	0.348	0.187
Supplier Development (Suppdevt)	0.234	0.268
Customer Involvement (Custinv)	0.255	0.126
Pull (Pull)	0.283	0.113
Continuous Flow (Flow)	0.102	0.073
Single Minute Exchange of Dies (SMED)	0.096	0.913
Statistical Process Control (SPC)	0.373	0.143
Human Resource Management (HRM)	0.297	0.944
Total Productive/Preventive Maintenance (TPM)	0.210	0.087
Operational Performance (COP)	0.438	0.505
Environmental Performance (CEP)	0.189	0.748
Financial Performance (CFP)	0.131	0.546

2007; Bardhan, Mithas, and Lin 2009). Following the procedure used by Belhadi, Touriki, and Fezazi (2018), we calculated the minimum necessary sample size using the gamma-exponential method (Kock and Hadaya 2018) to ensure that this sample size is sufficient to analyse our model. We found that the minimum sample size for our model was 146 cases (where the minimum absolute significant path coefficient = 1.97, significant level = 0.05 and required power level = 0.80), which our study meets. Because we are using a soft modelling approach (in this case PLS path-modelling), our sample size of >200 already meets rule of thumb. Therefore, the reliability of the conclusions may be considered robust, with a small standard error. Furthermore, we tested for bias in sampling characteristics as recommended by the recent literature, including non-response bias and common method bias (Latan 2018, Malhotra, Kim, and Patil 2006).

A test for non-response bias, which could potentially emerge from the duration of time elapsed before responding was conducted via an independent sample t-test. The results of the analysis in Table 4 show that there are no significant differences ($p < 0.05$) between early and late respondents in this procedure (Dillman, Smyth, and Christian 2014). This indicates that non-response bias is not a threat to the validity of our results. In addition, we assessed the missing values, as another robust approach to detecting this bias (Groves 2006). Our results found missing values as being missing completely at random (MCAR), which supports the previous t-test result, indicating that our data is free of non-response bias. In addition, we tested for common method bias using the full collinearity VIFs (AFVIF) approach as proposed by Kock (2017). The AFVIF value we obtained was $1.799 < 3.3$, which shows that common method bias is not a potential threat to our results.

3.4. Data analysis

We analysed the data using the PLS path-modelling (PLS-PM) approach. Although there has been much debate about the use of PLS-PM in recent years (Latan and Noonan 2017; Petter 2018), we argue that this approach is more appropriate than covariance-based SEM (CB-SEM) in our case. This is because PLS-PM provides the following advantages in our study. First, PLS-PM is a causal-predictive method, which enables us to test and predict relationships between latent variables simultaneously (Lohmöller 1989; Noonan and Wold 1986; Wold 1982). In this situation, we chose to use Consistent PLS (PLSc) to conduct theory-driven testing of the relationship between lean manufacturing and business performance. Second, PLS-PM enables us to tackle hierarchical component models within large systems with many dimensions and indicators (van Riel et al. 2017; Latan 2018; Lohmöller 1989). Finally, PLS-PM is an approach that is useful for testing non-linear relationships between latent variables. As noted by Schermelleh-Engel et al. (2010), PLS-PM will provide better estimation results in large systems with many dimensions and indicators for non-linear effects compared to other methods, which is in accordance with our model (Dijkstra and Schermelleh-Engel 2014). In this way, the problem of identifying models and Heywood cases in CB-SEM, for example, is avoided. Because non-linear relationships are not straight lines but curves, they can be U-shaped (or inverted U-shaped) or S-shaped (or inverted S-shaped). Hair et al. (2018, p. 67) confirm that these four non-linear patterns can be identified using PLS-PM. In line with this assertion, Kock (2018) argues that PLS-PM can easily identify U- or S-shaped patterns in the relationship between latent variables through Warp 3 algorithms.

Our data analysis procedures were divided into four sub-processes. First, we assessed whether the dimensions of lean manufacturing under study were valid, ensuring that these dimensions could be used for the next stage of analysis. While previous research has examined these dimensions, our research involves different locations and contexts, which present challenges to some lean practices. We used a repeated indicators approach to test the multidimensional construct of lean manufacturing to ensure the dimensions are significant.

Second, after obtaining the significant dimensions of lean manufacturing, we used confirmatory factor analysis (CFA) to verify the convergent and discriminant validity of the constructs, as well as the reliability of internal consistency. Since both constructs in the model are second-order constructs, we followed the guidelines provided by van Riel et al. (2017). We assessed convergent validity by using factor loading and average variance extracted (AVE) values for each dimension. A factor loading value >0.60 indicates that the indicators can be used to measure the constructs, while an AVE value of >0.5 indicates that the indicators can appropriately explain the variance of the constructs (Bandalos 2018; Price 2017). In addition, we assessed the reliability of the constructs using ρ_A and Cronbach's alpha. ρ_A and Cronbach's alpha values >0.70 show that the indicator has good consistency in measuring the constructs within the model (Henseler, Hubona, and Ray 2017; Nunnally and Bernstein 1994). Lastly, we assessed discriminant validity using the HeteroTrait-MonoTrait (HTMT) criterion. This is considered more precise than the Fornell-Larcker criterion, and reduces bias in measurement. An HTMT value of <0.90 between constructs indicates good discriminant validity (Benitez et al. 2019; Latan et al. 2018).

Third, we assessed the structural model by looking at the coefficient of determination (R^2), effect size (f^2), Q^2 predictive relevance and goodness of fit model. Finally, we tested the proposed hypothesis using a 95% confidence interval via a bootstrapping approach. Furthermore, in order to evaluate and determine the pattern of non-linear effects in our model, we followed the guidelines provided by Hair et al. (2018, p. 76), which include: (a) evaluation of the sign and significance of the direct relationship between two variables (in our case, lean manufacturing and business performance); (b) evaluation of the sign and significance of the quadratic effect; (c) assessment of the magnitude of the quadratic effect by looking at effect size; and (d) determination of non-linear pattern based on previous results and assessment of scatter plots.

4. Results

We used the SmartPLS 3 software for data analysis (Ringle et al. 2015), selecting a weighting scheme (path); the maximum number of iterations on the PLS algorithm used was 300. In terms of bootstrapping, we chose a bias-corrected and accelerated (BCa) bootstrap, with a resample number of 10,000 (Streukens and Leroi-Werelds 2016) and 5% significance (one-tailed). The results obtained are described below.

Table 5. Assessment of lean manufacturing dimensions.

Construct	Coef(β)	p values	VIF
Supplier Feedback (Suppfeed)	0.163	0.000	2.099
JIT Delivery by Suppliers (SuppJIT)	0.101	0.000	3.041
Supplier Development (Suppdevt)	0.093	0.000	2.204
Customer Involvement (Custinv)	0.094	0.000	1.799
Pull (Pull)	0.071	0.000	1.656
Continuous Flow (Flow)	0.178	0.000	2.003
Single Minute Exchange of Dies (SMED)	0.154	0.000	2.164
Statistical Process Control (SPC)	0.177	0.000	4.241
Human Resource Management (HRM)	0.165	0.000	3.937
Total Productive/Preventive Maintenance (TPM)	0.149	0.000	2.495

4.1. Assessment of lean manufacturing dimensions

A repeated indicators approach was used to evaluate the adoption of lean practices in the companies studied. This approach allows us to identify the elements of lean practices that make up the second order in the model (Type II: reflective-formative), in order to better explain the relationships between these dimensions and the constructs. In addition, we also tested collinearity among the dimensions of lean manufacturing. The results in Table 5 show that the formation of constructs (lean practices) are valid, where the adoption of these ten dimensions are applied to our sample.

Table 5 indicates that lean practices can be divided into ten key elements, following previous studies. From the results of this analysis, we obtained positive beta values (β) for all dimensions, which were significant at $p < 0.05$. A positive beta value indicates that an increase in one or more dimensions will improve this lean manufacturing practice. In addition, we also obtained results of <5 for the variance inflation factor (VIF) in all dimensions of lean practices, which indicates that there is no correlation between dimensions in this construct. Therefore, the issue of collinearity is not a threat to our results. Furthermore, Figure 2 represents the underlying structure; that is, the adoption of lean practices in the companies studied, which involves the implementation of six internal practices (single minute exchange of dies, human resource management, continuous flow, total

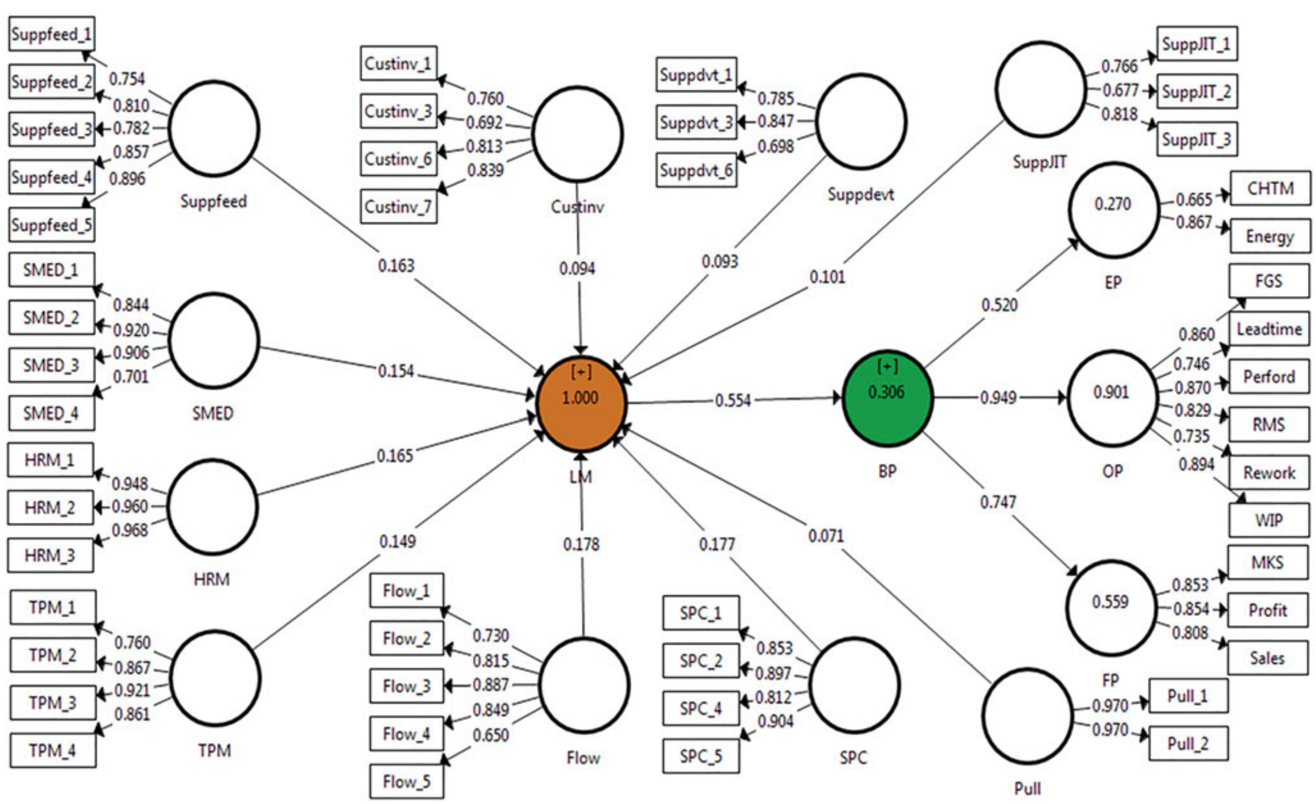

Figure 2. Evaluation of the measurement and structural models.

Table 6. Correlations and discriminant validity results.

Constructs	Mean	S.D	1	2	3	4	5	6	7	8	9	10	11	12	13
Custinv	4.98	1.46	***0.90***	0.665	0.191	0.422	0.337	0.326	0.489	0.275	0.552	0.592	0.396	0.506	0.391
EP	2.40	0.60	0.226	***0.90***	0.537	0.650	0.409	0.694	0.324	0.465	0.333	0.857	0.681	0.543	0.634
FP	2.52	0.78	0.145	0.253	***0.90***	0.423	0.510	0.628	0.396	0.430	0.489	0.518	0.370	0.108	0.427
Flow	4.36	1.60	0.344	0.353	0.353	***0.90***	0.648	0.549	0.285	0.656	0.675	0.795	0.660	0.516	0.246
HRM	3.20	1.68	0.292	0.243	0.445	0.581	***0.90***	0.394	0.398	0.715	0.809	0.852	0.729	0.463	0.447
OP	2.89	0.72	0.280	0.403	0.535	0.485	0.366	***0.90***	0.335	0.411	0.428	0.524	0.496	0.434	0.824
Pull	4.21	1.87	0.419	0.062	0.338	0.258	0.377	0.310	***0.90***	0.303	0.628	0.394	0.165	0.202	0.376
SMED	3.41	1.56	0.223	0.249	0.361	0.570	0.650	0.372	0.275	***0.90***	0.647	0.840	0.668	0.476	0.415
SPC	3.31	1.88	0.458	0.173	0.412	0.588	0.749	0.389	0.575	0.580	***0.90***	0.788	0.565	0.401	0.416
SuppJIT	2.70	1.73	0.424	0.426	0.353	0.579	0.747	0.388	0.299	0.614	0.588	***0.90***	0.833	0.694	0.782
Suppdevt	3.92	1.77	0.257	0.323	0.287	0.512	0.595	0.396	0.136	0.541	0.452	0.626	***0.90***	0.772	0.696
Suppfeed	4.87	1.38	0.442	0.311	0.065	0.460	0.435	0.388	0.162	0.442	0.372	0.538	0.601	***0.90***	0.568
TPM	4.55	1.66	0.520	0.184	0.198	0.393	0.581	0.335	0.364	0.377	0.679	0.530	0.443	0.521	***0.90***

Below the diagonal elements are the correlations between the construct values. Above the diagonal elements are the HTMT values.

Table 7. Structural model results.

Constructs	R^2	Adj. R^2	f^2	Q^2	AFVIF
Lean manufacturing (LM)	–	–	0.442	–	
Business Performance (BM)	0.306	0.303	–	0.305	1.799
LM × LM→BP	0.378	0.372	0.117	0.241	2.643

Table 8. Relationships between variables (direct and quadratic effects).

Structural path	Coef(β)	S.D	p values	95% BCa CI	Conclusion
LM→BP	0.554	0.052	0.000**	(0.631, 0.003)**	H1 supported
LM × LM→BP	0.233	0.067	0.000**	(0.285, 0.044)*	H1 supported

**, *statistically significant at the 1 percent and 5 percent levels, respectively.

production/preventive maintenance, pulled processes and statistical quality control), and four external practices (supplier feedback, supplier development, JIT by supplier and customer involvement).

4.2. Assessment of measurement model

To assess the measurement model in the second step, we examined the values of loading factors and AVE for convergent validity. The results of our analysis in Table 2 confirm that all indicator dimensions for the lean manufacturing practices met convergent validity and reliability requirements, indicating that these indicators are adequate in explaining the constructs and that they have consistency.

We also tested the convergent validity and reliability of internal consistency for the BP variable. The results of this analysis, shown in Table 3, convey similar conclusions to the previous variable.

We also assessed discriminant validity using the HeteroTrait-MonoTrait (HTMT) ratio. The HTMT value is required to be $<$0.90 for all constructs in the model. From the results of this analysis, shown in Table 6, all HTMT values were found to meet this threshold.

4.3. Structural model assessment

The third step, after confirming all the indicators of the variables as reliable and valid, was to assess the results of the structural model and test the hypothesis. Since the PLS-PM algorithms use the iteration method following multiple regression series, path coefficient interpretation in PLS-PM is equal to the standardisation of regression coefficients. We used the same measure in multiple regression to assess collinearity between constructs in the model. Variance inflation factor (VIF) values are recommended to be $<$3.3, with $<$5 still being acceptable for all variable dimensions in the model (Field 2016). The results of our analysis show that there is no collinearity problem interfering with the results. Furthermore, we evaluated the structural model by looking at the coefficient of determination (R^2 or adjusted R^2), f^2 and Q^2. The coefficient of determination measures the predictive power of the model, and this coefficient represents the amount of variance in the endogenous variable that can be explained by all exogenous variables. A coefficient of determination above 0.20 can be considered high in some disciplines, but values between 0.25 and 0.50 are generally considered good.

In Table 7, it can be seen that the values of R^2 and adjusted R^2 produced are good, ranging from 0.303–0.306. Additionally, the effect size value generated by LM in the model is in the large category: $0.442 > 0.35$ (Cohen 1988). The Q^2 predictive relevance value generated excellent values for the endogenous variables ($0.305 > 0$), indicating that the model has predictive relevance (Wold 1982). The goodness of fit value generated through the standardised root mean squared residual (SRMR) is equal to $0.074 < 0.08$, which indicates that our model fits the empirical data. Hair et al. (2017) state that, when using PLS-PM, it is important to recognise that the term 'fit' has a different meaning than in the context of CB-SEM. Thus, the threshold is likely too low for PLS-PM.

4.4. Hypothesis testing

In the last step, we tested the quadratic effect hypothesis. We produced the non-linear effects with quadratic functions, which are available in SmartPLS with an orthogonalization approach (Hair et al. 2018; Latan et al. 2018), an approach which can minimise the problem of collinearity arising from the interaction of two variables. The results of our analysis are presented in Table 8.

In Table 8, we can see that the relationship LM→BP was positive and significant, with $\beta = 0.554$, and significant at $p < 0.000$ ($p < 0.01$ at 95% BCa CI). This means that the first assumption in testing the quadratic effect was fulfilled. The same results have been obtained in other studies (e.g., Godinho Filho, Ganga, and Gunasekaran 2016; Chavez et al.

2015; Alcaraz et al. 2014; Fullerton, Kennedy, and Widener 2014). This shows a positive effect on business performance, including the operational, financial and environmental performance of those companies that implemented lean practices. In addition, we found a non-linear relationship in $LM \times LM \rightarrow BP$, with a coefficient value (β) of 0.233 and significant at $p = 0.000$ ($p < 0.05$ at 95% BCa CI). The positive and significant coefficient value of the $LM \times LM \rightarrow BP$ relationship satisfies the second assumption for testing the quadratic effect (Hair et al. 2018). This means that Hypothesis 1 is supported. We also evaluated the value of f^2 to indicate whether the non-linear relationship is relevant. We calculated the quadratic f^2 value using the following formula:

$$f^2 = \frac{R^2 \text{ model with quadratic effect} - R^2 \text{ model without quadratic effect}}{1 - R^2 \text{ model with quadratic effect}} = \frac{0.378 - 0.306}{1 - 0.378} = 0.1158$$

From the results of the above calculations, we obtained a value of f^2 at $0.1158 > 0.025$ which, according to Hair et al. (2018), is included in the large category. This means that the quadratic effect on the relationship between LM and BP is more relevant and stronger than the linear effect, according to which effect the relationship between the two is not a straight line, but is, rather, curved. When the pattern of relationships between two variables is non-linear, the use of linear assumptions becomes biased and inconsistent, as found in many previous studies. Jaccard and Jacoby (2010) have noted that one dubious reason for ignoring non-linear relationships is that many families of statistical techniques assume linear relationships. As expressed by Kock (2018, p. 101), "the apparent simplicity of strictly linear modelling, or linear estimations of possibly nonlinear relationships, is nothing but a mirage." Therefore, the relationship between LM and BP follows a non-linear effect, and thus fulfils our third assumption.

Finally, to determine the pattern of the quadratic effect, we evaluated scatter plots in order to ascertain whether this relationship follows an S- or a U-shaped pattern. This evaluation was performed using WarpPLS 6.0 software with specific settings for the Warp 3 algorithms. The process of detecting outliers from data is done before estimating the model parameters (in this case - the third stage of WarpPLS step). Our results show that there are no outliers in our case with the standardised value < 2.58. On other hand, following Kock (2018), outliers do not affect the calculation of estimated parameters in PLS-PM, because this technique is based on a resampling method (e.g., bootstrapping). In addition, eliminating outliers can be considered a questionable research practice (QRP), which has been highlighted recently in top-tier journals (e.g., Banks et al. 2016; O'Boyle, Banks, and Gonzalez-Mulé 2017).

We use the latent variables score of the indicators to estimate and obtain scatter plot from this non-linear relationship. This approach is considered more appropriate to get the best-fitting curve. Given that the two variables are in the second-order form, this is the most appropriate approach to test the quadratic effect. The scatter plot results from the use of this method, as shown in Figure 3, support the assertion that the relationship between LM and BP follows an S-curve pattern, in accordance with our hypothesis. Kock (2018) argues that the S-curve pattern shows a non-linear effect which follows a curved line from the lower left to the top right. An S-curve can be seen as a combination of two connected U-curves, one of which is inverted. Since S-shaped functions can take sigmoid (logistic), hyperbolic sine or hyperbolic tangent forms, an S-curve can sometimes be difficult to identify and interpret. Figure 4 shows the results of our PLS-PM for quadratic effect.

4.5. Additional testing

We also tested for endogeneity bias, which posed another threat to our results. Endogeneity testing is intended to maintain the robustness of the analytical results. Endogeneity bias generally arises from the selection of non-random samples, in which there may be bidirectional relationships between variables, or as a result of the effect of omitted variables (Ketokivi and McIntosh 2017; Zaefarian et al. 2017). Endogeneity bias will cause the PLS algorithm to be distorted and thus threaten the validity of the results. To control for this, we used the Heckman test to obtain propensity scores in assessing endogeneity with the help of the Stata software. We found that the significance obtained from both models remains the same (see Table 9), which means that endogeneity bias is not a potential threat to our results.

5. Discussion

The confirmation of our research hypothesis means that: (a) the relationship between the adoption of lean manufacturing practices and business performance is significant; and (b) this relationship follows a non-linear and S-shaped pattern.

Building on the confirmation of our research hypothesis, it can be asserted that: (a) the adoption of lean manufacturing practices enables organisations to achieve significant and simultaneous performance improvements in terms of operational, financial and environmental measures; and (b) the S-shaped form of the relationship between lean manufacturing and business performance implies that the positive and significant relationship between lean practices and business performance will continue until a point at which the adoption of further practices will not bring further positive changes in business performance. In sum, organisations may be able to significantly improve business performance after beginning to adopt some lean practices, until a saturation point is reached.

As a consequence of these findings, in order to wisely allocate resources for improving the adoption of lean practices, managers need to be aware that there are inertial and saturation points in the adoption of lean manufacturing practices. For instance, a bundle of lean practices (e.g., continuous flow, statistical process control, human resources

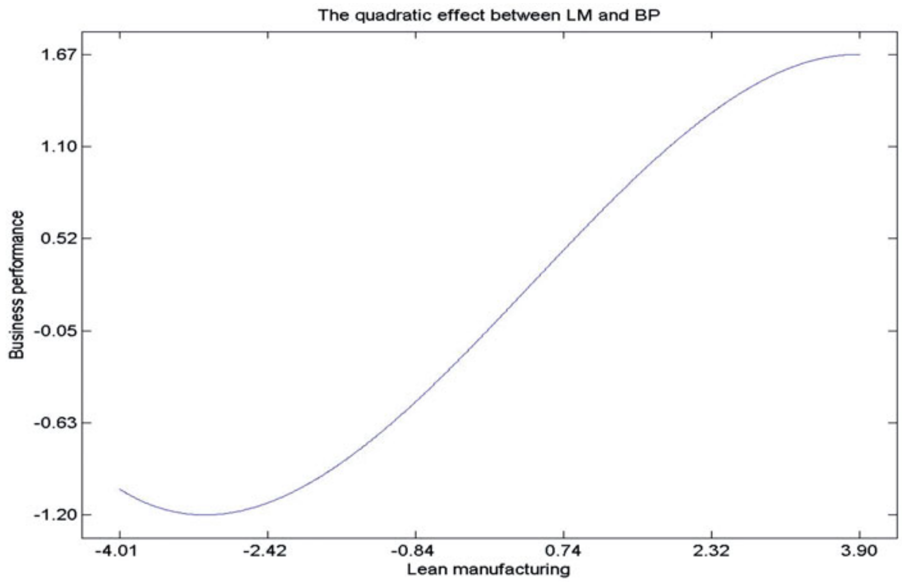

Figure 3. Scatter plots the quadratic effect between LM and BP.

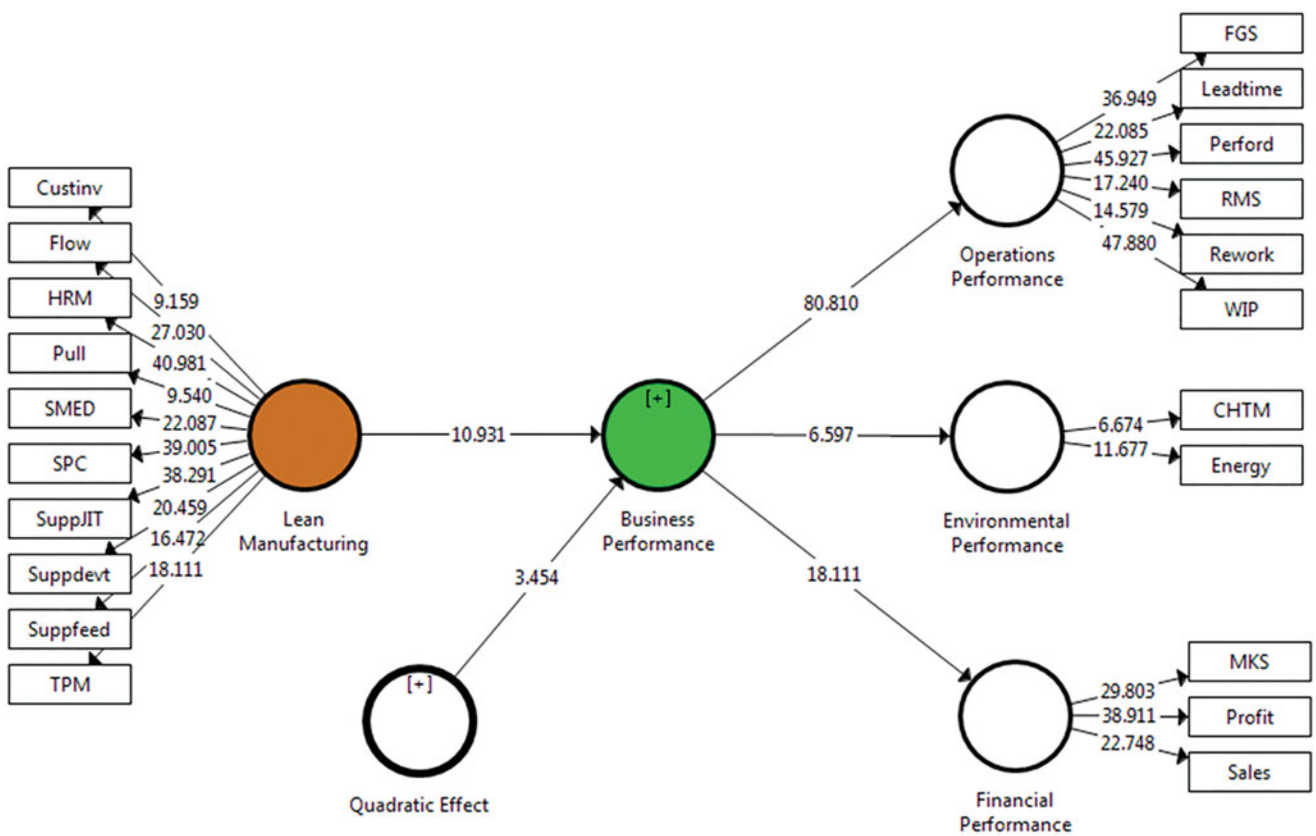

Figure 4. Testing of hypothesis.

Table 9. Endogeneity test.

Structural path	Coef(β)	S.D	p values	z	Conclusion
LM→BP	0.486	0.067	0.006**	4.14*	Not different
LM × LM→BP	0.214	0.053	0.027**	2.46*	Not different

**, *statistically significant at the 1 percent and 5 percent levels, respectively.

management) should be prioritised and adopted first, rather than another bundle of practices (e.g., supplier and client development), in order to help firms produce positive effects on business performance and overcome the inertial point. However, investing continuously in the first bundle of lean practices alone would not be worthwhile, because those practices would at some point (the saturation point) cease to have a significant impact on improvements on business performance, due to the S-shaped effect.

In conclusion, organisations can achieve significant improvements in business performance through the adoption of lean manufacturing practices, and for this purpose organisations do not necessarily need to adopt a wide range of lean practices from the initial stages of their lean implementation journey, but rather to identify those practices which act as floor and ceiling points. Netland and Ferdows (2016) have highlighted that the time of implementation of lean practices is not enough of a factor alone to assist organisations in improving operational performance; nevertheless, depth and breadth of implementation of lean practices may be significant.

This article contributes to the literature on lean manufacturing in three ways. First, it moves forward the debate on the relationship between lean practices and business performance, providing strong support for the S-shaped curve, which Netland and Ferdows (2016) identified by means of a longitudinal study; as a consequence of the identification of this pattern, it is possible to guide managers towards effective decision-making regarding investment in lean practices, and organisations should invest in those practices that act as floor points, and be cautious of the saturation points which enhance lean practices. Second, it simultaneously tests operational, financial and environmental performance as a result of the adoption of lean manufacturing practices, filling a gap, as environmental performance has so far been relatively neglected in this relationship (Danese, Manfè, and Romano 2018; Garza-Reyes et al. 2018). As a result of our simultaneous testing, the breadth of effects of lean practices on business performance is further understood. Third, it analyzes the theme of lean manufacturing based on an established theoretical perspective – contingency theory –as recommended by Danese, Manfè, and Romano (2018), thus enabling the lean manufacturing field to advance theoretically while also testing and validating Netland and Ferdows (2016)'s work. Netland and Ferdows (2016, page 1118) state that 'S-curve theory can be validated in settings different from ours'; accordingly, this article has confirmed that the S-shaped curve theory is able to explain the relationship between the adoption of lean manufacturing and business performance, even under non-ideal local operating conditions.

6. Conclusions

6.1. Implications for theory

This article contributes to lean manufacturing theory by testing whether the relationship between the adoption of lean manufacturing practices and business performance follows a non-linear and S-shaped pattern. Netland and Ferdows (2016) previously showed such a relationship in the company Volvo. Our study tests their research, providing validation of the S-shaped curve using data from 233 Brazilian companies situated in a region with different contextual variables. Furthermore, the article confirms the relevance of understanding contextual variables when analysing the adoption of lean manufacturing practices.

6.2. Implications for managers

This article provides an inertial and saturation perspective on the adoption of lean manufacturing practices, which managers need to be aware of in order to prudently allocate resources for improving the adoption of lean practices. Organisations should invest in those practices that act as floor points and be cautious about reaching the saturation point of enhancing lean practices. Therefore, managers should expect that initial investments in lean manufacturing practices will take time to pay off in terms of improvements on firms performance, due to the S-shaped effect. In addition, organisations do not necessarily need to adopt a wide range of lean practices from the initial stages of a lean implementation journey, because a wide range of lean practices will not proportionally result in better business performance, due to the S-shaped effect.

Managers may be able to further explore the synergies between lean and green approaches, because the adoption of lean practices enables organisations to simultaneously improve operational, financial and environmental performance.

6.3. Study limitations and guidelines for future research

Future avenues of research within the theme of lean practices and business performance should address the confirmation of the non-linear S-shaped pattern, applying other contextual variables as boundary conditions. Future research may also explore and propose mechanisms to assist managers in identifying floor (inertial) and ceiling (saturation) points in the adoption of lean practices.

There are inevitably certain limitations inherent in this study. The first is the lack of longitudinal data collection. This article is based on a survey methodology, so it was not possible to analyse the relationship between lean practices and performance over the period of the adoption of lean practices within the sample studied, in order to observe likely changes in such a relationship. Another limitation is related to the business sectors studied – the manufacturing industry. This presents an opportunity for future research to consider the commerce and service sectors, thus leading to the generalisation of our results. Another limitation concerns the environmental performance measure evaluated by the research instrument used in this study. Incorporating a wider range of measures, or correlation with environmental performance standards such as the Environmental Management System (EMS) recommended by the International Organisation for Standardisation (ISO 14001), would address this limitation. A final limitation is related to sample size, due to difficulties in obtaining valid and completed questionnaires in this research. Future studies may wish to use sample including companies from other regions of Brazil and from other countries.

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Informed consent

Informed consent was obtained from all individual participants included in the study.

Disclosure statement

The authors declare that they have no conflict of interest.

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Appendix A

Lean practices studied

Lean practice	Lean practice Lean operating element	Code
Supplier feedback (Suppfeed)	We frequently are in close contact with our suppliers	Suppfeed_1
	Our suppliers frequently visit our plants	Suppfeed_2
	We frequently visit our supplier's plants	Suppfeed_3
	We give our suppliers feedback on quality and delivery performance	Suppfeed_4
	We strive to establish long-term relationship with our suppliers	Suppfeed_5
JIT delivery by suppliers (SuppJIT)	Suppliers are directly involved in the new product development process	SuppJIT_1
	Our key suppliers deliver to plant or JIT basis	SuppJIT_2
	We have a formal supplier certification programme	SuppJIT_3
Supplier development (Suppdevt)	Our suppliers are contractually committed to annual cost reductions	Suppdevt_1
	Our key suppliers are located in close proximity to our plants	Suppdevt_2
	We have corporate level communication on important issues with key suppliers	Suppdevt_3
	We take active steps to reduce the number of suppliers in each category	Suppdevt_4
	Our key suppliers manage our inventory	Suppdevt_5
	We evaluate suppliers on the basis of total cost and not per unit price	Suppdevt_6
Customer involvement (Custinv)	We frequently are in close contact with our customer	Custinv_1
	Our customers frequently visit our plants	Custinv_2
	Our customers give us feedback on quality and delivery performance	Custinv_3
	Our customers are actively involved in current and future product offerings	Custinv_4
	Our customers are directly involved in current and future product offerings	Custinv_5
	Our customers frequently share current and future demand information with marketing department	Custinv_6
	We regularly conduct customer satisfaction surveys	Custinv_7
Pull (Pull)	Production is "pulled" by the shipment of finished goods	Pull_1
	Production at stations is "pulled" by the current demand of the next station	Pull_2
	We use a kanban, squares, or containers of signals for production control	Pull_3
Continuous flow (Flow)	Products are classified into groups with similar processing requirements	Flow_1
	Products are classified into groups with similar routeing requirements	Flow_2
	Equipment is grouped to produce a continuous flow of families of products	Flow_3
	Families of products determine our factory layout	Flow_4
	Pace of production is directly linked with the rate on customer demand	Flow_5
Single minute exchange of dies (SMED)	Our employees practices setups to reduce the time required	SMED_1
	We are working to lower setup times in our plant	SMED_2
	We have low setup times of equipment in our plant	SMED_3
	Low supply lead times allow responding quickly to customer requests	SMED_4
Statistical process control (SPC)	Large numbers of equipment/process on shop floor are currently under SPC	SPC_1
	Extensive use of statistical techniques to reduce process variance	SPC_2
	Charts showing defects rates are used as tools on the shop floor	SPC_3
	We use fishbone type diagrams to identify causes of quality problems	SPC_4
	We conduct process capability studies before launching a new product	SPC_5
Human resource management (HRM)	Shop-floor employees are key to problem solving teams	HRM_1
	Shop-floor employees drive suggestion programmes	HRM_2
	Shop-floor employees lead product/process improvement efforts	HRM_3
Total productive/preventive maintenance (TPM)	We dedicate a portion of everyday to planned equipment maintenance related activities	TPM_1
	We maintain al our equipment regularly	TPM_2
	We maintain excellent records of all equipment maintenance related activities	TPM_3
	We post equipment maintenance records on shop floor for active sharing with employees	TPM_4

Source: Shah and Ward (2007); Godinho Filho, Ganga, and Gunasekaran (2016).

Appendix B

Performance indicators

Indicator	Concordance Scale						
Sales	1	2	3	4	5	6	7
Market share	1	2	3	4	5	6	7
Lead time	1	2	3	4	5	6	7
Perfect order (right product, delivered in the right quantity, on the right date, free of defects and with the correct documentation)	1	2	3	4	5	6	7
Levels of stocks of finished products	1	2	3	4	5	6	7
Levels of raw material stocks	1	2	3	4	5	6	7
Levels of inventory of materials in process	1	2	3	4	5	6	7
Rework rates	1	2	3	4	5	6	7
Profitability	1	2	3	4	5	6	7
Consumption of hazardous/harmful/toxic materials	1	2	3	4	5	6	7
Energy consumption	1	2	3	4	5	6	7